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European Commission, Joint Research Centre

January 2015

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Abstract

We revisit a central task of the extant liquidity literature, which is to identify effective measures of liquidity. We critically assess the influential practice of identifying the best liquidity measures based on monthly correlations by comparing and contrasting correlations between monthly and daily averages of high-frequency benchmarks and low-frequency proxies of liquidity, as well as by examining the coherences between such measures. Furthermore, we propose MIDAS regressions as a way of investigating the bilateral relationships between benchmarks and proxies without averaging out potentially valuable high-frequency information, as is common practice. We conclude that the empirical correlations between benchmarks and proxies in general become weaker as the frequency over which these relationships are examined becomes higher, and that standard practices may lead to misleading conclusions. One implication of our results is that any liquidity measure needs to be assessed against the relevant timeframe for conversion into cash.

JEL Classification: C58, G12, G28

Keywords: Liquidity; Market Microstructure; High-Frequency Data; Sovereign Bonds; MIDAS; Coherence.

* We thank participants at the 1st Conference on Recent Developments in Financial Econometrics and Applications, at the 20th International Conference in Computing in Economics and Finance, as well as Alessandro Fontana, Andrea Pagano and Beatrice Pataracchia for useful comments and suggestions. Any errors are our own responsibility. The content of this presentation does not reflect the official opinion of the European Commission. Responsibility for the information and views expressed in the article lies entirely with the author(s).

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1. Introduction

Liquidity measures have received renewed interest following the financial crisis. In particular, in December 2010, the Basel Committee on Banking Supervision (BCBS) announced the introduction of a Liquidity Coverage Ratio (LCR) into the new Basel III regulatory framework. The main objective of the LCR is to enhance the short-term resilience of banks in the event of a severe liquidity stress scenario. The LCR requires banks to hold sufficient unencumbered high-quality liquid assets (HQLA) to meet the bank's liquidity needs for 30 calendar days in a significant stress scenario. In case of 'financial instability' banks are allowed to use their stock of HQLA[1].

A gradual phase-in schedule has been proposed to ensure that the LCR can be introduced without disruption to the orderly strengthening of banking systems or the ongoing financing of economic activity. Specifically, the Basel Committee on Banking Supervision (2013) suggests phasing in the LCR starting January 2015, gradually increasing from 60% to 100% by 2019. Furthermore, national authorities have taken up the task of adjusting Basel III rules on the LCR to better reflect national and regional specificities. For example, US regulators adopted on 10 October 2014 a final rule that implements the LCR. They broadened some categories of debt and equity securities that can be counted as high quality liquid assets and clarified that only banks with

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[1] The LCR rules apply to about 10% of banks' balance sheets. The European Banking Authority (2013a) reported on an impact assessment of the LCR (using end-of-2012 balance sheets of 357 EU banks from 21 EU countries with total assets of EUR 33,000 billion) that the aggregate stock of liquid assets amounted to EUR 3,739 billion on an LCR denominator of EUR 3,251 billion http://europa.eu/rapid/press-release_MEMO-14-579_en.htm . Globally it concerns approximately $ 15,000 billion of bank assets.

assets exceeding $250 billion would be considered for the full set of LCR rules. On the same day, the European Commission presented its detailed rules for the LCR application in Europe, with a broader coverage of banks including smaller banks and broadening the eligible assets in particular as regards covered bonds. The European Commission has been tasked by co-legislators to specify the detailed general liquidity coverage requirements, including the HQLA. The European Banking Authority (EBA) advises the European Commission (EC) and analyses the relative liquidity of asset classes for the purpose of determining which assets should be eligible for inclusion in banks' liquidity buffers.

One implication of the above is that the need for good liquidity measures is as high in the context of the current regulatory environment as it has ever been. Liquidity of an asset in general refers to how quickly and cheaply it can be converted into cash, or it is "*the degree to which an asset or security can quickly be bought or sold in the market without affecting the asset's price.*" [2] There is a large literature on liquidity measures, attempting to translate the general definitions of liquidity into concrete and quantitative concepts based on market data.[3] There is however no consensus on a common best measure based on available information. One issue that has been recognized in this literature as being key is the availability and frequency of market data that is used for calculating liquidity measures. Another key issue that has not received as much attention though, is that liquidity depends on the relevant timeframe and the stress scenario considered. "Quickly" in the above definition can mean within seconds, within hours, within days, weeks or even a month, depending on the context.

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[2] This definition is quite standard in the literature. See, for instance, Earne and Sherk (2013).

[3] For example Goyenko et al. (2009) provide an overview of measures.

The existing literature classifies liquidity measures according to two dimensions: (i) Trade-based measures (e.g. Amihud price impact, trading volume) versus order-based measures (e.g. quoted bid-ask spread, percent quoted spread); and (ii) intra-day benchmarks versus proxies (on the basis of lower-frequency (daily) data, daily, monthly, quarterly or annual liquidity proxies are developed). High-frequency liquidity benchmarks are often viewed as being more accurate and complete measures of liquidity. However, as high-frequency data is expensive, not always available, and difficult to handle due to size and irregular-frequency issues, low-cost liquidity proxies are often preferred for many purposes in academic and policy circles.

Recent literature improves upon such common practices by attempting instead to identify the best daily proxies using time-series and cross-sectional correlations of proxies and benchmarks. See, *inter alia*, Goyenko et al. (2009), Fong et al. (2011), and Marshall et al. (2013) on stocks and Schesstag et al. (2013) on U.S. corporate bonds. However, correlating benchmarks and proxies faces a double challenge: both mixed frequencies (high and low) and irregularly-spaced variables. These problems are dealt with by resorting to the aggregation of both proxies and benchmarks to monthly or quarterly averages. Based on such aggregation and correlation exercises, this literature typically provides substantial evidence that empirically justify the use of proxies. For instance, as Goyenko et al. (2009) state, "*the evidence is overwhelming that both monthly and annual low-frequency measures capture high-frequency measures of transaction costs. Indeed in many applications the correlations are high and the mean square error low enough that the effort of using high-frequency measures is simply not worth the cost.*" A similar approach that focuses on low-frequency statistics of liquidity measures seems to be influential with policy authorities which are currently tasked with implementing the Basel III/LCR regulatory framework; for instance, see EBA (2013b). [4]

In this study, we question this influential practice of identifying the best liquidity measures by correlating monthly (or even quarterly or cross-sectional) aggregates of benchmarks and proxies. A key concern associated with averaging the liquidity benchmarks at a low frequency is that such averaging removes the extra information and dynamics that come at the higher frequency.[5] This is a central advantage of the high-frequency data and a reason why the literature typically considers benchmarks to be better than proxies. For instance, the practice of using monthly averages may fail to reflect the ability (or lack thereof) of investors to transact immediately and the cost associated with this, which is the essence of liquidity. In the unfolding policy context of LCR/Basel III this concern is very relevant. In a liquidity stress scenario, banks need to be able to sell assets within days to cover liquidity needs. Short-term, high-frequency dynamics of liquidity are thus important and ignoring those could lead to misleading assessments and conclusions.

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[4] As discussed earlier, the European Commission and the European Banking Authority are tasked with translating the heuristic notion of liquidity, and some general criteria and guidance for classifying liquid assets, into a concrete classification framework for assets classes of high and extremely high liquidity based on objective criteria, which could serve as a basis for the implementation of the LCR in the EU. And, according to EBA (2013b), "*Monthly price impact measures are defined by taking the monthly median of the daily measure for each asset. When making cross asset class analysis, the average value across the relevant assets of the monthly medians has been taken*."

[5] For volatility of equity returns (which is strongly related to market liquidity), Dobrev and Szerzen (2010) find that model inference without high-frequency data takes insufficient account of skewness and kurtosis, underestimating risk during bad times and overestimating risk during good times.

We further investigate the above issues through a series of exercises. First, we compute and contrast daily and monthly correlations for various proxies and benchmarks, for a series of sovereign bonds[6] coming from both "core" and "periphery" EU countries. Next, we attempt to get a more complete picture of such frequency issues by considering the frequency domain, and specifically by looking at the coherences between benchmarks and proxies. Finally, we move beyond even daily correlations and towards capturing intra-day dynamics. In particular, rather than aggregating the high-frequency benchmarks to daily or monthly averages, we employ underlying intra-day measures directly in Mixed Data Sampling (MIDAS) regressions, which is a parsimonious regression-based approach for handling models where the dependent variable is of a different (lower) frequency than that of the explanatory variables. Our findings provide empirical support to concerns such as the ones outlined above; for example, correlations between benchmarks and proxies tend to become substantially weaker as the frequency over which these relationships are examined becomes higher.

The remainder of this paper is structured as follows: Section 2 discusses the liquidity measures and the data we use, Section 3 provides the details of our methodology and results, as well as the policy implications of our results, and Section 4 concludes.

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[6] Our focus on sovereign bonds reflects the currently unfolding regulatory environment of Basel III with its emphasis on sovereign debt for the calibration of the LCR numerator (e.g., see Basel Committee on Banking Supervision (2013)).

2. Liquidity measures and data

We use sovereign bond data. Globally, sovereign debt securities make up between 15 - 20% of the total stock of debt and equity outstanding, and are the second category of market assets behind equities. Sovereign bonds are considered as assets of extremely high liquidity and credit quality in the LCR framework (EBA (2013b)). No haircut is applied to their HQLA weight and they may make up 100% of the LCR (no ceiling). The importance of sovereign bonds in bank asset portfolios is illustrated by the sovereign bond holdings of more than EUR 2.7 trillion that the 64 banks covered by the 2013 European Banking Association stress tests reported in their December 2012 balance sheets. This reflects a share of their total assets on average in excess of 10%.

We obtain our sovereign bond market data by combining two MTS (Mercato Telematico dei Titoli di Stato) datasets: a low-frequency daily and a high-frequency intra-day dataset. MTS is the major wholesale market[7] for fixed income securities in Europe in which all major international financial institutions participate. EuroMTS is the reference pan-European electronic market for Euro benchmark bonds, or bonds with an outstanding value of at least €5 billion. The MTS platform liquidity is guaranteed by quoting requirements for market makers with minimum quote sizes varying between EUR 2.5 million and EUR 10 million. Participants can join the MTS

[7] Pelizzon et al. (2013) report for instance that the MTS market share of interdealer transactions in Italian sovereign bonds ranges between 80 and 85%.

markets either as a market maker or market taker and are subject to minimum capital requirements, as well as trading requirements. [8]

We consider 4 sovereigns: Germany, Finland, Italy and Portugal. We choose these four to have a mix of large and small markets, with high and lower credit quality. The dataset covers two calendar years: 2011-2012. This time period reflects a wide range of market circumstances and covers the Eurozone sovereign debt crisis. Our sample is composed of 95 unique bond codes (ISINs): 46 for Italy, 29 for Germany, 8 for Finland and 12 for Portugal.

The low frequency MTS daily data contains daily traded volume, average daily bid-ask spread, closing price, closing mid-quote, yield to maturity, modified duration, convexity, bond type, issue date, issuer name, maturity date, coupon. The high-frequency data provides for every trade the size, price, millisecond time stamps, direction of the trade (buy or sell) and yield. It also provides the pricing of the order book with three levels of depth throughout the day, resulting in a very large dataset with up to 1000 quotes per bond per day on average for the most traded bonds. For example, in our sample the number of quotes amounts to more than 25 million across the four countries, the total number of trades is more than 100,000 and the total traded volume across the sample considered is more than EUR 500 billion. The trading activity is unevenly

[8] For the EuroMTS market, market makers need to have a net worth of at least EUR 375 million. All market makers must commit to providing two-way quotes for the securities assigned to them and display them for all bonds at least five hours per day. For sovereign bonds, proposals must be formulated for a minimum quantity equal to EUR 10 million, EUR 5 million, EUR 2.5 million depending on the MTS market and instrument (bucket of maturity, liquid/ benchmark security). Odd lots of EUR 0.5 million and multiples up to EUR 2.5 million with manual matching are subject to market makers' acceptance.

spread across bonds, with trading activity limited to a few trades per month in a sizable share of bonds.

To illustrate our concerns regarding influential practices of identifying the best liquidity proxies, we need to select a number of commonly used proxies and benchmarks to contrast their daily and monthly correlations, and for the rest of our analysis. The literature has produced a wide variety of alternative proxies and benchmarks for measuring liquidity.[9] There is little agreement on the best measures to use. Each captures specific aspects of liquidity. Some of the popular low-frequency proxies can only be calculated for longer periods based on daily data (e.g. Roll (1984), zeros (number of zero return days in a given period), Kyle price impact (requiring regression analysis)). As we assess accuracy of actual daily proxies compared to the high-frequency intraday benchmarks, we identify proxies that can be calculated on a daily basis using daily data. From the remaining proxies we consider: (i) Amihud price impact[10]: $Amihud = \frac{abs(R_{i,t})}{Volume_t}$ [11] (ii) number of trades; and (iii) traded volume. As benchmarks, we use: (i) the intraday quoted bid-

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[9] Fong et al. (2011) provide an overview of the most used proxies and benchmarks.

[10] Several studies (e.g. Fong et al. (2011), Schestag et al. (2013), Goyenko et al. (2006) and EBA (2013b)) find that the Amihud measure is a superior price-impact proxy when compared to other liquidity measures. It is the absolute value of the daily return on the asset, divided by the traded volume. $Amihud = Abs(R_{i,t}/Volume_t)$.

[11] We calculate the return (R) in the Amihud price impact measure using the previous day's closing mid-quote rather than the last traded price. This has advantages in our context (a market with low trading frequency): the conventional Amihud measure requires two consecutive trading days to be calculated. First, as we may not always have two consecutive trading days for the less liquid bonds, we would lose many observations with the conventional measure. Second, as the trading is infrequent, the return measure based on previous day trading would pick up much more noise and news that occurred between the two trades than an end-of-day mid-quote.

ask spreads; (ii) the quote slope: $Quoteslope = \frac{P_{ask}(t) - P_{bid}(t)}{\ln(q_{ask}(t)) + \ln(q_{bid}(t))}$; and (iii) the number of quotes per hour.

2.1. Cleaning the data

Due to the very big data files reflecting all trades and quotes over a two-year period, construction of the liquidity measures required substantial efforts. As the low- and high-frequency data files provided by MTS contain raw information, several actions needed to be taken in order to clean the data before calculating the proxies and the benchmarks discussed above. As previously noted, the Amihud price-impact measure is calculated using the "mid price" from the previous day. As reported in the MTS documentation file the mid price (i.e. the average of the best bid and ask quote) for each ISIN is collected at or before 5pm. However, if the spread is beyond three hundred basis points the bid ask is considered as non-tradable and is not reported by MTS. For those cases we calculate the mid price manually using the high-frequency data at 5pm. In the case where no quotes are reported at 5pm the last mid price of the book throughout that day is used (for example by using the bid-ask at 4pm). For the calculation of the proxies, the MTS low-frequency files are also checked for double recording of dates and double records are deleted as that would lead to a miscalculation of the low frequency measures. Another issue regarding the two different MTS source files (i.e. at low and high frequency) is the treatment of cases where for some ISINs, only low-frequency data are reported and no data are available at the high-frequency level. Those dates are excluded from our calculations. High-frequency bid-ask quotes are reported with millisecond timestamps and quotes are updated on average every minute. However on some dates, for several ISINs across the four countries, no quotes have been reported between 9am to 12pm. For those cases the first quote in the order book after 12pm is used to replace the 9am to 12pm quotes. These cleaning exercises concern 182 “ISIN-days” out of a total of more than 44000 “ISIN-days”. In some instances it is also observed that, within the day, no quotes are placed in the order book for a time longer than an hour. Since for our purposes hourly bid-ask spread (BAS) averages are employed for the analysis, if that hour is missing the last bid-ask spread from the previous hour is used.

2.2. Describing the measures

Table 1 presents summary statistics on the liquidity measures per ISIN per day. The table illustrates the liquidity profile of the markets we consider, with infrequent trades and frequent quoting at tight spreads by market makers. The mean traded volume per ISIN ranges across countries from slightly less than EUR 1 million for Portugal to EUR 20 million for Italy. The rather low mean reflects many days without trades. The number of trades per day per ISIN ranges from a mean of 0.15 for Portugal to 3.98 for Italy. The distribution of the daily number of trades is skewed as reflected by the 0 median number of trades for all except Italy (for which it is 1). In each of the 4 countries, the daily volume for individual ISINs can be as high as several hundreds of millions of euros. The liquidity of the market is suggested by frequent quoting, varying between 45 and 76 per hour on average across all ISINs over the two years.[12] Median bid-ask spreads range from 9 to 31 basis points for Germany, Finland and Italy, pointing to liquid

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[12] Due to the market-maker commitments, quotes always are significant in volume terms (multiples of EUR 5 million).

markets, but the standard deviation is high, up to multiples of the median, reflecting substantial variation over time and across ISINs. The high Portuguese bid-ask spread (415 basis points in the median) reflects an illiquid market, possibly due to sovereign debt sustainability concerns that forced the country to request EU/IMF financial assistance in Spring 2011. Its sovereign bond market remained stressed throughout the period with infrequent market trading, no primary bond issuances and high bid-ask spreads. For all countries, the very high maximum numbers for quote-slope and bid-ask spread reflect periods in which market makers perhaps have withdrawn their bids usually following or anticipating major events that can have an important price impact.

Figure 1 shows boxplots of the high frequency measures hourly average over the trading day and across ISINs for the period 2011-2012. Each box reflects the variation of the hourly-average high-frequency liquidity benchmarks across ISINs and over time for the hour considered. Median, 5th, 25th, 75th, and 95th percentile are shown. Bid-ask spreads and quote slopes are somewhat higher and more dispersed during the first hour of trade. There seems to be slightly more dispersion in the number of quotes per hour between 12 p.m. and 2 p.m. The distribution of the bid-ask spread and the quote slope is clearly non-Gaussian with a very strong skewness, especially in Germany and Italy. No such skewness appears for the number of quotes per hour. In Portugal, there is consistently more active quoting in the afternoon after 1 pm than in the morning.

3. The relationship between liquidity benchmarks and proxies: An empirical investigation

We study the empirical relationship between benchmarks and proxies in several complementary ways. First, in a few examples we consider the extent to which our rankings of various sovereign bonds on the basis of their liquidity can be affected by the liquidity measure we use. Second, we compare and contrast lower-frequency and higher-frequency correlations across pairs of benchmarks and proxies. In particular, we assess the influential approach of assessing liquidity proxies by correlating monthly averages of proxies with monthly averages of benchmarks. Subsequently, we investigate the robustness of our analysis by studying the relationship between benchmarks and proxies in the frequency domain, and also by using MIDAS regressions. Finally, we discuss some of the implications of our findings.

In all the exercises that follow we consider 9 pairs, constructed from the 3 benchmarks and 3 proxies that were selected in Section 2. Amihud price impact, daily number of trades and daily traded volume are the three liquidity proxies. As benchmarks, we use the hourly averages of intraday quoted bid-ask spreads, the quote slopes and the number of quotes per hour.

3.1. Assessing liquidity using benchmarks and proxies: Some examples

As discussed earlier, when it comes to the question of using proxies instead of benchmarks the existing literature provides some comforting evidence. One would thus expect to find that our qualitative conclusions and rankings of assets on the basis of their liquidity do not change depending on whether we use benchmarks or proxies. However, this turns out not to be the case.

One example comes from the sovereign bonds of Germany and Finland. If we look at benchmarks (specifically the bid-ask spread and the quote slope) German bonds come out as more liquid than Finnish bonds in our sample and over the time period considered. However, this ranking is reversed if we look at any of the proxies (i.e., Amihud, number of trades, and traded volume), according to which Finish bonds are more liquid than their German counterparts over the same period.

Additional examples come from a recent market stress period. Specifically, we look at the period of October 31st 2011 to December 23rd 2011, a peak time for the Composite Indicator of Systemic Stress (CISS) of the European Central Bank (see Hollo et al. (2012)). For two of the weeks in that period (namely 11/7/2011-11/11/2011 and 12/5/2011-12/9/2011) if we were to mechanically apply the Amihud measure we would find the Portuguese sovereign bonds to be substantially more liquid than their Italian counterparts according to the Amihud measure, whereas these Italian bonds are vastly more liquid than the Portuguese bonds according to the bid-ask spread, and over the same two weeks. Furthermore, and over the entire crisis period, Italian bonds are clearly less liquid than either German or Finnish bonds according to the benchmarks, while being substantially more liquid than the same German and Finnish bonds over the same period, according to the number of trades and the traded volume. Examples such as the two just mentioned can be particularly troubling, as it is arguably during crisis times when we need accurate liquidity measures and assessments the most.

Such findings do raise a red flag regarding the widespread practice of using benchmarks and proxies interchangeably. However, they are based on particular examples, and could perhaps be viewed as circumstantial. We thus proceed in what follows to a more systematic analysis of these issues.

3.2. Monthly and daily correlations

We calculate the correlations of the monthly averages of the daily proxies and of the intraday benchmarks for the individual bond ISINs over the period 2011-2012 for all four countries, mimicking widespread practices in the existing literature, as discussed earlier. Then we calculate the correlations of the daily proxies with the daily averages of the intra-day benchmarks, again for the individual bond ISINs of all countries over the same period. Results are presented in Table 2 for the averages for each pair across all bonds and in Figure 2 for the individual bonds.

The results, summarized in Table 2, are striking. Across countries and across pairs, daily correlations are substantially lower than monthly correlations in almost all cases (with the only exception being the three Amihud pairs for Portugal) [13]. Indeed monthly correlations are on average twice as high (Finland and Italy) or more than twice as high (Germany and Portugal) as the daily correlations. For the great majority of benchmark/proxy pairs we have monthly correlations above 20% (in absolute value), while almost none of the respective daily

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[13] Note that all correlations (both daily and monthly, for all pairs and countries) have the expected sign, except possibly for the pair between Amihud and quotes per hour, which has positive correlations for Germany and Finland, but negative for Italy and Portugal. This finding regarding the Amihud/quotes per hour pair is in line with existing literature (for instance Pelizzon et al. (2013) find that "...*under conditions of stress…frequent quote revisions do not necessarily translate into higher liquidity"*).

correlations are above 20% (in absolute value) [14]. Indeed it is only the pairs including Amihud that have daily correlations which are generally in excess of even 10%.

Furthermore, these results also illustrate how the choice of frequency can be consequential for the best proxy contest: For example, for the case of Germany, and on the basis of monthly correlations, the number of trades per day would be considered the best proxy for the bid-ask spread and the quote slope, while on the basis of daily correlations, Amihud performs better. Another example is Portugal: Volume wins the race on the basis of monthly correlations, whereas if we look at daily correlations the clear winner is Amihud.

The panels of Figure 2, which contain the respective individual bond results for all four countries, show that both the magnitude and the sign of differences between monthly and daily level correlations can vary substantially across individual bond ISINs. They also clearly corroborate the above findings: Monthly correlations are generally much higher than their daily counterparts[15]. In general, the average country-level patterns of Table 2 discussed above are consistent with what we observe at the individual ISIN level, across all nine pairs.

In a nutshell, we find here that correlations between benchmarks and proxies become substantially weaker as the frequency at which such relationships are examined becomes higher. These results raise a red flag regarding the influential practice, encountered both in the academic

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[14] Specifically, we have monthly correlations in excess of 20% for seven out of nine pairs for Germany and Italy, six out of nine pairs for Portugal, and three out of nine for Finland. None of the daily correlations are above 20% for Germany and Finland, while two of them are above 20% for Portugal and Italy.

[15] Similar to the country-level results, the one exception to this is the three Amihud pairs for Portugal, for which daily correlations are higher for many ISINs.

and policy literatures, of providing empirical support for the use of proxies, and indeed of distilling the best proxies, on the basis of substantial low-frequency correlations (and especially monthly correlations) between proxies and benchmarks. This practice could lead to misleading results and conclusions when it does not give sufficient consideration to the specific context in question that necessitates measuring liquidity in the first place, and especially to the relevant time horizon for conversion into cash.

In what follows we conduct a series of exercises whose primary goal is to further assess and robustify the above results and conclusions.

3.3. The frequency domain: Coherences between benchmarks and proxies

We seek here to get a more complete picture of the relationship between liquidity benchmarks and proxies at various frequencies by considering the frequency domain. Specifically, we look at the pairwise coherences between benchmarks and proxies. Using notation such as in Hamilton (1994), we have that the coherence $h_{YX}(\omega)$ at frequency ω between benchmark X and proxy Y is as follows:

$$h_{YX}(\omega) = \frac{[c_{YX}(\omega)]^2 + [q_{YX}(\omega)]^2}{s_{YY}(\omega)s_{XX}(\omega)}$$

where $c_{YX}(\omega)$ is the cospectrum (i.e., the real component of the cross-spectrum) and $q_{YX}(\omega)$ the quadrature spectrum (i.e., the imaginary component of the cross-spectrum) between X and Y, while $s_{YY}(\omega)$, $s_{XX}(\omega)$ are the spectra of Y and X, respectively (both assumed to be different from 0). Thus the coherence accounts for both in-phase and out-of-phase cycles, and if it is large[16] at frequency ω, then it can be said that benchmark X and proxy Y share significant cycles at that frequency.

Figure 3 depicts coherences, based on daily data, for six pairs of proxies (number of trades and volume) and benchmarks (BAS, quote slope, and quotes per hour), for all four countries, for two bonds per country – the ones having the minimum or maximum benchmark/proxy monthly correlations[17] (as discussed in the previous section). We do not include the coherences based on the Amihud measure. As this variable is highly irregularly spaced, the task of interpreting the coherences, and in particular the task of attributing different frequencies to, say, monthly cycles in a way that would be consistent across bonds would be highly problematic.

Note that each frequency ω is associated with cycles of period $\frac{2\pi}{\omega}$. So, for instance, a month corresponds to a value of about 0.27 to 0.35 (depending on how many trading days we have in a month) in the horizontal axis of these figures.

If there was little loss associated with the strategy discussed earlier of looking at monthly correlations between benchmarks and proxies, then the coherences corresponding to monthly cycles would be high compared to coherences elsewhere. However, this is not the case: Examining all the coherences for all the pairs across benchmark/proxy pairs and countries, we

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16 The coherence can be shown to be a number between 0 and 1, assuming that X and Y are covariance-stationary with absolutely summable autocovariance matrices (Hamilton (1994)).

17 Including here the (hundreds of) figures for all the pairs would take too much space; the remaining figures are available from the authors.

conclude that for the great majority of cases, there are many peaks at various other cycles, which are as high or higher than any peaks observed around the monthly cycle.

While these exercises in the frequency domain can be viewed as a robustness check on the comparisons between correlations of the previous section, they still suffer from one potentially key deficiency, namely that they are always based on daily observations (or daily averages, for the cases of the benchmarks). We turn to this issue next.

3.4. Modeling the dynamic relationship between benchmarks and proxies: A MIDAS approach

The analysis of the previous sections clearly illustrates how one issue that has been largely ignored in the existing literature, namely the frequency aspect of the various liquidity measures, and in particular the practice of averaging out information, can substantially affect our results and conclusions. Of course, even higher-frequency daily correlations are susceptible to such criticisms as they rely on daily averages of the benchmarks, and thus average out potentially valuable intra-day information. One may think that daily averaging of benchmarks is unavoidable in any investigation of their relationship with proxies, given that proxies are defined at a daily (or lower) frequency.

However, recent econometric literature offers an answer to this and similar challenges encountered when faced with mixed-frequency data. Mixed Data Sampling, or MIDAS regressions (see, e.g., Andreou et al. (2010), Ghysels et al. (2004)) allow us to handle situations where the dependent variable is of a different (lower) frequency than the explanatory variable(s), in a way that is both parsimonious, and data-driven. In this section we look at the dynamic relationship between benchmarks and proxies using MIDAS techniques, which deal with mixed-frequency issues without averaging out (too much) information coming from intra-day data. We employ a MIDAS approach whose low frequency (for the proxies) is daily and whose high frequency is hourly (so we compute, for every trading day 8 hourly averages of the higher frequency benchmark data[18]).

More specifically, we estimate standard MIDAS models of the following form:

$$Y_t = \mu + \beta \sum_{i=0}^{n-1} w_{n-i}(\theta) X_{t,n-i} + \varepsilon_t,$$

where t and i are indexes for the lower and higher frequencies, respectively, and $w_{n-i}(\theta)$ are the *MIDAS weights*, a function of unknown parameters θ (to be estimated, together with parameters μ and β, using Nonlinear Least Squares). We consider various weighting functions that are common in the literature. For instance, in the exercises that follow we use an exponential Almon lag polynomial specification: $w_i^{almon}(\theta_1, \theta_2) = \frac{e^{\theta_1 i + \theta_2 i^2}}{\sum_{i=1}^{n} e^{\theta_1 i + \theta_2 i^2}}$.

We estimate the above specification for all nine pairs of benchmarks and proxies discussed above, and for all countries and all possible bonds per pair. The panels of Figure 4 present the R^2s per bond, for all the pairs, for the four countries. The R^2s vary, but are very low in general. For instance, per-pair country averages are lower than 3% in 22 out of 36 country/pairs (with

[18] While constructing hourly averages entails some loss, averaging out some information is inevitable in a MIDAS context given the highly irregular frequencies of the raw benchmark data.

several of these R^2s being less than even 1%). Conversely, in only 6 out of these 36 cases do we have R^2s that are higher than 10%.

One can usefully think of these MIDAS regressions as revisiting the daily correlations discussed earlier in a way that does not discard (too much) high-frequency information of the benchmarks[19]. Theoretical results established in the literature (Andreou et al. (2010)) imply in our context that when we replace daily averages of benchmarks with the benchmarks themselves, we gain in asymptotic efficiency. This is likely to lead to higher R^2s as well. Indeed, one could make the case that the daily correlations presented earlier are so low, because of the argument in Andreou et al. (2010): We average out the high frequency variable. With our MIDAS regressions we partly remove this constraint, but we still get R^2s that are very low[20]. So, in a sense we robustify here our results of low daily correlations.

It would also be interesting to examine the intraday MIDAS weights and look for evidence of possible patterns in the within-day relationship between benchmarks and proxies. After all, there is evidence (see Pelizzon et al. (2013)) on the existence of intraday patterns of individual liquidity measures. Figure 5 provides a sample of plots of such weights for bonds having the

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[19] We still discard high frequency information, since we are employing hourly averages of the benchmarks.

[20] We make this statement more specific to our context by considering the medians (over our 36 country/pair cases) of the ratios, computed for all bonds, of the R^2s from these MIDAS regressions to the squares of the daily correlations. The country averages of these median ratios are many times lower than their counterpart ratios of the squares of the monthly correlations over the squares of the daily correlations.

minimum or maximum benchmark/proxy monthly correlations (as discussed in Section 3.2).[21] The MIDAS weights are on the vertical axis, and hours (eight per trading day on the horizontal axis). Upon examining all the figures (for all bonds, countries and pair), we conclude that there is a wide spectrum of intra-day patterns in these weights, with no strong regularity in the weight patterns observed across benchmark/proxy pairs and countries. [22]

One key message from the above exercises is that even when the intra-day variability of liquidity benchmark measures is accounted for, the empirical evidence on a possible relationship between benchmarks and proxies remains very weak. Indeed, these results, in conjunction with the results from the correlations exercises above, suggest that the empirical relationship between

[21] As in the previous section with the coherence figures, including the (hundreds of) figures for all the pairs would take too much space; the remaining figures are available from the authors.

[22] Regarding possible patterns or stylized facts that emerge from these figures, the following can be said: First, and for the cases of Finland, Germany, and Italy, weights with higher magnitudes tend to appear more in the first half of the trading day than in the second half, whereas for Portugal the weights are about evenly split. Second, for Italy and for Portugal, there is a clear majority of panels where there is more than one non-zero weights (with the exception of the Amihud/quotes-per-hour pair for both Italy and Portugal, and the Volume/quotes-per-hour pair for Italy, for which there is a majority of panels with only one non-zero weight). Conversely, for Finland, there is a clear majority of panels where there is only one non-zero weight (with the exception of the Amihud/BAS and Amihud/quote slope pairs). Finally, the respective results for Germany are more evenly split, with a clear majority of more than one non-zero weights for the cases of four pairs (Trades/BAS, Trades/quote slope, Volume/BAS, Volume/quote slope), and the opposite for the remaining five pairs.

benchmarks and proxies becomes weaker as the frequency over which this relationship is examined becomes higher.

Overall, it is quite clear by now that the frequency issue is crucial; for instance, and as discussed earlier, proxies should not be considered as adequate substitutes for benchmarks regardless of the time frame considered. This is a realization that is not evident in the existing literature and which could have some significant policy implications, especially in the context of the current Basel III/LCR framework. We turn to a brief discussion of such implications next.

3.5. Implications of the results

These results have implications for findings in the liquidity literature, for policy tasks related to banking regulation and supervision and for banks' liquidity management. As banks' LCR liquidity buffers may only be used in case of financial instability and require conversion into cash in a matter of days during stressed market conditions, any accurate approach to assessing assets and asset classes that qualify as (extremely) high quality and liquid needs to take account of higher frequency dynamics and behavior under market stress conditions. Those conditions are particularly badly captured by correlations of monthly aggregates, as monthly aggregates average out higher-frequency information that is relevant when there is a need to sell assets within a short timeframe and under non-average conditions.

Liquidity proxies should not be assessed in a general and abstract way, but rather against the particular needs of the context in question; the specific reasons that call for liquidity measurement in the first place need to be examined. The relevant timeframe for conversion into cash needs to be considered so as to take account of the appropriate degree of higher frequency dynamics. This is likely to be particularly relevant in the currently evolving context of Basel III/LCR.

4. Conclusions

One central goal of the expansive literature on liquidity is to identify good measures of liquidity per se. This goal has acquired increased significance in the last few years, in the wake of the financial crisis and the new Basel requirements on banks. Much of the recent literature has approached this task by investigating the relationship between benchmarks and proxies through monthly (or even lower-frequency) correlations. In this paper we critically assess such standard practices. We compare correlations between (monthly and daily averages of) proxies and benchmarks, we look at their coherences as well, and also we propose MIDAS regressions as a way of investigating the bilateral relationships between proxies and benchmarks without averaging out potentially valuable intra-day information.

We demonstrate that higher-frequency information that is ignored by the influential practice of considering monthly averages is actually consequential, and that the relationship between liquidity benchmarks and proxies can become substantially thinner as the frequency becomes higher. Thus, such standard practices for assessing liquidity proxies - and ceteris paribus for assessing the liquidity of assets and asset classes - may lead to misleading conclusions on liquidity when, for instance, there is a need to convert assets into cash within a short amount of time. Any liquidity proxies need to be assessed against the particular needs and timeframe of the liquidity context being considered.

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Table 1: Descriptive statistics of liquidity measures

Proxies	country	mean	std	min	median	max
Amihud	DE	3.27E-12	1.11E-11	0	1.09E-12	5.44E-10
	FI	1.42E-12	2.40E-12	0	5.76E-13	2.21E-11
	IT	7.14E-12	2.16E-11	0	1.44E-12	6.97E-10
	PT	3.10E-11	5.32E-11	0	1.26E-11	5.17E-10
Volume (million Euro)	DE	3.49	12.01	0	0	390.50
	FI	8.37	22.29	0	0	255.00
	IT	19.31	38.31	0	5	902.50
	PT	0.87	5.11	0	0	187.50
Trades	DE	0.72	2.47	0	0	71
	FI	1.00	2.57	0	0	29
	IT	3.98	6.94	0	1	124
	PT	0.15	0.78	0	0	30
Benchmarks	**country**	**mean**	**std**	**min**	**median**	**max**
BAS	DE	0.199	0.696	0.001	0.090	202.44
	FI	0.217	0.504	0.004	0.150	62.76
	IT	0.567	0.943	0.002	0.310	162.64
	PT	6.961	16.767	0.050	4.150	538.92
Quoteslope	DE	0.0064	0.0217	0.00003	0.0028	6.2799
	FI	0.0066	0.0152	0.00014	0.0046	0.0066
	IT	0.0180	0.0303	0.00006	0.0100	5.2719
	PT	0.2244	0.5431	0.00155	0.1345	18.2910
Quotesperhour [A]	DE	67	16	37	68	114
	FI	75	12	56	74	113
	IT	76	12	51	76	114
	PT	49	9	35	47	77

Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). Countries: Germany (DE), Finland (FI), Italy (IT) and Portugal (PT). Time period: 2011-2012.

A: Average per bond over the 2 years

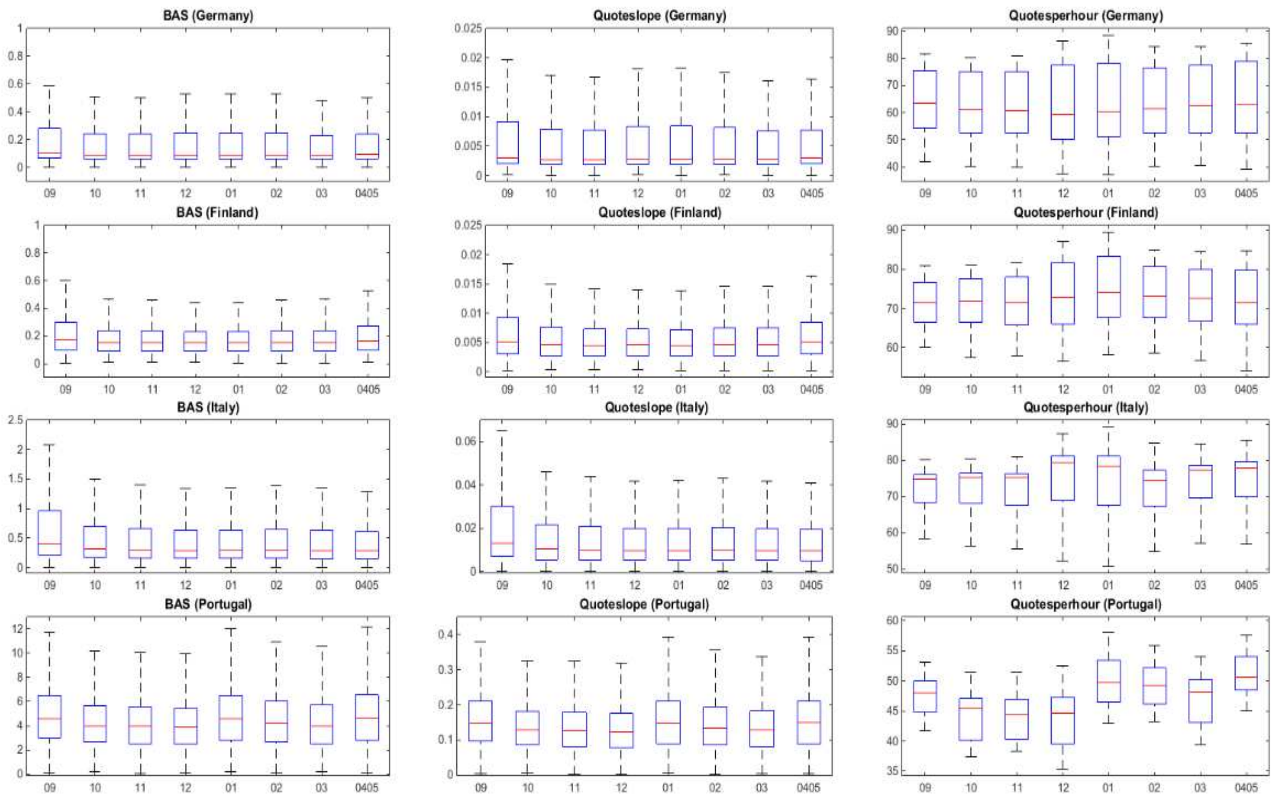
Table 2: Average correlations between proxies and benchmarks

		Daily			Monthly		
		Amihud	Trades	Volume	Amihud	Trades	Volume
DE	**BAS**	0.158	-0.083	-0.066	0.263	-0.269	-0.223
	Quoteslope	0.161	-0.082	-0.066	0.267	-0.268	-0.224
	Quotesperhour	0.147	0.027	0.020	0.241	0.039	0.027
FI	**BAS**	0.196	-0.047	-0.046	0.289	-0.069	-0.060
	Quoteslope	0.198	-0.048	-0.046	0.291	-0.067	-0.059
	Quotesperhour	0.110	0.016	0.017	0.285	0.061	0.063
IT	**BAS**	0.329	-0.187	-0.198	0.654	-0.318	-0.368
	Quoteslope	0.327	-0.183	-0.195	0.658	-0.308	-0.360
	Quotesperhour	-0.047	0.088	0.092	-0.114	0.189	0.206
PT	**BAS**	0.391	-0.113	-0.113	0.252	-0.361	-0.382
	Quoteslope	0.393	-0.112	-0.113	0.253	-0.360	-0.382
	Quotesperhour	-0.147	0.041	0.065	-0.082	0.113	0.193

Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). Countries: Germany (DE), Finland (FI), Italy (IT) and Portugal (PT). Time period: 2011-2012.

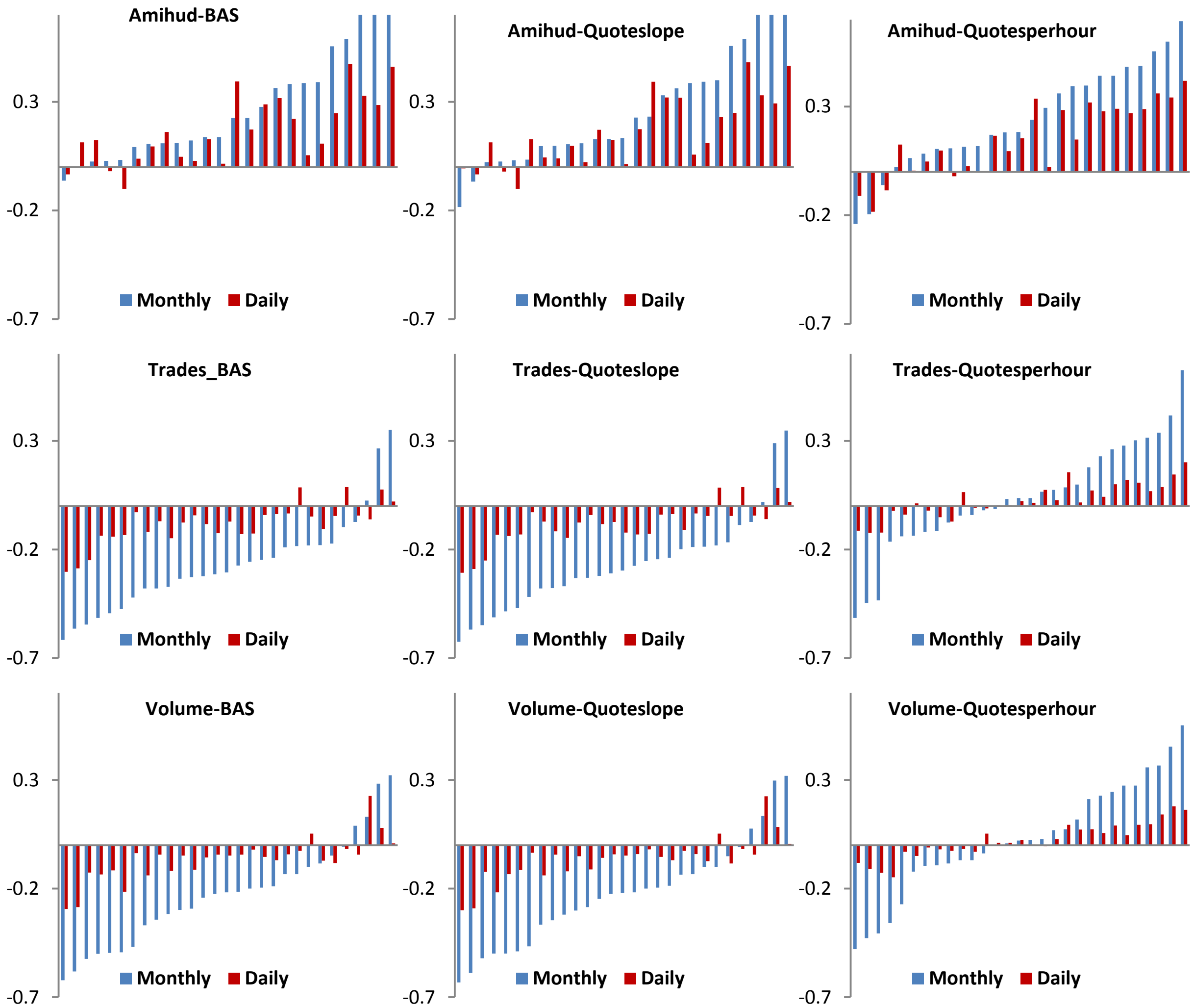
Figure 1: Box plots of the high frequency benchmarks



Source: MTS, authors' calculations

Note: Box plot reflect variation across ISIN and over trading days in the period 2011-2012 for each liquidity benchmark per country at 8 hourly averages over the full trading day (9:00 and 17:20). The last bar reflects averages of measures between 16:00 and 17:20.

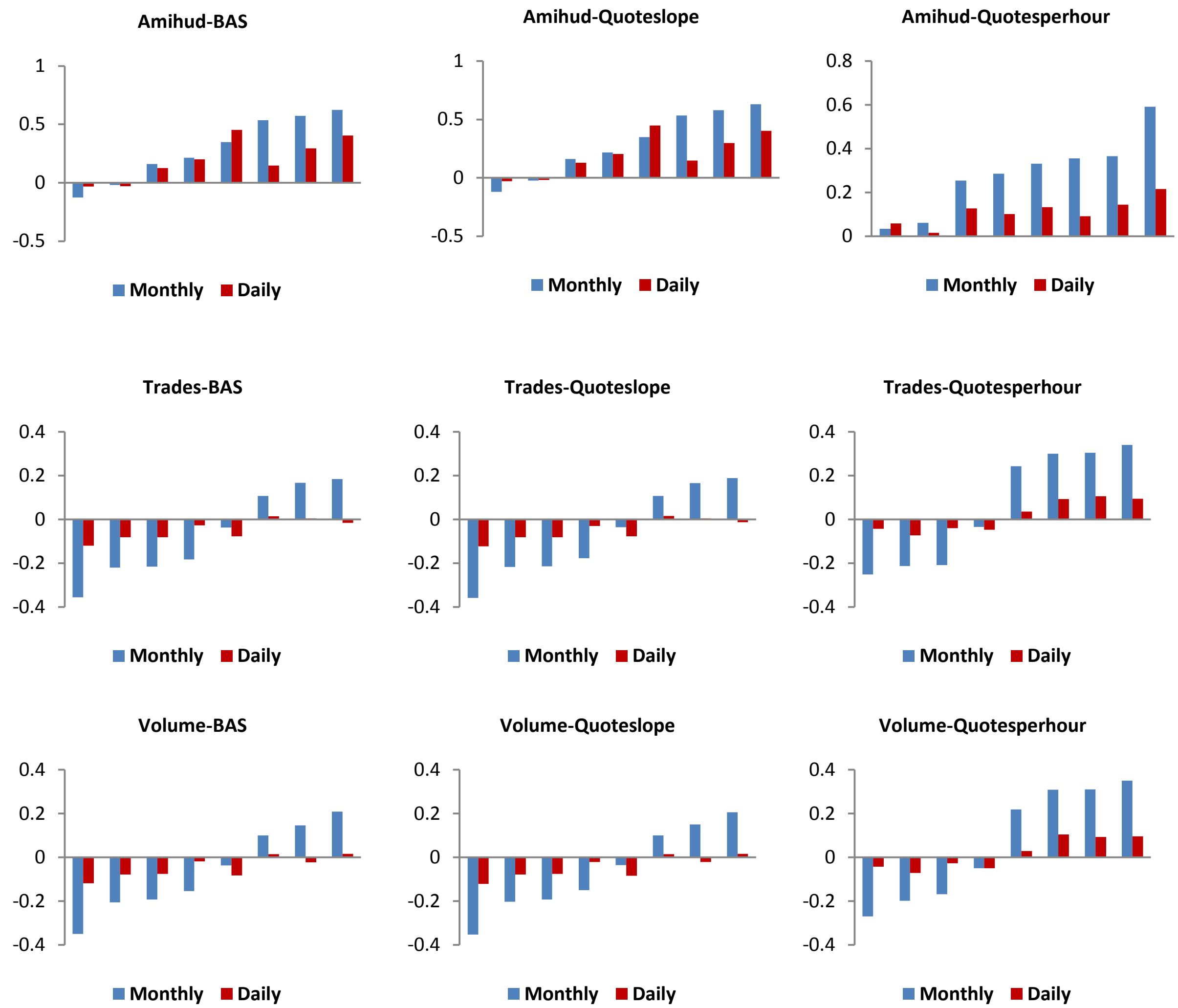
Figure 2.1.: Correlations between the liquidity proxies and benchmarks - Germany



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). Correlations have been ranked from low to high monthly correlation for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

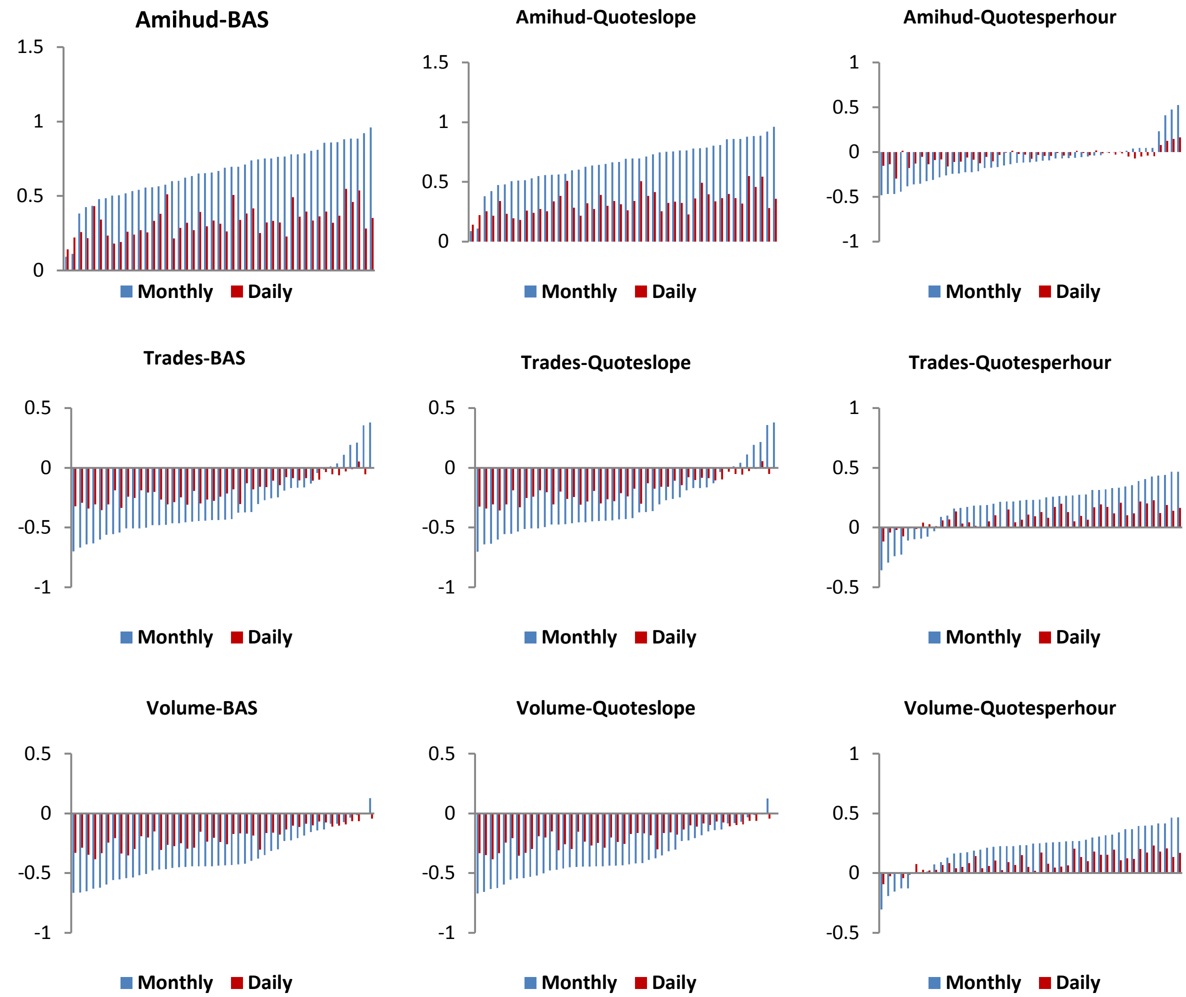
Figure 2.2: Correlations between the liquidity proxies and benchmarks - Finland



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). Correlations have been ranked from low to high monthly correlation for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

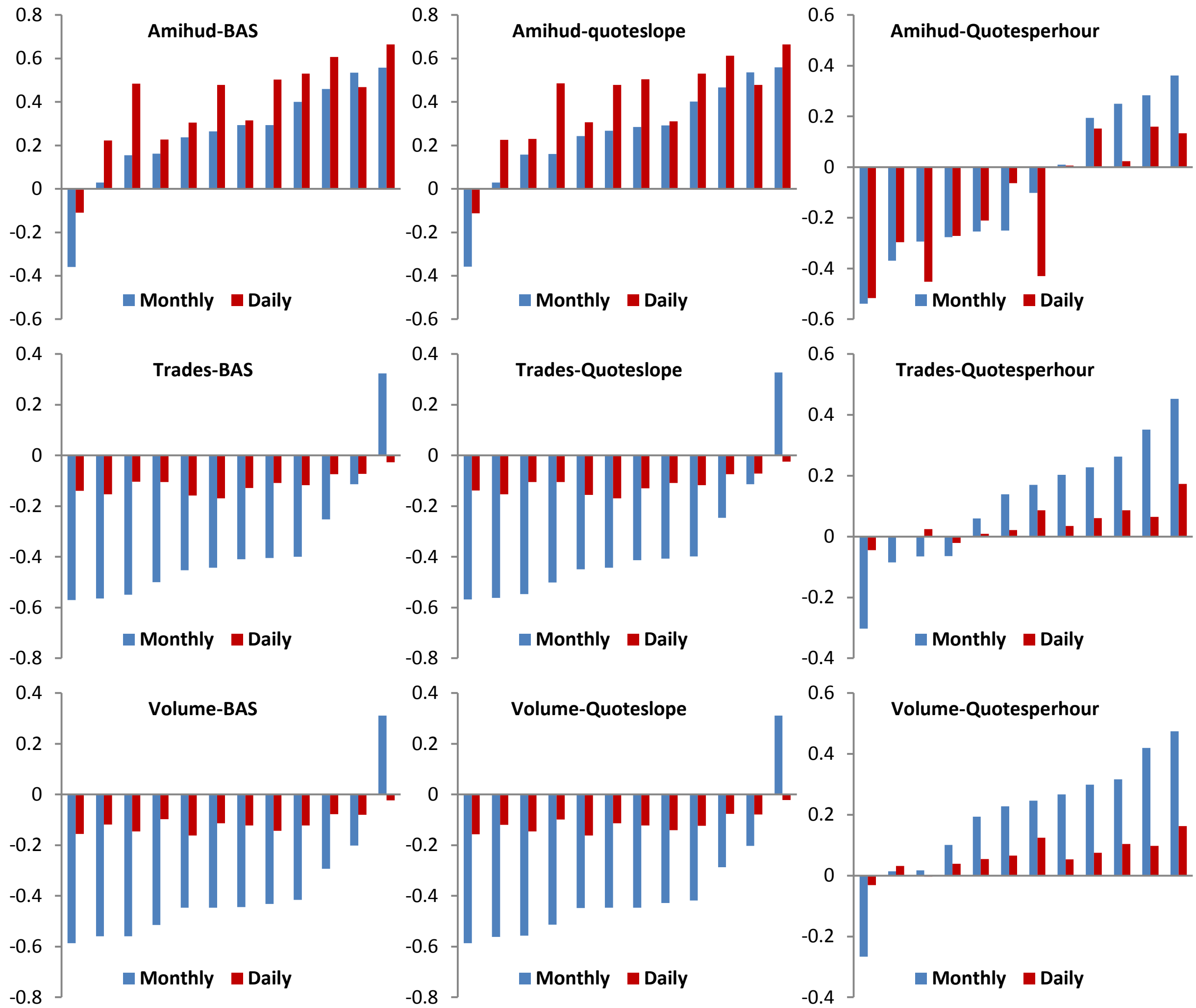
Figure 2.3: **Correlations between the liquidity proxies and benchmarks - Italy**



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). Correlations have been ranked from low to high monthly correlation for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

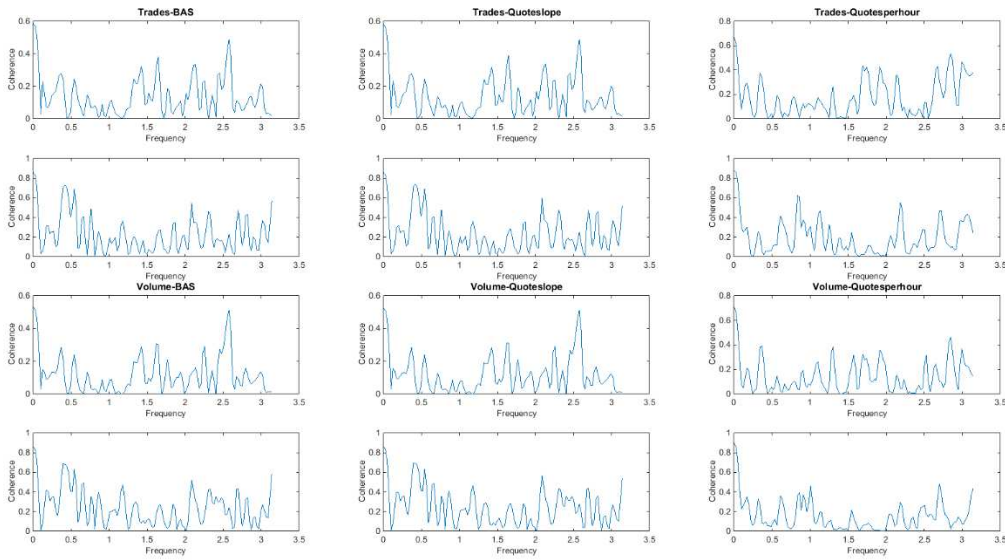
Figure 2.4: **Correlations between the liquidity proxies and benchmarks - Portugal**



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). Correlations have been ranked from low to high monthly correlation for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

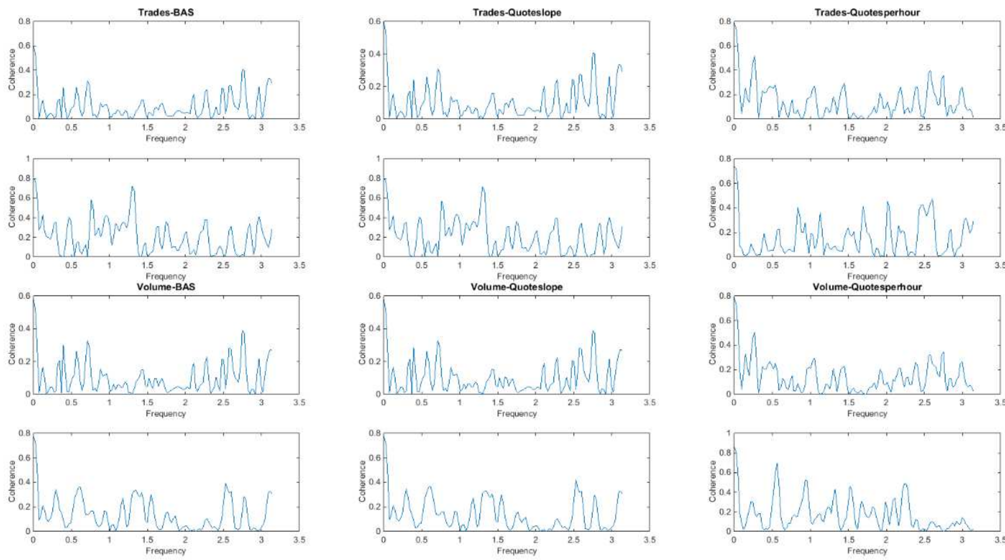
Figure 3.1: Coherence plots of the liquidity measures - Germany



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

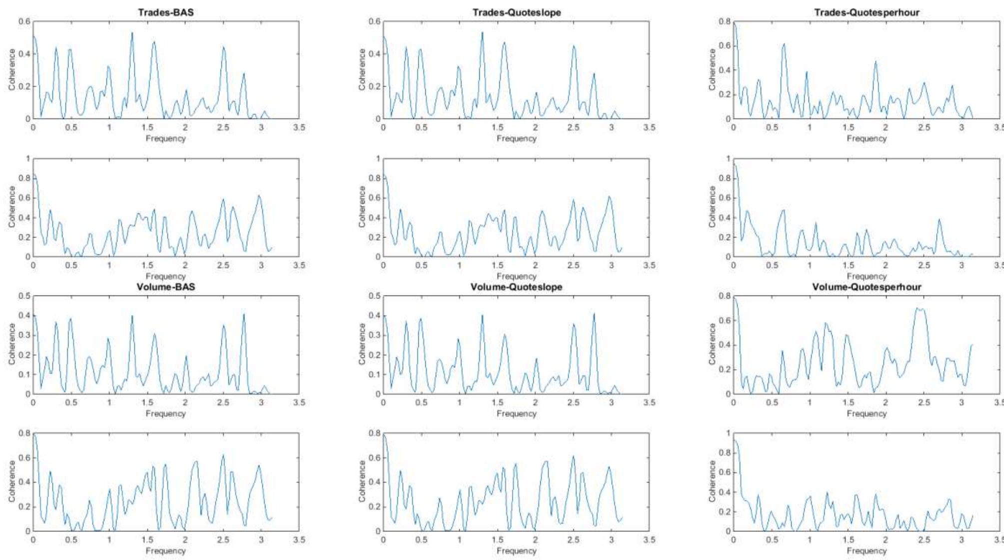
Figure 3.2: **Coherence plots of the liquidity measures - Finland**



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

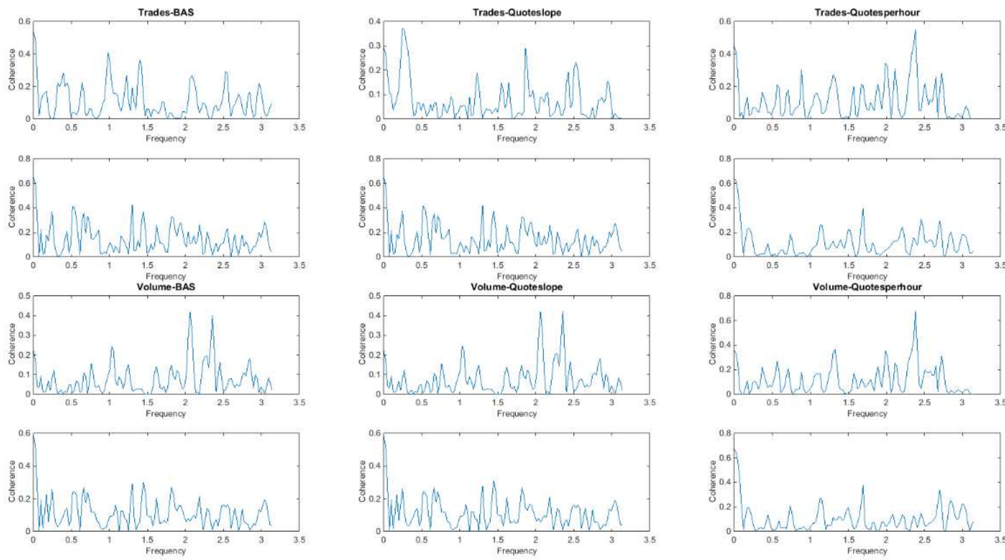
Figure 3.3: **Coherence plots of the liquidity measures - Italy**



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

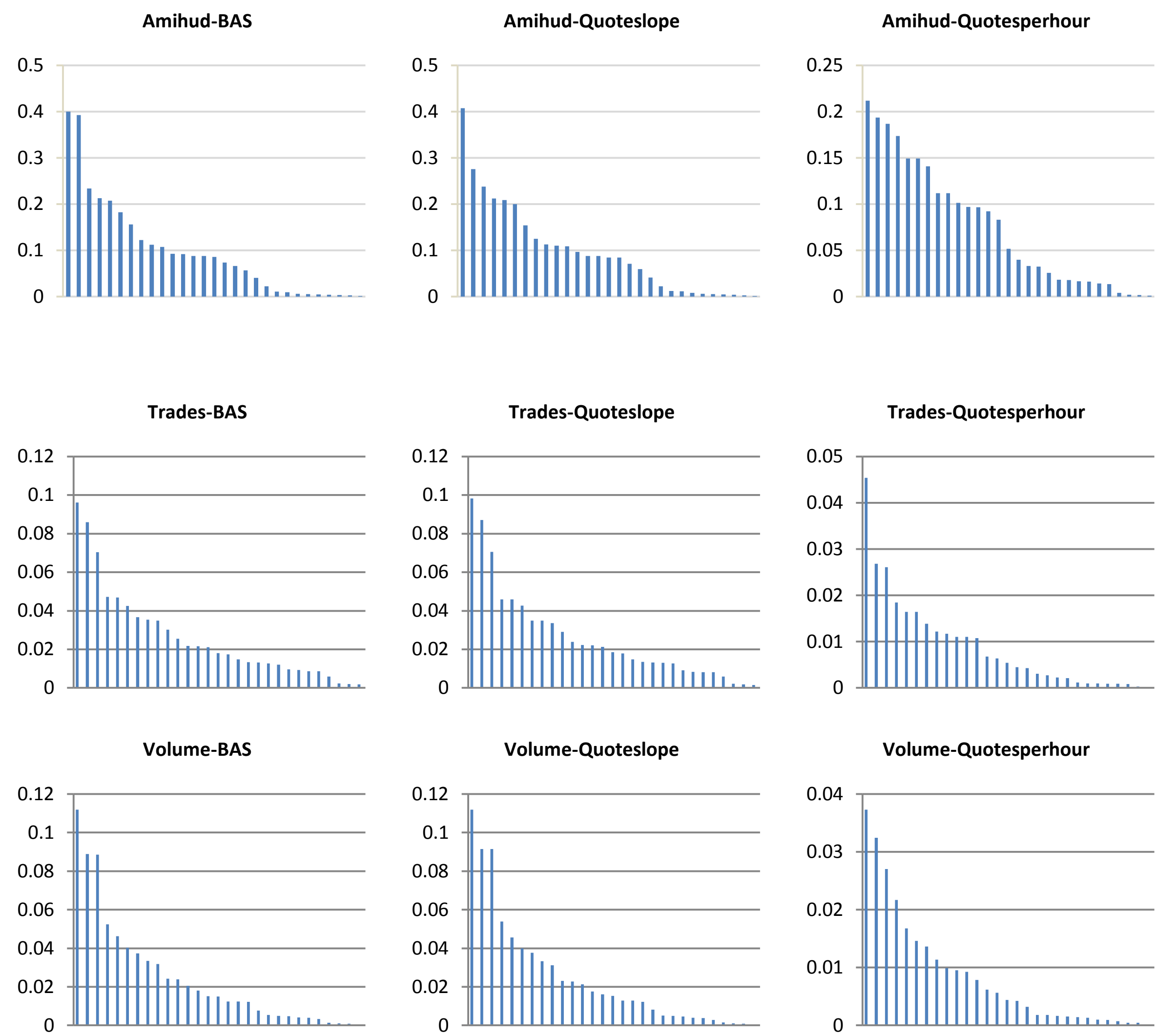
Figure 3.4: **Coherence plots of the liquidity measures - Portugal**



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

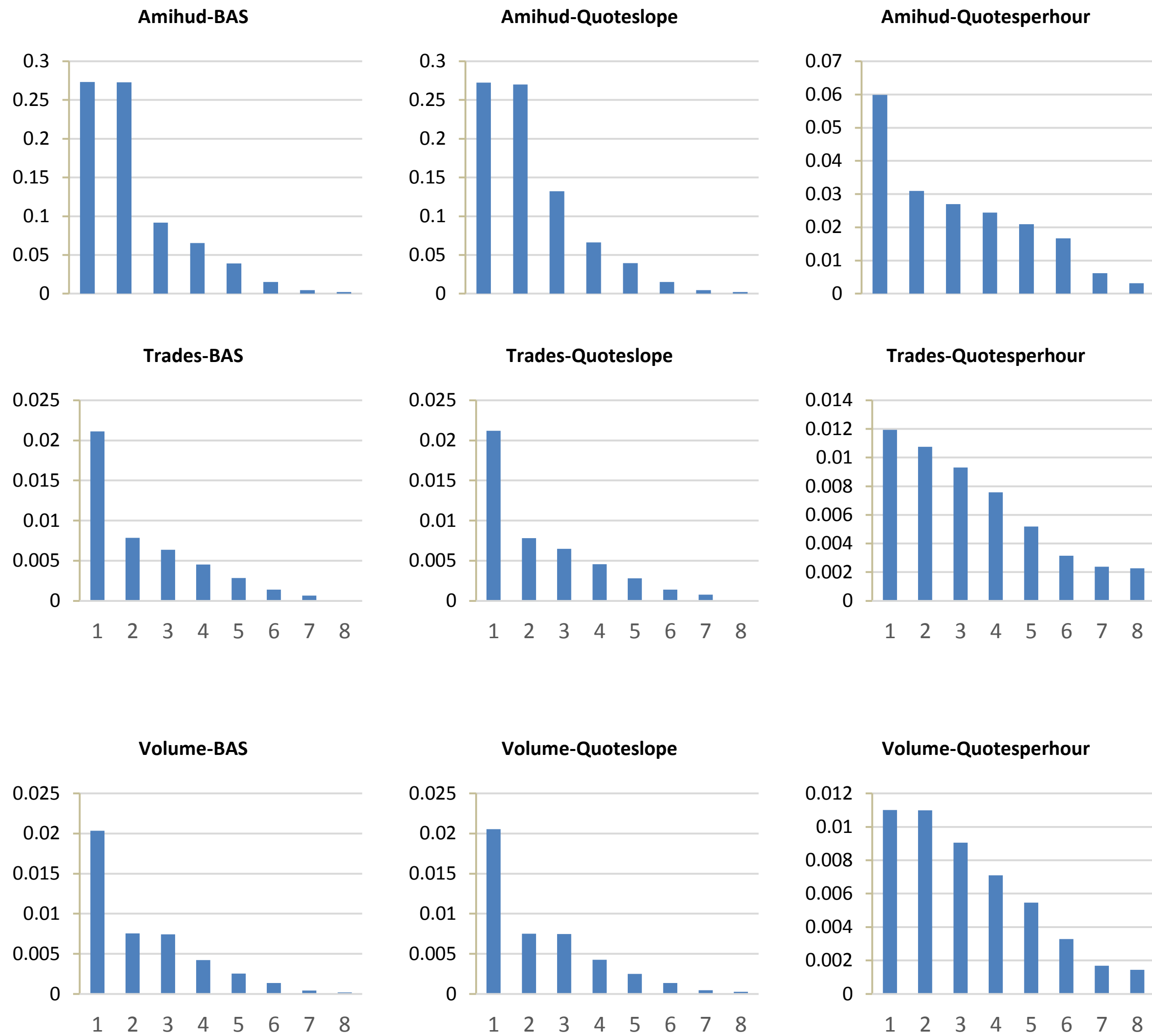
Figure 4.1: R^2's of MIDAS regressions - Germany



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). R^2's have been ranked from high to low for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

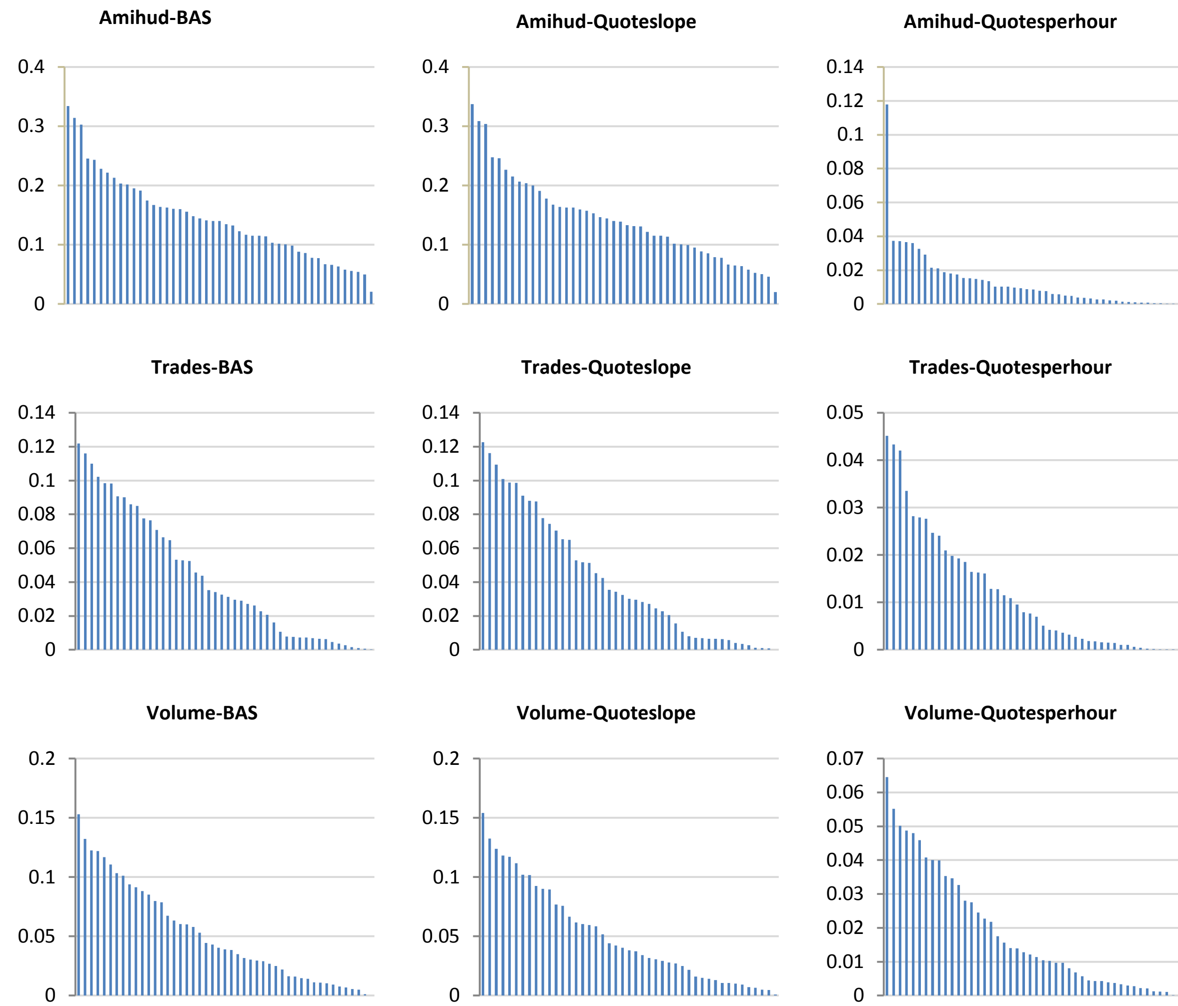
Figure 4.2: R^2's of MIDAS regressions - Finland



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). R^2's have been ranked from high to low for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

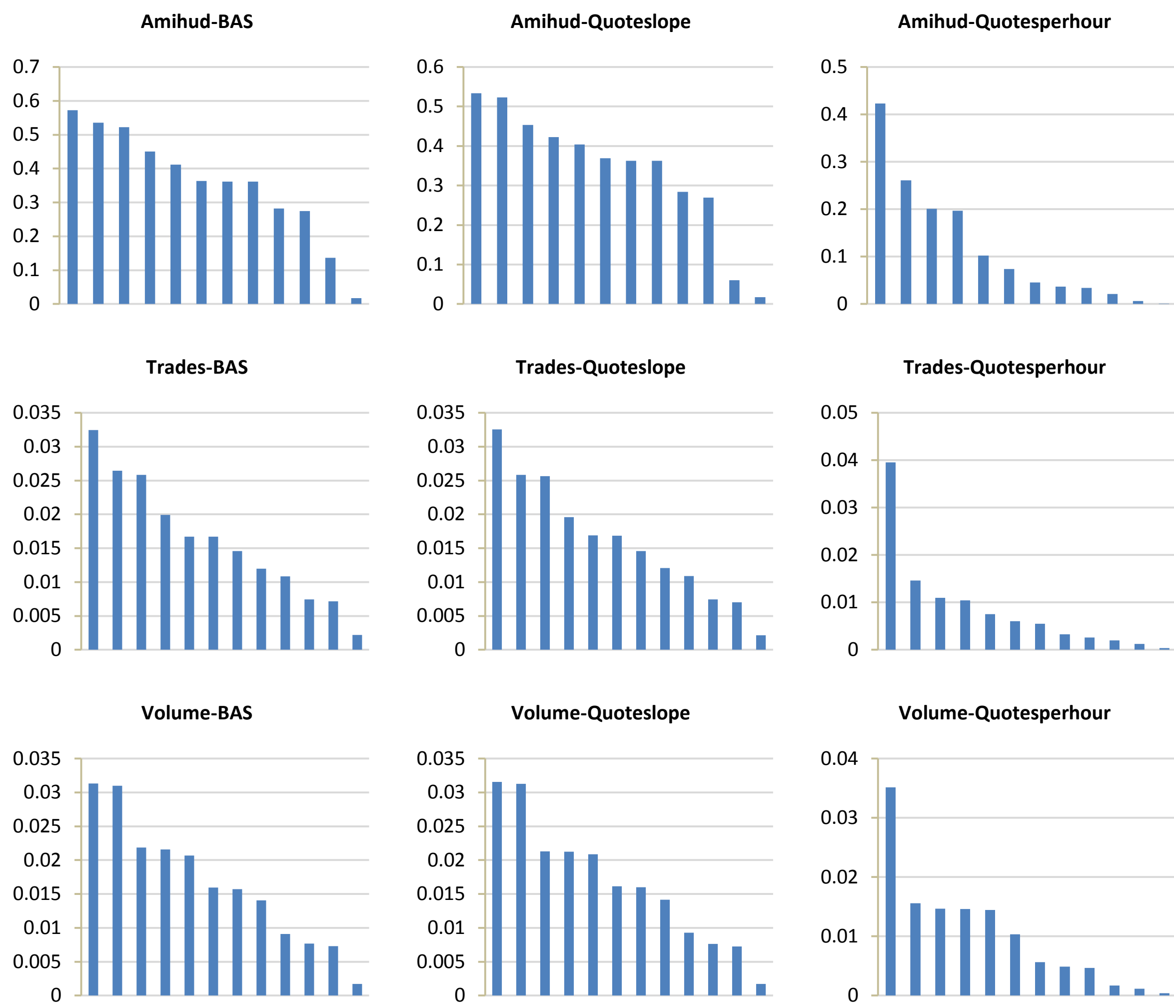
Figure 4.3: R^2's of MIDAS regressions - Italy



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). R^2's have been ranked from high to low for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

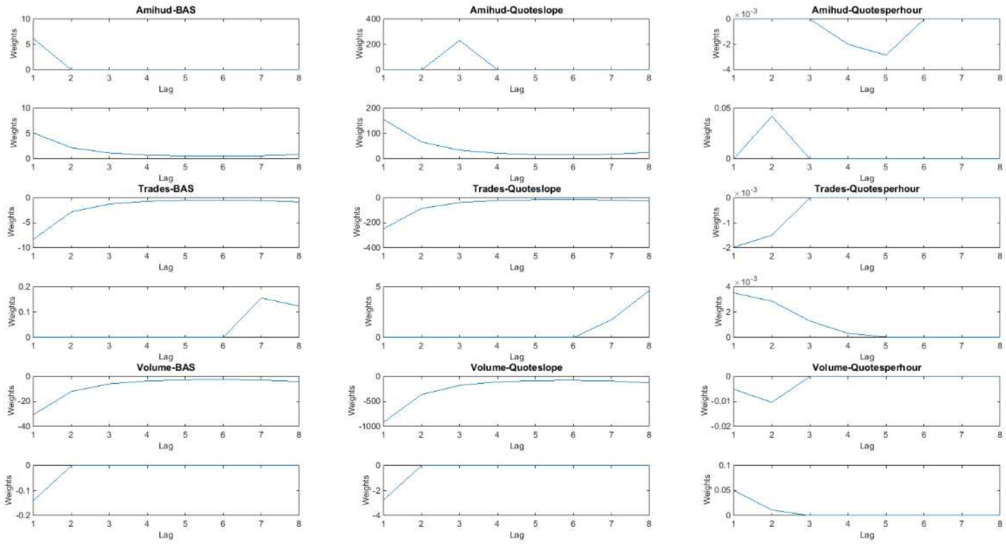
Figure 4.4: R^2's of MIDAS regressions - Portugal



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). R^2's have been ranked from high to low for each pair. The order does not necessarily reflect the same ISINs across graphs. Time period: 2011-2012.

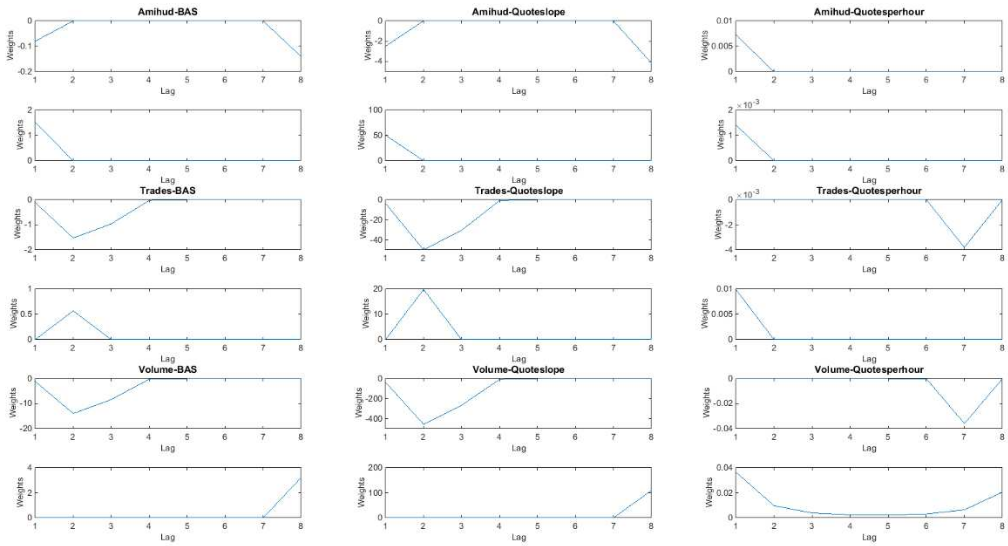
Figure 5.1: MIDAS weights - Germany



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). MIDAS weights are on the vertical axis, and hours (eight per trading day) on the horizontal axis. For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

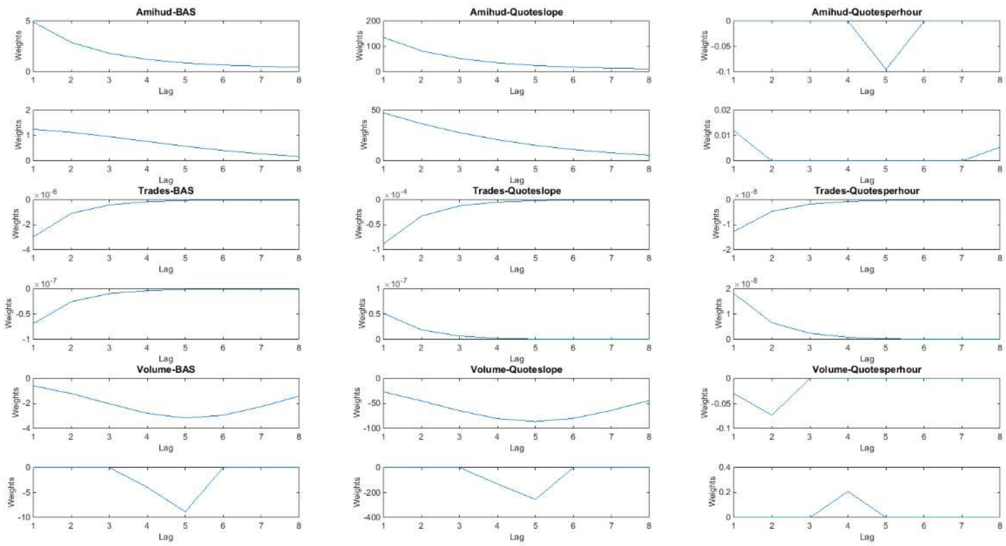
Figure 5.2: MIDAS weights - Finland



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). MIDAS weights are on the vertical axis, and hours (eight per trading day) on the horizontal axis. For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

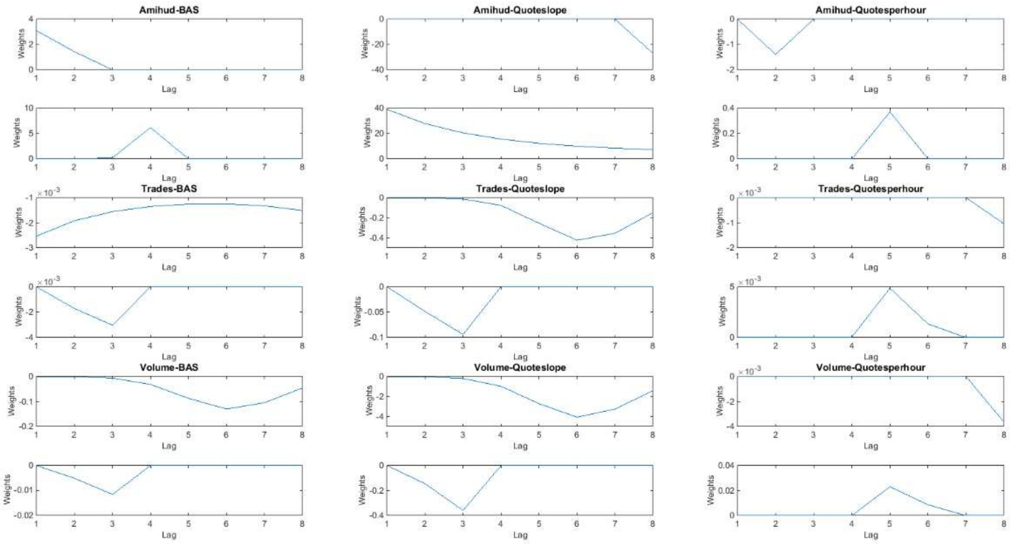
Figure 5.3: MIDAS weights - Italy



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). MIDAS weights are on the vertical axis, and hours (eight per trading day) on the horizontal axis. For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.

Figure 5.4: MIDAS weights - Portugal



Source: MTS, authors' calculations

Note: Liquidity proxies: (i) Amihud (ii) daily volume (Volume) and, (iii) daily number of trades (Trades). Liquidity benchmarks: (i) bid ask spread (BAS) (ii) quote slope (Quoteslope) and, (iii) number of quotes per hour (Quotesperhour). MIDAS weights are on the vertical axis, and hours (eight per trading day) on the horizontal axis. For each benchmark/proxy pair the top (bottom) panel represents the individual German sovereign bond with the minimum (maximum) monthly correlation for that pair. Time period: 2011-2012.