UNIVERSITÀ DEGLI STUDI DI ROMA
"TOR VERGATA"

FACOLTA' DI ECONOMIA

DOTTORATO DI RICERCA IN ECONOMIA DELLE ISTITUZIONI E DEI MERCATI MONETARI E FINANZIARI

XX CICLO

Three Essays in Empirical Finance

Alessandro Girardi

A.A. 2007/2008

Docente Guida/Tutor: Prof. Gustavo Piga
Coordinatore: Prof. Gustavo Piga

Three Essays in Empirical Finance

Alessandro Girardi

A Thesis Submitted in Fulfillment of the Requirements for the Doctoral Thesis

Doctorate in Money and Finance

Coordinator: Professor Gustavo Piga

Department of Economics and Institutions

University of Rome "Tor Vergata"

Supervisor: Professor Gustavo Piga

September 2008

Contents

Summary

The Informational Content of Trades on the EuroMTS Platform

Drivers of Liquidity and Trading Activity Dynamics in the European Treasury Bond Markets

The Contribution of Domestic, Regional, and International Factors to Latin America's Business Cycle

Summary

Financial markets constitute the leading thread of the research activities carried out to prepare this thesis. The present research investigates several aspects of financial markets by adopting a specific-to-general perspective, going from market microstructure issues to macro-finance subjects.

This thesis consists of three articles. In the first Chapter, I adopt a microeconomic perspective so as to investigate the process of price formation in the MTS (Mercato Telematico dei Titoli di Stato) system, the most relevant electronic trading platform for trading European government securities. The second Chapter consists of bridging a market microstructure analysis of the MTS system to macroeconomic conditions as well as spillover across financial segments and monetary policy developments in the Euro area. Finally, in the third Chapter I embrace a genuine macroeconomic perspective in order to analyze whether financial developments in the Euro area and other industrialized countries (namely Japan and the US) have a role in explaining business cycle fluctuations in selected Latin American (LA) economies.

Acknowledgments

I would like to express my profound appreciation and indebtedness to my thesis advisor, Professor Gustavo Piga, for his encouragement, guidance, and help during my academic journey. I would like to thank Dr. Paolo Paesani for mentoring and constant support throughout my entire doctoral study. Their work and careers served me as precious examples of a passionate and rigorous approach to research.

I thank Dr. Melisso Boschi for his help, encouragement, and thoughtful advice and for allowing me to use our joint work in Chapter 3 of this thesis. I also thank Professor Miche le Bagella, Professor Guglielmo Maria Caporale and my colleagues their many helpful comments and support. I am grateful to Sergio de Nardis and Roberto Basile from Institute of Studies and Economic Analyses (ISAE) for having allowed me to attend the compulsory activities scheduled by the Ph.D. Scientific Board and to Antonio Caruso from MTS Italy from providing me most of the data I have used in Chapter 2 of this thesis.

Financial support from ISAE, Cassa Depositi e Prestiti S.p.A., Department of Economic and Institutions of the University of Rome "Tor Vergata" and MTS Italy is also gratefully acknowledged.

The Informational Content of Trades on the EuroMTS Platform

Abstract

Using twenty-seven months of daily transaction prices data for 107 European Treasury bonds, this paper presents unambiguous evidence that trading government securities on the EuroMTS platform contributes to disclose information about their (unobservable) efficient price. We find that trades conveying information in terms of price discovery occur on the centralized European marketplace when the level of market liquidity is sufficiently high, even controlling for institutional features. Implications of the empirical findings in the light of the debate about the possible restructuring of the regulatory framework for the financial segment of the market for Treasury securities in Europe are also discussed.

Keywords: Price discovery, liquidity, MTS system.

JEL Classification: G10, C21, C32.

1 – Introduction

Over the past few years, the study of European government bond markets has received increasing attention by the financial and economic literature. The growing availability of high-quality transaction data, thanks to the development of inter-dealer electronic trading platforms and greater willingness by some market participants to share their proprietary information with the academic community, has stimulated a number of empirical works aimed at shedding light on the way such a financial segment functions. Previous works have analyzed the dynamic relationship between trading activity and price movements (Cheung et al., 2005) or between yield dynamics and order flows (Menkveld et al., 2004), on the determination of the benchmark status among government securities of similar maturity (Dunne et al., 2007), on the analysis of yield differentials between sovereign bonds in the Euro area (Beber et al., 2008). With respect to this growing literature, the objective of this paper is to investigate the process of price discovery, that is the timely incorporation into market prices of heterogeneous private information or heterogeneous interpretation of public information through trading, in the most relevant electronic platform for euro-denominated government bonds: the MTS (Mercato Telematico dei Titoli di Stato) system.

One of the most striking features of the MTS platform concerns the parallel listing of benchmark government securities (i.e. is on-the-run bonds with an outstanding value of at least 5 billion euro that satisfy listing requirements such as number of dealers acting as market makers) on a domestic and on a European (EuroMTS) platform. Despite their similar architecture, the domestic MTS and the EuroMTS markets reflect different scopes of functioning, with the former aiming at satisfying issuer' liquidity needs within a regulated and efficient setting and the latter serving as a pure inter-dealer market. According to a more skeptical view, instead, most observers call attention to the possble redundancy of the centralized European trading venue ("the redundancy hypothesis" in Cheung et al., 2005) as all bonds being traded on that market are a fraction of the bucket of securities traded on the respective MTS platforms. On the grounds of this dispute and in an effort to sharpen our understanding of the process of price formation in the MTS system, this paper focuses in sequence on i) assessing whether domestic MTS and the EuroMTS markets price benchamark Treasury securities equally; ii) quantifying the percentage of price discovery taking place in the centralized European platform; and iii) establishing the causative determinants of the informational content of trades on the EuroMTS market.

Here is an overview of our empical investigation. Using an original and extensive dataset of daily transaction prices for 107 government bonds over a 27-month horizon (from January 2004 to March 2006), we employ the methodology proposed by Harris et al. (1995) and Hasbrouck (1995) to document that about 20 percent of price discovery occurs in the European trading platform. Tobit estimation results show that trades conveying information in terms of price discovery occur on the EuroMTS market when trading activity is high and when price volatility is low. Trade cost differentials, instead, seem to have a scarce role in explaining market players' preferences in choosing the EuroMTS trading venue rather to the domestic MTS platforms to trade government fixed income instruments. The strong relationship between measures of the contribution of the EuroMTS marketplace and observable market characteristics to price discovery remains unaffected even when institutional features related to the market making activity of primary dealers as well as controls for the maturities of bonds and the interplay between primary and secondary market for Treasury securites are included as additional covariates. These conclusions are robust across a number of alternative empirical specifications.

The paper is structured as follows. In Section 2, we describe the key institutional features of the MTS system along with the set of the research questions tackled throughout the rest of the paper. The empirical framework is discussed in Section 3. Data and estimation results are presented in Section 4 and Section 5. Conclusions and discussions of the results in the light of the debate on the possible restructuring of the European secondary market for Treasury securities follow. Appendices containing the list of bonds involved in the empirical investigation and the construction of the covariates in the cross-sectional analysis conclude.

2 – Institutional features of the MTS system

2.1 – A duplicated market setting for benchmark securities

Trading on the secondary Treasury market can occur *via* four channels: inter-dealer (B2B) platforms and dealer-to-customer (B2C) electronic trading platforms, either multi-dealer or single-dealer, OTC inter-dealer via voice brokers and OTC dealer-to-customer trading. B2B platforms serve essentially for the trading of Treasury bonds and generally operate via cross-matching methods. In the European case, MTS, Icap/BrokerTec Eurex Bonds and eSpeed are the most prevalent B2B platforms. As pointed out by Pagano and von Thadden (2004), the ability to bring together issuers, with long-term financing needs, and dealers, willing to place liquid funds in interest-bearing securities, and to induce them to a mutual commitment (the "liquidity pact") constitutes the key to the widespread success of the MTS system. Galati and Tsatsaronis (2003) estimate that the MTS system accounts for 40 percent of government bond transactions in Europe and, according to the computations in Persaud (2006), for around 72 percent volume of electronic trading of European cash government bonds.

All government marketable securities issued by euro area Member States are listed on their respective domestic MTS platforms. Only benchmark securities, or on-the-run bonds with an outstanding value of at least 5 billion euro that satisfy a number of listing requirements, are admitted, instead, to trading on the wholesale European market (EuroMTS).[1] For benchmark securities, thus, dealers are allowed to post their quotes on both market simultaneously (parallel quoting).

In the MTS system, market makers' quotes are aggregated in a single order book to match best anonymous bids and offers automatically, subject to non-discretionary priority rules. Trades are anonymous and the identity of the counterpart is only revealed after an order is executed for clearing and settlement purposes, so as to avoid free-riding generated by the existence of less sophisticated traders and allowing for liquidity providers to reduce their

---

[1] Designed by the Italian MTS Group, the London-based EuroMTS was set up in 1999 as a trading venue for euro-denominated benchmark bonds.

exposure when trading (Albanesi and Rindi, 2000).[2] As far the type of market participants, we can categorize them either as market makers (primary dealers) or as market takers (dealers). Primary dealers have to obey a number of obligations, which include: *i)* stringent capital requirements and trading protocols, *ii*) obligation to continuously post firm two-way prices for a selected subset of securities; *iii*) price-posting for at least five hours per day and for a certain minimum quantity; *iv*) possibility to be subject to maximum spread obligations. In return, they are the market participants entitled to participate in supplementary auctions and may gain other privileges. By contrast, dealers cannot enter quotes into the system and are obliged to trade bonds on the basis of bid/ask quotes placed by the primary dealers. In the primary market, a subset of primary dealers is committed to subscribe to specified shares of auctions, thus establishing a possible interplay between practices on the primary market and trading strategies in the secondary market.

2.2 – Empirical issues

As a background to the discussion, we present in Figure 1 (the logarithm of) daily transaction prices of a typical benchmark security (code: IT0003242747) traded on the MTS system, over the period January 2004 - March 2006.

[Figure 1 about here]

Since transaction prices of the same bond recorded in multiple markets are not independent of one another, their discrepancies are expected to be temporary in nature. Figure 1 shows indeed a close overlapping of the two log-price series, albeit some deviations occur. As the same security is traded in two different market places, the process of price formation driven by incorporating heterogeneous private or heterogeneous interpretation of public information into market values is split among trading venues. Since benchmark government bond trading takes places for the most part in the domestic MTS markets, the

---

[2] The full anonymity has been recently reached by means the introduction of the central counterparty (CCP) system, which aims at eliminating any risk faced by participants in trading with other dealers. For a detailed discussion of the MTS system, see Scalia and Vacca (1999).

informational content of prices recorded in the EuroMTS platform may be doubtful. In the MTS system, indeed, the centralized European trading venues seems to be a prototype of "satellite market" (in the sense of Hasbrouck, 1995), competing with a number of large domestic markets. Thus, the first issue (price discovery) we address can be stated as: *What is the contribution of trading in a centralized European market to price discovery for benchmark government securities?*

Finally, the speed at which information arrivals are processed by market participants in a certain trading venue may be influenced by market-specific characteristics (Eun and Sabherwal, 2003; Chakravarty et al., 2004, among others) as well as by institutional arrangements (Huang, 2002). The last part of our empirical anlysis is devoted to ascertain the causative determinants of the degree of privce discovery taking place in the EuroMTS platform. By distingiushing between proxies for liquidity conditions (trading activity, volatility and transaction costs measures) and institutional features, we seek to establish which class of factors have an influence in the process of price formation in the centralized European platform. Thus, the second reserch question (drivers of price discovery) is the following: *What are the cross-sectional determinants of the contribution of the satellite European marketplace to price discovery?*

3 – The empirical framework

3.1 – Dynamics of benchmark government securities in the MTS system

Consider a government benchmark security traded on the EuroMTS (E) and the domestic MTS (D) platforms. The (log-) price in market $j = E, D$ at time t, p_t^j, can be represented as the sum of a permanent component, ϕ_t, and a market-specific transient part, υ_t^j:

$$p_t^j = \phi_t + \upsilon_t^j \tag{1}$$

Given its forward-looking nature, only new information arrivals (due to macroeconomic releases and policy announcements and statements) should cause revisions to what is built into the current price of the bond (Andersson et al., 2006). The law of motion of the permanent term is $\phi_t = \phi_{t-1} + \mu_t^\phi = \phi_0 + \sum_{i=1}^{t} \mu_i^\phi$, where the ϕ_0 term captures initial conditions and μ_t^ϕ is an uncorrelated white noise process such that $E(\mu_t^\phi) = 0$, $E(\mu_t^\phi)^2 = \sigma_\phi^2$, $E(\mu_t^\phi \mu_s^\phi) = 0$ for $s \neq t$. Under this set of assumptions, ϕ_t resembles a random walk. The transitory disturbance υ_t^j, instead, is a covariance stationary process, following an ARMA scheme $\upsilon_t^j = \sum_{i=1}^{\infty} \delta_i^j \xi_{t-i}^j = \delta^j(L)\xi_t^j$, where the elements of the polynomial in the lag operator L, $\delta^j(L)$, are market-specific parameters and ξ_t^j's are independently distributed with mean zero and constant variance.[3] Thus, the difference between a generic pair of bond prices recorded in the two trading venues is:

$$p_t^E - p_t^D = \delta^E(L)\xi_t^E - \delta^D(L)\xi_t^D = \varepsilon_t \tag{2}$$

where the disturbance ε_t is a linear combination of stationary processes and thus stationary itself. Thus, p_t^E and p_t^D are expected to be driven by a common factor, the $\sum \mu_i^\phi$ term, which represents the efficient price related to news cumulating over time, while the ε_t term should capture market-specific transient noises, affecting the speed at which market participants in a specific platform process information flows.[4]

3.2 – The econometric approach

The empirical implication of equation (2) can be suitably captured by specifying, for each

---

[3] Given only the observed transaction prices, the decomposition in equation (1) is unidentified. The literature on permanent and transitory decompositions offers several ways to split the price vector in permanent and transient components, depending on the conditions imposed on the relationships between ϕ_t and υ_t^i and on the stochastic properties of these two components. In this work, we focus on the approaches proposed by Harris et al. (1995) and Hasbrouck (1995).

[4] This is a standard practice used in the analysis of stock market prices (see, among others, Hasbrouck, 1995; Harris et al. 1995). As pointed out by Albanesi and Rindi (2000), in the case of bond prices, such a representation is correct as far as the series used do not include the whole life of the asset.

pair (p_t^E , p_t^D), a dynamic system and testing whether the two log-price series, albeit individually non-stationary, are linked to one another by a stationary long-run equilibrium. Adopting the same notation as introduced above, the following Vector Error Correction (VEC) model (Johansen, 1995) constitutes the basis of our investigation:

$$\begin{bmatrix} \Delta p_t^E \\ \Delta p_t^D \end{bmatrix} = \Pi \cdot \begin{bmatrix} p_{t-1}^E \\ p_{t-1}^D \end{bmatrix} + \sum_{j=1}^{k-1} A_j \cdot \begin{bmatrix} \Delta p_{t-j}^E \\ \Delta p_{t-j}^D \end{bmatrix} + \begin{bmatrix} u_t^E \\ u_t^D \end{bmatrix}, \; E\left(u_t \cdot u_t'\right) = \Sigma = \begin{bmatrix} \sigma_E^2 & \rho\sigma_E\sigma_D \\ \rho\sigma_E\sigma_D & \sigma_D^2 \end{bmatrix} \quad (3)$$

where Δ is the first difference operator, A's are matrices of autoregressive coefficients up to the order $k-1$, u's are the residuals with variance-covariance matrix Σ, where ρ is the correlation coefficient and σ's are standard deviations. If condition (2) holds, we expect rank equal to 1 for matrix Π, i.e. the log-two price series sharing a common stochastic factor. In this case, the long-run matrix can be factored as:

$$\Pi = \begin{bmatrix} \alpha^E \\ \alpha^D \end{bmatrix} \cdot \begin{bmatrix} 1 & -1 \end{bmatrix} \quad (4)$$

with $\alpha^E < 0$ and $\alpha^D < 0$.

The common factor models proposed by Harris et al. (1995) and Hasbrouck (1995) are elegant ways to capture where price discovery occurs for securities traded in multiple markets.[5] Harris et al. (1995) attribute superior price discovery to the market that adjusts the least to price movements in the other market by decomposing the common factor itself:

$$\gamma_E = \frac{\alpha^D}{\alpha^D - \alpha^E}, \; \gamma_D = \frac{\alpha^E}{\alpha^E - \alpha^D} \quad (5)$$

so that, the contribution of the EuroMTS (domestic MTS) marketplace to price discovery,

[5] While these approaches have been applied to stock (Huang, 2002), credit derivatives (Blanco et al., 2005) and foreign exchange (Tse et al., 2006) markets, there is scant empirical evidence for the market of government fixed income securities. Noteworthy exceptions are the works by Upper and Werner (2002), Brandt et al. (2007) and Chung et al. (2007), where the dynamic interactions between spot and future prices are examined. In this work, instead, we focus on two cash markets.

γ_E (γ_D), is defined to be a function of both α's. Based on the Cholesky factorisation of the matrix Σ, Hasbrouck's model assumes, instead, that the degree of price discovery occurring in a trading venue should be (positively) related its contribution to the variance of the innovations to the common factor (market's information share). Since price innovations are generally correlated across markets, the matrix Σ is likely to be non-diagonal. In such an occurrence, Hasbrouck's approach can only provide upper and lower bounds on the information shares of each trading venue. For the EuroMTS market, these bounds are:

$$S_E^{ub} = \frac{(\gamma_E\sigma_E + \rho\gamma_D\sigma_D)^2}{(\gamma_E\sigma_E + \rho\gamma_D\sigma_D)^2 + \gamma_D^2\sigma_D^2(1-\rho^2)} \ , \ S_E^{lb} = \frac{\gamma_E^2\sigma_E^2(1-\rho^2)}{\gamma_E^2\sigma_E^2(1-\rho^2) + (\rho\gamma_E\sigma_E + \gamma_D\sigma_D)^2}$$

respectively. However, Baillie et al. (2002) argue that the average of these bounds:

$$\zeta_E = \frac{1}{2}(S_E^{ub} + S_E^{lb}) \tag{6}$$

provides a sensible estimate of the markets' roles in the mechanism of determination of the efficient price. Both γ_E and ζ_E can range in the interval [0,1], where high values of the two statistics indicate sizable contribution of the EuroMTS market to price discovery.[6]

4 – Data and preliminary analyses

4.1 – Data description

Data are taken from MTS Time series database. Daily observations cover the period from January 2, 2004 to March 31, 2006. For each trading day, we have a time stamp, the nominal value of trading volume, the average size of trades, the last transaction price recorded before the 17.30 Central European Time close, and the average best bid/ask spread throughout the trading day.[7] Furthermore, we use information on the issuer country, the issuing and

[6] See Ballie et al. (2002), among others, for a detailed discussion and a formal derivation of the two price discovery measures.

[7] Previous studies on price discovery have used data of varying frequency, ranging from daily (Blanco et al., 2005) to few seconds (Hasbrouck, 1995). Green and Joujon (2000) argue that daily resettlement creates a strong argument for using daily closing prices, since they determine the cash flows of traders.

maturity dates, the hours in a trading day that dealers must have an active quote, the maximum spread that is quoted and the minimum quantity that a dealer can bid or offer.

In the empirical analysis, we consider government bonds issued by euro area Member States (except for Luxembourg). For each country, we select all benchmark government bonds traded in January 2004 maturing after the end of our estimation horizon; a total of 107 securities. Table 1 summarises the selected bonds, classified by issuer and maturity. Their codes are reported in Appendix A.

[Table 1 about here]

4.2 – Unit root and cointegration tests

Standard cointegration methods require equally spaced data without missing values. Following Upper and Werner (2002), in the presence of missing observations we use the last available transaction price ("fill-in" method). The estimation horizon ranges from 557 to 585 observations, with an average value of 580 daily datapoints. As a preliminary exercise, we check for the presence of a unit root in each of 214 individual transaction price series expressed in logarithms. ADF tests (Dickey and Fuller, 1979) are performed on the series, both in levels and first differences. In each case, we are unable to reject the null hypothesis of a unit root at conventional levels of significance. On the other hand, differencing the series appears to induce stationarity. The KPSS stationarity tests (Kwiatkowski et al., 1992) corroborate these results (not reported to save space).

Given the evidence of $I(1)$-ness for all individual series, testing for cointegration between each pair (p_t^E , p_t^D) is the logical next step. This translates into the estimation of 107 VEC models, as the one in equation (3), testing whether the restriction (4) is not rejected by the data. The order of autoregression k of the biavriate models (3), formulated in their isomorphic Vector AutoRegression (VAR) representation, is chosen on the basis of the AIC in order to ensure richer dynamics. Overall, the order of autoregression is quite limited: $k=1$, $k=2$, $k=3$ and $k=4$ is chosen for 62, 25, 15 and 5 entities of reference, respectively.

The trace test (Johansen, 1995) suggests choosing rank 1 for the Π matrix in 104 models, giving support to our *a priori* theoretical assumptions.[8] The symmetry and proportionality assumption implied by condition (2) is tested by means a χ^2-distributed LR test with one degree of freedom. In 88 entities of reference, the over-identifying restriction is not rejected by the data (at least) at the 10 percent level of significance, while in 6 cases (at least) at the 5 percent level. For the remaining 10 models the evidence is less conclusive, even though the cointegration test developed by Horvath and Watson (1995) supports the existence of a $[1 \quad -1]'$ cointegration vector.[9] All in all, our evidence leads to conclude that the architecture of the MTS system allows to eliminate persistent discrepancies between the prices of the same bond traded on the domestic MTS and the European platforms.

4.3 – Speed of covergence towards the long-run equilibrium

The dynamic properties of the 104 bivariate dynamic systems (3) with a reduced rank for the matrix Π reveal that the feedback coefficients associated to the Δp_t^E equation are statistically significant at the 1 percent level in all models; by contrast, only one-half of the estimated α^D coefficients turn out to be statistically significant (at the 1 percent level in 24 entities of reference, at the 5 percent in 15, at the 10 percent in the 12 remaining cases). Furthermore, both α^E and α^D are correctly signed, implying direct convergence towards the long-run relationship in all but six models (where the estimated α^D's turn out to be negative).

---

[8] In three entities of reference (FI0001005514, GR0110014165, IT0003522254), the rank of the long-run matrix turns out to be two. Even though this finding is at odds with the conclusions from the unit root/stationarity tests (which suffer from well-know problems of lack of power), it confirms that condition (2) holds in these three cases too.

[9] The test statistics of the null of no cointegration against the known alternative of rank one with $\beta' = [1 \ -1]$ is computed as $2(\ln LL_{VECM} - \ln LL_{VAR})$, where LL denotes the value of the likelihood function under the respective model. Results from this test are available on request.

Discarding the entities of reference with wrongly signed α^D's, departures from the equilibrium condition are corrected for the most part in the European platform, with the average value for $|\alpha^E|$ equal to 0.26 as compared to 0.06 for α^D (Table 2).[10] This conclusion is confirmed by testing the null $H_0 : |\alpha^E| = \alpha^D$: the LR test statistics turns out to be greater than 3.84 (the 95 percent critical value for a χ^2 distribution with one degree of freedom) for a majority of bonds (82 out of 98 entities of references).[11]

[Table 2 about here]

5 – Price discovery in the EuroMTS platform and its determinants

5.1 – Estimated price discovery measures

Price discovery measures (5) and (6) are a more direct way to assess whether trading Treasury fixed income instruments on the centralized European platform convey information to determine their (unobservable) efficient price. Estimated values of γ_E for individual entities of reference range from 0.2 percent (IT0003357982) to 55.9 percent (IE0031256328), while the ζ_E measure takes values from 2.7 percent (AT0000383864) to 55.5 percent (IE0031256328). Table 3 reports the results aggregated by issuing countries.

The median of the two measures is the same (17.4 percent), with an average value slightly higher for ζ_E (20.6 percent) than the one for γ_E (19.7 percent). Based on the

---

[10] Our estimates indicate half-life deviations from the equilibrium condition, $n = \ln 0.5 / \ln[1-(|\alpha^E| + \alpha^D)]$, lasting around two days, on average. As a result, the ratio between the sample length in terms of data points and the half-life is around 300. This adds confidence to our results, especially in the light of the Monte Carlo study by Hakkio and Rush (1991), who show that in cointegration analysis, the ratio of the length of the data set to the half-life is more relevant than the length of the data set alone.

[11] A similar picture is obtained by comparing the R^2_{adj} for the two dynamic equations of the system (3) under condition (4). We find that, on average, the explained variation of Δp_t^E is around 13.9 percent, while the one for Δp_t^D is only 1.6 percent.

standard error of the mean values, these averages are significantly different from zero at the 1 percent level. The evidence here reported suggests that trades taking place on the EuroMTS market have a sizable informational content, going up against the "redundancy hypothesis", in a way consistent with the conclusions in Cheung et al. (2005).[12] Furthermore, a standard t-test for the equivalence of the mean (γ_E minus ζ_E) produces a test statistics equal to -0.56 with a p-value of 0.58, thus confirming that the estimated EuroMTS market's share is equivalent irrespective of which of the two price discovery measures is taken into account. Finally, the correlation coefficient between γ_E and ζ_E turns out to be very high (0.81) and statistically significant at the 1 percent level, implying that the two price discovery measures lead to non-conflicting conclusions.[13]

[Table 3 about here]

5.2 – Determinants of price discovery: liquidity conditions and institutional features

In keeping with previous works (Eun and Sabherwal, 2003; Chakravarty et al., 2004), price discovery measures are likely to be systematically related to proxies for market liquidity

---

[12] Notice that the "fill-in" method does not affect the estimates of the long-run relationship equilibrium, but may influence the short-term information flow, since non-trading may produce a lower information share for the less frequent trading market even if the trades that take place do contain information (Lehmann, 2002). Since trades on the EuroMTS are *fewer* than those occurring on the domestic trading venue for every pair of bonds involved in the analysis, the problem is less severe than it could appear. Thus, our statistically significant estimates of γ_E and ζ_E can be interpreted as *lower* bounds.

[13] As a robustness check, we follow Blanco et al. (2005) and replace wrongly signed α^D's by zero. Summary statistics for γ_E and ζ_E computed for the larger sample (104 models) are quite similar to those reported in Table 4. The average values of γ_E and ζ_E (0.1853 and 0.2031, respectively) are statistically not different according to a standard t-test (p-value 0.31), with the same standard deviations of the mean with respect to the values in Table 4. Furthermore, by comparing the mean value of γ_E (ζ_E) for the sub-sample of 98 bonds to the one for the larger sample of 104 securities, the t-test for the equivalence of the mean suggests not rejecting the null with a p-value of 0.54 (0.84).

conditions. It is generally understood that a well-functioning market should be characterised by *i*) high trading volumes, *ii*) low price volatility and *iii*) tiny bid/ask spreads. Appendix B illustrates how we extract relative measures (EuroMTS minus domestic MTS) of trading activity ($ntra$), price volatility ($rsig$) and transaction costs measures (quoted bid/ask spreads associated with transactions, $qspr$, and effective spreads, $espr$, respectively) from (equally-weighted) daily averages over the sample span of reference as well as the additional covariates described below.

Since institutional arrangements may confound the linkage between observable market characteristics and price discovery (Huang, 2002) we extend our set of regressors so as to include controls for a number of institutional features. Costly continuous quoting obligations faced by market makers suggest including continuous quoting hours, $hour$, the maximum spread that can be quoted, $mspr$, and the minimum quantity that dealers have to bid or to offer, $mqty$. We expect a negative (positive) relation between $hour$ ($mspr$) and the degree of contribution to price discovery; a positive effect of $mqty$ on the price discovery measures (5) and (6) may be consistent, instead, with the "large trader's blessing" hypothesis (Scalia and Vacca, 1999), according to which anonymous trade favours large traders and, thus, the occurrence of larger transactions in size.

A number of studies (Pagano and Von Thadden, 2004, among others) emphasize that the degree of financial integration in Europe appears to be inversely related to the level of risk-taking market participants are ready to assume. Following Dunne et al. (2007), we control for maturity effects by distinguishing short/medium term bonds (with maturity less than 6.5 years) from bonds with longer maturity (more than 6.6 years) through a dummy variable, $smty$. Finally, since auctioning government securities may involve risks for the issuer (market squeezes, price manipulations, speculative behaviours, bidders' collusion), we employ a syntetic indicator, $prot$, developed by Bagella et al. (2006), which measures the effectiveness of the framework of rules introduced by euro area governments to protect themselves from those risks.[14] A positive effect of $prot$ on γ_E or ζ_E indicates that higher government's levels of protection against auctioning risks may persuade against concentrating trading activity on the domestic market.

5.3 – Cross-sectional analysis: Tobit estimates

We use a Tobit estimator as our dependent variables, γ_E and ζ_E, are restricted to lie between 0 and 1 by construction. Table 4 provides the maximum likelihood estimation results for benchmark specifications (Panel [A]), which include only observable market characteristics in the set of regressors, and for specifications augmented by controls for institutional features (Panel [B]), separately for γ_E and ζ_E. All specifications include an intercept term so as to capture possible non-observable country-specific effects. Model [1] differs from Model [2] with respect to the bid/ask spread used as explanatory variable. Statistically significant coefficients at the 95 percent level confidence interval, calculated using the bootstrap method with 500 replications, are reported in bold. Following the recommendations in Veall and Zimmermann (1994), we use the McKelvey-Zavoina-Pseudo-R^2 as a measure of the goodness of fit for our regressions.

[Table 4 about here]

Estimation results from Panel [A] are impressive: roughly 60 percent of the cross-sectional variation in γ_E and ζ_E is explained by observable market characteristics alone.[15]

[14] Bagella et al. (2006) indicate a group of five countries (Belgium, France, Germany, Ireland and the Netherlands) with a high protection against auctioning risks, with Finland and Greece showing a slightly lower degree of protection; the remaining countries (Austria, Italy, Portugal and Spain) exhibit, instead, a quite weak framework of rules.

[15] Notice that the absence of censoring problems in our sample allows for an almost direct interpretation of the estimated coefficients as marginal effects. This is confirmed by a comparison of the coefficients of observable market characteristics from the Tobit model in Table 4 and the marginal effects (calculated at the sample mean of the regressors) for the unconditional expected value of the dependent variable. Details on these regressions are available on request.

In particular, Tobit regressions show that trades conveying information occur on the EuroMTS platform when the level of trading activity is sufficiently high and the level of price volatility is sufficiently low.[16] By contrast, the relative spread term is not statistically significant in three out of four specifications, suggesting that trading costs differentials across marketplaces cannot be accounted as a major factor for choosing a platform rather the other, as previously found by Cheung et al. (2005). Comparing the above-discussed results to the estimates in Panel [B] several considerations emerge.[17] *First*, goodness of fit statistics show that the augmented specifications are able to capture a slightly larger part of the overall cross-sectional variation relative to the one of their counterparts collected in Panel [A]. *Second*, estimated coefficients of proxies for market liquidity conditions are very close to those obtained in the benchmark specifications. *Third*, the sign of the statistically significant coefficients of the additional regressors are broadly consitent with our economic priors. *Fourth*, institutional variables are jointly significant at the 5 percent level according to a simple χ^2-distributed likelihood ratio test.[18]

All in all, our findings point out that liquidity conditions seem to have a major role in explaining cross-sectional variability of EuroMTS market's share to price discovery, while institutional features are of second order importance. In the following Section, we discuss the

---

[16] The use of relative number of transactions (defined as the ratio between the nominal amount of trades and their average size) in place of $tvol$ in the specifications collected in Table 4 gives similar results.

[17] Given the lack of significance of $mspr$ in all regressions, estimation results in Table 4 refer to specifications, which do not include that covariate. The magnitude and the statistical significance of coefficients for observable market characteristics remain unaffected by the inclusion of $mspr$. Furthermore, assessing the statistical significance of the estimated parameters by using standard errors calculated with the Huber-White sandwich estimator of variance in place of those obtained from bootstrap techniques leads to similar conclusions.

[18] We take into account possible asymmetries by adding interaction terms between indicators of market functioning and $smty$ or $prot$, alternatively. In none of these regressions we are able to detect statistically significant asymmetric effects.

sensitiveness of our findings to modifications and extensions of the baseline empirical design.

5.4 – Robustness and extensions

As a check of robustness we use linear regression models for logit transformations of the price discovery measures, ${}^{*}\gamma_E = \ln[\gamma_E/(1-\gamma_E)]$ and ${}^{*}\zeta_E = \ln[\zeta_E/(1-\zeta_E)]$, respectively. The OLS estimation results are presented in Table 5.

[Table 5 about here]

Notice that the strong positive (negative) link between price discovery measures and trading activity (price volatility) is confirmed, giving support to our previous conclusions. The two main differences with respect to the Tobit estimates in Table 4 refer to the institutional variables: *first*, the maturity effect is statistically significant in all regressions; *second*, $mqty$ turns out to be statistically significant in the specifications where ${}^{*}\zeta_E$ is the dependent variable. This finding may suggest the existence of possible informational asymmetries between uninformed dealers and traders who behave like informed investors (Fleming and Remolona, 1999) with their trades based on superior inventory and order flow information (Huang et al., 2002).[19]

Finally, we re-examine the interplay between primary and secondary government bond. Favero et al. (2000) point out that financial integration in Europe may increase investors' interest on the characteristics of bond issues rather than on the nationality of issuers, leading to euro area governments to compete each other for the same pool of funding. The need for a highly liquid secondary Treasury bond market is expected to be of crucial importance mostly for large issuers and/or debtors. Accordingly, we identify as large issuers those countries (namely, France, Italy and Germany) with more than 100 billion euro of issuance (in 2005) by means the dummy $liss$, while we indicate Belgium, France, Italy and Germany as large

[19] Since the nature of private information in government bond markets differs markedly from the notion widely used when analyzing equity markets, a closer investigation of such an issue for the European case is an area which would clearly repay further research.

debtors through the variable *debt*. We replicate the regressions in Table 4, with *i*) *liss* and *debt* as an additional covariate, alternatively; *ii*) *liss* or *debt* in place of *prot*. Overall, the evidence from set of regressions (not reported) indicates no differenced patterns in price discovery revelation on the EuroMTS market between large and small issuers or between large and small debtors. While the above discussed relationship between statistics about the informational content of trades on the EuroMTS platform and proxies for market liquidity conditions is robust with respect to the inclusion of these institutional controls, primary market developments are likely to affect EuroMTS market's share to price discovry mainly through regulatory practices in auctioning government securities, with country dummies capturing non-modelled institutional factors (such as national gross issuances and the amount of outstanding public debt).

6 – Conclusions and further discussions

This paper is a contribution to the growing empirical literature on the European Treasury bond markets. To our knowledge, this is the first work to directly measure the relative contribution of trading in a domestic (MTS) versus a centralized European (EuroMTS) marketplace to price discovery for benchamark government securities. To that purpose, we employ an original and extensive dataset as compared to that of the existing literature. Our sample is of independent interest because its construction involved tracking daily observations for 107 pairs of bonds over a 27-month horizon (from January 2004 to March 2006).

We reach two main findings. *First*, the architecture of the MTS system is able to eliminate persistent price discrepancies for the same bond traded on the two markets. The determination of the efficient price appears to take place on both platforms, with about 20 percent of price discovery occurring in the EuroMTS platform. *Second*, a number alternative specifications reveal a systematic linkage between cross-sectional variability of the relative contribution of EuroMTS to price discovery on one hand and trading activity and price volatility on the other. Trade cost differentials, instead, seem to have a scant role in explaining market players' preferences in trading government fixed income instruments on the European platform rather the domestic MTS market. The inclusion of additional covariates in the set of regressors so as to control for institutional features does not wipe out the strong relationship between EuroMTS market's share to price discovery and market liquidity conditions. These conclusions are robust across a number of modifications and extensions of the baseline empirical design.

Aside from their scientific merit, our findings have relevant implications for regulators attempting to identify conditions likely to promote further integration in the European financial system. In accordance with the principles of the Directive 2004/39/EC, disciplining the functioning of Markets in Financial Instruments in Europe (MiFID), favouring transparency is an essential mean to achieve an adequate price formation process. However, the relationship between transparency and price discovery is less than obviuos. On the one hand, the exposure of quotes forces market makers to be competitive, making it easier to find the best prices, especially for market takers, who are likely to be less sophisticated than larger market participants. On the other hand, order visibility may reduce the readiness of dealers willing to keep large transactions confidential to participate in the market. This may erode liquidity and impact the efficiency of price formation. Our results suggest that a proliferation of alternative trading platforms may be harmful in fostering integration of the European government bond market if the *potential* gains from competition across trading venues do not counterweight costs due to increased fragmentation in market liquidity.

A fuller understanding of the liquidity properties of the MTS system is an empirical issue that calls for further investigation. Possible improvements of the research agenda may include a closer scrutiny on whether and how information asimmetries among market participants affect the price formation mechanism in the European market of Treasury securities. A second venue for further advances may take into account a richer specification of the relationship between price discovery measures and their determinants across securities *and* over time. In this respect, the analysis of the dynamics of market liquidity and trading activity indicators could be fruitful to increase market participants' confidence on trading securities on EuroMTS. These issues are left for future research.

Appendix A. List of selected government bonds

The government bond markets covered in our dataset are those of Austria, Belgium, Spain, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands and Portugal. For each country, we select all benchmark government securities traded in January 2004 with maturity date subsequent the end of our estimation horizon (March 2006). 107 bonds satisfy such a requirement and their codes are reported below:

AT0000383518, AT0000383864, AT0000384227, AT0000384821, AT0000384938, AT0000384953, AT0000385067, AT0000385356, AT0000385745, AT0000385992; BE0000286923, BE0000291972, BE0000296054, BE0000297060, BE0000298076, BE0000300096, BE0000301102, BE0000302118, BE0000303124; DE0001135176, DE0001135192, DE0001135200, DE0001135218, DE0001135226, DE0001135234, DE0001135242, DE0001141380, DE0001141398, DE0001141406, DE0001141414, DE0001141422, DE0001141430; ES0000012239, ES0000012387, ES0000012411, ES0000012445, ES0000012452, ES0000012783, ES0000012791, ES0000012825, ES0000012866, ES0000012882; FI0001004822; FI0001005167; FI0001005332, FI0001005407, FI0001005514, FI0001005522; FR0000187361, FR0000187635, FR0000187874, FR0000188328, FR0000188690, FR0000188989, FR0000189151, FR0010011130, FR0103230423, FR0103840098, FR0104446556, FR0105427795, FR0105760112, FR0106589437; GR0110014165, GR0114012371, GR0114015408, GR0124006405, GR0124011454, GR0124015497, GR0124018525, GR0124021552, GR0124024580, GR0128002590, GR0133001140, GR0133002155; IE0006857530, IE0031256211, IE0031256328, IE0032584868; IT0001448619, IT0003080402, IT0003171946, IT0003190912, IT0003242747, IT0003256820, IT0003271019, IT0003357982, IT0003413892, IT0003472336, IT0003477111, IT0003493258, IT0003522254, IT0003532097, IT0003535157, IT0003611156, IT0003618383; NL0000102101, NL0000102317, NL0000102606, NL0000102671, NL0000102689, NL0000102697; PTOTECOE0011, PTOTEGOE0009, PTOTEJOE0006, PTOTEKOE0003, PTOTEWOE0009, PTOTEXOE0016.

Appendix B. Construction of variables

Observable market characteristics. Let x^j be the (equally-weighted) daily average of a variable x over the sample span of reference, where $j = E, D$ indexes the EuroMTS (E) or the domestic MTS (D) platform, respectively. Following Eun and Sabherwal (2003) we compute the following log-transformations: $tvol = \ln[1 + (vol^E / vol^D)]$, where vol is the nominal amount of trades in million euro; $rsig = \ln[1 + (sig^E / sig^D)]$, where sig is the standard deviation of the first differenced logarithms of transaction prices (Δp^j); $qspr = \ln[1 + (qsp^E - qsp^D)]$, where qsp is the quoted bid/ask spread associated with the transaction; $espr = \ln[1 + (esp^E - esp^D)]$, where esp is the difference between transaction prices and the mid-point of the prevailing bid/ask quote.

Institutional variables. $smty$ is a dummy taking value 1, if bonds have a maturity (in terms of the difference between the maturity date and the issue date) less than 6.5 years, and 0, otherwise; $prot$ is a dummy taking value 1, if countries have a high overall auction risks covering degree (Belgium, France, Germany, Ireland and the Netherlands, Finland and Greece), and 0, otherwise; $hour$ is a dummy taking value 1, if the number of quoting hours for a bond on EuroMTS is higher than on the domestic MTS, and 0, otherwise; $mspr$ is a dummy taking value 1, if the maximum bid/ask spread for a bond on EuroMTS is lower than the one on the domestic MTS, and 0, otherwise; $mqty$ is a dummy taking value 1, if the minimum quantity for a bond on EuroMTS is higher than the one on the domestic MTS and 0, otherwise.

Other controls. $liss$ ($debt$) is a dummy taking value 1, if bonds are from large issuers (borrowers) - that is Italy, Germany or France (or Belgium) - and 0, otherwise; country dummies take value 1, when the bond is issued by the Treasury of that country, and 0, otherwise).

References

Albanesi S. and B. Rindi (2000), The Quality of the Italian Treasury Market, Asymmetric Information and Transaction Costs, Annales d'Economie et de Statistique, 60, p. 1-19.

Andersson M., L.J. Hansen and S. Sebestyén (2006), Which News Moves the Euro Area Bond Market?, ECB Working Paper, 631.

Bagella M., A. Coppola, R. Pacini and G. Piga (2006), Euro Debt Primary Market Annual Report, University of Rome "Tor Vergata" and UBM.

Baillie R.T., G.G. Booth, Y. Tse and T. Zabotina (2002), Price Discovery and Common Factor Models, Journal of Financial Markets, 5, p. 309-321.

Beber A., M.W. Brandt and K.A. Kavajecz (2008), Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market, Review of Financial Studies, forthcoming.

Blanco R., S. Brennan and I. Marsh (2005), An Empirical Analysis of the Dynamic Relation between Investment-Grade Bonds and Credit Default Swaps, Journal of Finance, 60, p. 2255-2281.

Brandt M.W., K.A. Kavajecz and S.E. Underwood (2007), Price Discovery in the Treasury Futures Market, Journal of Futures Markets, 27, p. 1021-1051.

Chakravarty S., H. Gulen and S. Mayhew (2004), Informed Trading in Stock and Option Markets, Journal of Finance, 59, p. 1235-1258.

Cheung C., F. de Jong and B. Rindi (2005), Trading European Sovereign Bonds: The Microstructure of the MTS Trading Platforms, ECB Working Paper, 432.

Chung C., B. Campbell and S. Hendry (2007), Price Discovery in Canadian Government Bond Futures and Spot Markets, Bank of Canada Working Paper, 4.

Dickey D.A. and W.A. Fuller (1979), Distribution of the Estimators for Autoregressive Time Series with a Unit Root, Journal of the American Statistical Association, 74, p. 427-431.

Dunne P.G., M.J. Moore and R. Portes (2007), Benchmark Status in Fixed-Income Asset Markets, Journal of Business Finance and Accounting, 34, p. 1615-1634.

Eun C.S. and S. Sabherwal (2003), Cross-Border Listings and Price Discovery: Evidence from

U.S.-Listed Canadian Stocks, Journal of Finance, 58, p. 549-576.

Favero C., A. Missale and G. Piga (2000), EMU and Public Debt Management: One Money, One Debt?, CEPR Policy Paper, 3.

Fleming M. and E. Remolona (1999), Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information, Journal of Finance, 54, 1901-1915.

Galati G. and K. Tsatsaronis (2003), The Impact of the Euro on Europe's Financial Markets, *Financial Markets, Institutions and Instruments*, 12, pp. 165-221.

Green C.J. and E. Joujon (2000), Unified Tests of Causality and Cost of Carry: The Pricing of the French Stock Index Futures Contract, International Journal of Finance and Economics, 5, p. 121–140.

Hakkio C.S. and R. Rush (1991), Cointegration: How Short Is the Long Run?, Journal of International Money and Finance, 10, p. 571-581.

Harris F., T. McInish, G. Shoesmith and R. Wood (1995), Cointegration, Error Correction, and Price Discovery on Informationally Linked Security Markets, Journal of Financial and Quantitative Analysis, 30, p. 563-579.

Hasbrouck J. (1995), One Security, Many Markets: Determining the Contributions to Price Discovery, Journal of Finance, 50, p. 1175-1199.

Horvath M.T.K. and M.W. Watson (1995), Testing for Cointegration when Some of the Cointegrating Vectors Are Prespecified, Econometric Theory, 11, p. 984-1014.

Huang R.D. (2002), The Quality of ECN and Nasdaq Market Maker Quotes, Journal of Finance, 57, p. 1285-1319.

Huang R.D., J. Cai, and X. Wang (2002), Information-based Trading in the Treasury Note Interdealer Broker Market, Journal of Financial Intermediation, 11, p. 269-296.

Johansen S. (1995), Likelihood-Based Inference in Cointegrated Vector Autoregressive Models, Oxford University Press.

Kwiatkowski D., P.C.B. Phillips, P. Schmidt and Y. Shin (1992), Testing the Null Hypothesis of Stationary against the Alternative of a Unit Root, Journal of Econometrics, 54, p. 159-178.

Lee T. and Y. Tse (1996), Cointegration Tests with Conditional Heteroskedasticity, Journal of Econometrics, 73, p. 401-410.

Lehmann B.N. (2002), Some Desiderata for the Measurement of Price Discovery across Markets, Journal of Financial Markets, 5, p. 259-276.

Menkveld A.J., Y.C. Cheung and F. de Jong (2004), Euro Area Sovereign Yield Dynamics: The Role of Order Imbalance, ECB Working Paper, 385.

Pagano M. and E.L. Von Thadden (2004), The European Bond Markets under EMU, Oxford Review of Economic Policy, 20, p. 531-554.

Persaud A.D. (2006), Improving Efficiency in the European Government Bond Market, Discussion Paper ICAP plc.

Scalia A. and V. Vacca (1999), Does Market Transparency Matter? A Case Study, BIS Papers, 2, p. 113-144 (with comments).

Tse Y., J. Xiang and J.K.W. Fung (2006), Price Discovery in the Foreign Exchange Futures Market, Journal of Futures Markets, 26, p. 1131-1143.

Upper C. and T. Werner (2002), How Resilient Are Financial Markets to Stress? Bund Futures and Bonds during the 1998 Turbulence, BIS Papers, 12, p.110-123.

Veall M.R. and K.F. Zimmermann (1994), Goodness of Fit Measures in the Tobit Model, Oxford Bulletin of Economics and Statistics, 56, p. 485-499.

Tables and Figures

Table 1 – Selected benchmark government bonds by maturity and issuer

	Short/medium maturity	Long maturity	Very long maturity	*Sum by country*	*Percentage by country*
ATS	0	8	2	*10*	*9.3*
BEL	2	5	2	*9*	*8.4*
ESP	3	5	2	*10*	*9.3*
FIN	3	3	0	*6*	*5.6*
FRF	6	5	3	*14*	*13.1*
GEM	6	5	2	*13*	*12.1*
GGB	3	6	3	*12*	*11.2*
IRL	2	1	1	*4*	*3.7*
MTS	7	6	4	*17*	*15.9*
NLD	2	3	1	*6*	*5.6*
PTE	2	3	1	*6*	*5.6*
Sum by maturity	*36*	*50*	*21*	*107*	.
Percentage by maturity	*33.6*	*46.7*	*19.6*	.	*100.0*

Note. The first and the second row (column) in italics present the sum and the percentage by maturity (issuer), respectively.

Table 2 – Estimated values of the feedback coefficients

	α^E	α^D	$\|\alpha^E\|+\alpha^D$
Mean	-0.2601	0.0594	0.3195
Minimum	-0.6561	0.0009	0.0547
Maximum	-0.0506	0.2304	0.6718
5th percentile	-0.5183	0.0066	0.1297
25th percentile	-0.3657	0.0222	0.1887
Median	-0.2345	0.0465	0.3042
75th percentile	-0.1457	0.0849	0.4395
95th percentile	-0.0898	0.1453	0.5761

Note. Computations based on 98 bivariate VEC models.

Table 3 – Estimated price discovery measures for the EuroMTS platform

	Number of bonds	γ_E	ζ_E
AUT - Austria	10	0.1430	0.0988
BEL - Belgium	8	0.1824	0.1803
ESP - Spain	10	0.2558	0.2446
FIN - Finland	5	0.1963	0.2149
FRF - France	14	0.1800	0.1623
GEM - Germany	12	0.2779	0.2664
GGB - Greece	10	0.2008	0.2624
IRL - Ireland	4	0.5016	0.4773
MTS - Italy	13	0.0559	0.1799
NLD - the Netherlands	6	0.2654	0.2114
PTE - Portugal	6	0.1081	0.1114
Median	.	0.1742	0.1740
Mean	.	0.1966	0.2064
Std. error of mean	.	0.0132	0.0117

Note. Values in the second and third numerical column are equally weighted averages across bonds issued by the same country. Computations based on 98 bivariate VEC models.

Table 4 – Determinants of price discovery on the EuroMTS platform: Tobit models

	Panel [A]				Panel [B]			
	Model [1]		Model [2]		Model [1]		Model [2]	
	γ_E	ζ_E	γ_E	ζ_E	γ_E	ζ_E	γ_E	ζ_E
tvol	**0.4397**	**0.4943**	**0.5313**	**0.5771**	**0.4520**	**0.4902**	**0.5352**	**0.5622**
	(0.1353)	(0.1188)	(0.1549)	(0.1391)	(0.1473)	(0.1401)	(0.1713)	(0.1576)
rsig	**-0.8556**	**-0.7593**	**-0.7756**	**-0.7184**	**-0.9210**	**-0.7841**	**-0.8630**	**-0.7720**
	(0.2850)	(0.2630)	(0.2735)	(0.2597)	(0.2866)	(0.2519)	(0.2962)	(0.2394)
espr	**-1.2744**	-0.5533	.	.	-0.8461	-0.00748	.	.
	(0.6288)	(0.6452)	.	.	(0.6618)	(0.6906)	.	.
qspr	.	.	0.2723	0.3133	.	.	0.2759	0.3291
	.	.	(0.3842)	(0.3482)	.	.	(0.4331)	(0.3409)
smty	.	.	.	.	0.0324	**0.0455**	0.0369	**0.0465**
	.	.	.	.	(0.0238)	(0.0227)	(0.0246)	(0.0228)
prot	.	.	.	.	**0.0893**	**0.1106**	**0.0936**	**0.1105**
	.	.	.	.	(0.0351)	(0.0298)	(0.0389)	(0.0340)
hour	.	.	.	.	**-0.0931**	**-0.0916**	**-0.1087**	**-0.0889**
	.	.	.	.	(0.0437)	(0.0354)	(0.0486)	(0.0336)
mqty	.	.	.	.	0.0139	0.0343	0.0227	0.0329
	.	.	.	.	(0.0256)	(0.0267)	(0.0265)	(0.0273)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES
σ	**0.0798**	**0.0745**	**0.0811**	**0.0743**	**0.0758**	**0.0687**	**0.0761**	**0.0681**
	(0.0058)	(0.0050)	(0.0060)	(0.0056)	(0.0059)	(0.0048)	(0.0059)	(0.0048)
LL	108.73	115.47	107.18	115.72	113.70	123.33	113.33	124.23
AIC	-189.46	-202.94	-186.37	-203.44	-191.41	-210.66	-190.65	-212.46
Pseudo-R^2	0.6247	0.5811	0.6127	0.5833	0.6610	0.6432	0.6583	0.6497

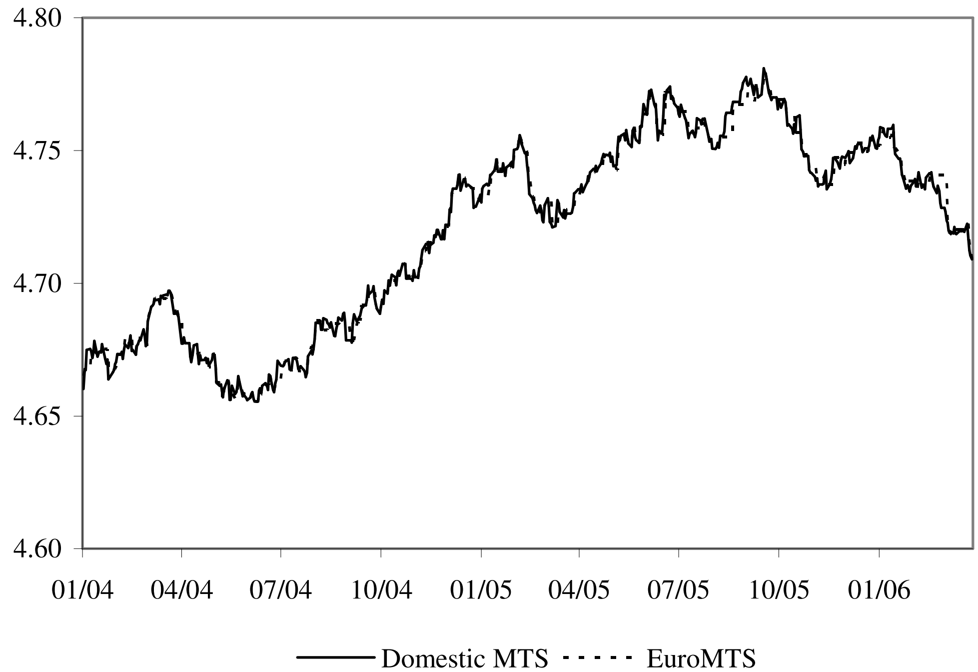
Note. The intercept term, albeit included among the regressors, is omitted for ease of exposition. Statistically significant coefficients according to the 95 percent level confidence interval, calculated using the bootstrap method with 500 replications, are in bold. The number of observations is 98. Definitions of the regressors are provided in Appendix B.

Table 5 – Determinants of price discovery on the EuroMTS platform: OLS estimates

	Panel [A]				Panel [B]			
	Model [1]		Model [2]		Model [1]		Model [2]	
	γ_E^*	ζ_E^*	γ_E^*	ζ_E^*	γ_E^*	ζ_E^*	γ_E^*	ζ_E^*
tvol	**2.6722**	**3.0393**	**3.5955**	**3.5923**	**2.5310**	**2.9618**	**3.3169**	**3.4028**
	(1.0961)	(0.7499)	(1.4753)	(0.8875)	(0.9806)	(0.8161)	(1.2806)	(0.9046)
rsig	**-6.8009**	**-6.1305**	**-5.7250**	**-5.8945**	**-7.4250**	**-6.4518**	**-6.6761**	**-6.4774**
	(2.4410)	(1.8755)	(2.2597)	(1.8174)	(2.3402)	(1.7342)	(2.1377)	(1.6911)
espr	**-18.0010**	-2.9919	.	.	**-11.8074**	1.8428	.	.
	(8.1859)	(4.5802)	.	.	(6.6005)	(4.8557)	.	.
qspr	.	.	2.1652	2.1720	.	.	2.1297	2.2515
	.	.	(3.5485)	(2.1984)	.	.	(3.9118)	(1.8475)
smty	.	.	.	.	**0.3063**	**0.3306**	**0.3637**	**0.3291**
	.	.	.	.	(0.1594)	(0.1343)	(0.1784)	(0.1280)
prot	.	.	.	.	**1.6794**	**1.1304**	**1.7403**	**1.1195**
	.	.	.	.	(0.6410)	(0.2749)	(0.6625)	(0.2851)
hour	.	.	.	.	**-1.3658**	**-0.9168**	**-1.5982**	**-0.8587**
	.	.	.	.	(0.6083)	(0.3077)	(0.6360)	(0.2957)
mqty	.	.	.	.	0.6918	**0.4164**	0.8233	**0.3838**
	.	.	.	.	(0.5015)	(0.1888)	(0.5673)	(0.2071)
Country dummies	YES	YES	YES	YES	YES	YES	YES	YES
LL	-109.97	-71.69	-114.11	-71.24	-99.12	-57.49	-100.94	-56.57
AIC	245.94	169.38	254.23	168.49	232.24	148.98	235.89	147.15
$AdjR^2$	0.4946	0.4998	0.4500	0.5043	0.5750	0.6071	0.5588	0.6144

Note. See note of Table 4.

Figure 1 – Daily transaction prices on the MTS system



Note. Dashed (continuous) line indicates the logarithm of daily transaction prices recorded in the EuroMTS (domestic MTS) platform for a 15-year bond (code: IT0003242747), over the period January 2004 - March 2006.

Drivers of Liquidity and Trading Activity Dynamics in the European Treasury Bond Markets

Abstract

Knowledge about time-series variations in Treasury bond market liquidity and trading activity is limited. Using high-frequency transaction data for the three largest European markets (France, Germany and Italy) over the period July 2006 - June 2007, this work explores how liquidity and trading activity evolve over time; to what extent their dynamics interact; whether their dynamics exhibit some common patterns across bonds. Controlling for seasonal factors, we find that these co-movements are non-linear and driven by inventory concerns, stock market volatility, macroeconomic releases and monetary authorities' liquidity management operations. Liquidity properties of this financial segment under financial distress are also discussed.

Keywords: Liquidity, trading activity, Treasury bond market, Europe, non-linearities, commonality.

JEL Classification: G1, G15, F36, C32, C33, C15

1 – Introduction

Despite monitoring market liquidity and trading activity is recognized as having important academic and practical implications, knowledge about time-series variations of these two market characteristics for the case of European Treasury bonds is surprisingly limited. Previous works focused on the markets of government securities in Europe have analyzed the dynamic relationship between trading activity and price movements (Cheung et al., 2005) or between yield dynamics and order flow (Menkveld et al., 2004), the determination of the benchmark status among European government securities of similar maturity (Dunne et al., 2007), the analysis of yield differentials between sovereign bonds in the Euro area (Manganelli and Wolswijk, 2007; Beber et al., 2008), the price discovery process in cash and future markets (Upper and Werner 2002) or in multiple cash markets (Girardi, 2008). We aim at contributing to this growing body of literature by seeking to establish an association between endogenously determined liquidity and trading activity conditions and common causative determinants for a plurality of European government fixed income securities.

To that purpose, we bring together somewhat different, albeit connected, fields of research. Our analysis is naturally related to the strand of research studying the properties of market liquidity (Chordia et al., 2001; Chordia et al. 2005, among others). Understanding which factors influence the abrupt manifestation of illiquidity conditions is of direct interest for investors' confidence in financial markets as liquidity determines the costs and the feasibility of dynamic trading strategies (Johnson, 2008). "Liquidity" for the specific financial segment of government bonds is even more relevant, since it involves policy implications for public debt management. A well-functioning secondary Treasury bond market, indeed, constitutes the most important channel for domestic funding of budget deficits and it can increase overall financial stability (Bank for International Settlements, BIS, 1999). A closely tied line of theoretical and empirical research emphasises that liquidity conditions and trading activity are intimately related and that their interaction plays an important role in the price discovery process (Brandt and Kavajecz, 2004). Information on the interplay between liquidity and trading activity is of decisive relevance for regulators, since market infrastructures may be improved so as to lessen debt-service costs over the medium to long term (International Monetary Fund and World Bank, 2000). This issue acquires further policy content in the light of the adoption of the Directive 2004/39/EC disciplining the functioning of Markets in Financial Instruments in Europe (MiFID), which has stimulated an intense debate among academics and practitioners on whether and how to extend the MiFID regime to the Treasury bond market (Paesani and Piga, 2007). Under a wider perspective, the growing financial integration makes assets closely linked by both trading strategies and cross-market arbitrage, so that they are expected to change simultaneously, generating co-movements across securities, which, in turn, may be associated to common determinants, as documented by a recent strand of financial literature (Hasbrouck and Seppi, 2001; Korajczyk and Sadka, 2008).

Using high-frequency transaction data for Treasury bonds with maturities of 5, 10 and 32 years for the three largest European markets, namely Italy, France and Germany, over the period July 3 2006 - June 29 2007, we investigate: *i*) how liquidity and trading activity evolve over time; *ii*) to what extent liquidity and trading activity dynamics interact; *iii*) whether liquidity and trading activity dynamics exhibit some common patterns across bonds and whether can be associated to variables such as observable bond and stock market characteristics, macroeconomic announcements or monetary policy developments. While these issues have been extensively discussed for the US stock market, there has been no comprehensive study on the drivers of liquidity and trading activity dynamics in the European Treasury bond markets to date. In an effort to sharpen our understanding of what driving factors do matter in explaining the evolution of liquidity and trading activity over time in the European market for medium- and long-term government securities, this paper is an attempt to fill this gap. A distinctive feature of our empirical investigation refers to the sample span, which ends a few weeks before the abrupt deterioration in the degree of liquidity in several financial segments and corresponds to the latest information available *before* such an exceptional episode of financial distress happened. Seen in this light, the present analysis may be of relevance to evaluate whether the ECB has been conducting a proper strategy in order to cushion the impact of financial distress, given the information set up to the first half of 2007. Aside from academic and policy merits, ascertaining how the European market for government securities reacts to financial distress has also implications not only for regulators willing to improve the functioning of that financial segment but also for investors willing to move their funds into less risky investment opportunities.

The rest of the paper is organised as follows. Section 2 presents empirical evidence on the evolution over time of liquidity and trading activity measures. In Section 3 we discuss the dynamic interaction between quoted spreads and order flow imbalances. Section 4 is devoted to identify common causative forces behind their co-movements for our sample of government fixed income instruments. Final remarks conclude.

2 – Data and measurement

2.1 – Data sources and summary statistics

As in Dunne et al. (2007), we analyze the three largest European markets (Italy, France and Germany), which account for over 70 percent of the European secondary bond market. Government bond data are taken from MTS (Mercato Telematico dei Titoli di Stato). The MTS system is an inter-dealer platform, which operates via cross-matching methods. Galati and Tsatsaronis (2003) estimate that MTS accounts for 40 percent of government bond transactions in Europe and, according to the computations in Persaud (2006), for around 72 percent volume of electronic trading of European cash government bonds.[20]

We use transaction-based data for benchmark Treasury bonds with maturities of 5, 10 and 32 years, since our focus is on liquidity in long-term fixed income markets. The sample

[20] For a detailed discussion of the MTS system, see Pagano and Von Thadden (2004), Cheung et al. (2005) and Girardi (2008), among others.

span covers trades occurred over the period from July, 3 2006 to June, 29 2007.[21] The dataset consists of tick-by-tick transaction prices and traded nominal volumes recorded at a highly precise time stamp. Our dataset makes it possible to recover the best proposals at a certain instant, and, thus, merging traded quantities and bid/ask prices as well as bid and offer depths selecting quote quantities that in time are closest to the time of the transactions. A striking feature of the MTS dataset is the availability of security identifier information, such as to which side initiated the trade (i.e. whether a trade is a buy or a sell order), whether the aggressor (i.e. who initiates the trade) is a market maker or a market taker, whether a trade has taken place on the domestic MTS or on the EuroMTS platform. Based on data from opening hours of the MTS system (from 8:15 to 17:30 Central European Time, CET), Table 1 provides the list of bond codes along with information on issue dates, maturity dates and summary statistics on trading activity.

[Table 1 about here]

2.2 – Definition of liquidity and trading activity measures

The first logical step concerns the definition of proper measures of the relevant market characteristics for our empirical investigation. Below we describe how we extract trading activity and liquidity indicators from transaction and quoted data.

Our preferred indicator of liquidity is quoted bid-ask spreads, $qspr$, since this measure represents the liquidity risk of the bond market better than effective spreads (Goldreich et al., 2005). A similar choice is made in Pasquariello and Vega (2007).[22] Quoted spreads are

---

[21] We delete the first months of trading when the security is on-the-run, since an illiquidity premium has been documented for the off-the-run issues (Ahimud and Mendelson, 1991) and some months are commonly required so as to trade volumes of new issues prevail over off-the-run issues. Further, while a government fixed income instrument may acquire the benchmark status *de jure* once auctioned in the primary market, it becomes *de facto* a benchmark bond once its trading volume exceeds the one for the old benchmark. Therefore, the benchmark bond is the most actively traded bond and switches from the old benchmark only after it has reached some critical size and is accepted as the new benchmark by the market.

[22] Tightness, depth and resiliency are three perspectives according to which the concept of market liquidity can be

defined as the difference between the best bid and best ask divided by midquote prices, (equally weighted) averaged during half-hour time intervals. Following to Chordia et al. (2001), we also construct a synthetic liquidity indicator, $cliq$, as the ratio between $qspr$ and market depth, which is computed as (equally weighted) average of the quoted ask depth times ask prices and bid depth times bid prices, during half-hour time intervals.

A natural indicator for trading activity is given by the amount of nominal trades occurred in a given time period. The variable $tvol$ is constructed as the sum of (buy or sell initiated) transaction volumes during half-hour intervals. As in Jones et al. (1994), we measure trading activity using order flow imbalances rather than volume because excess buy-side or sell-side order flows are closer related to trading costs as they represent aggregate pressure on the inventories of market makers (Chordia et al. 2002) and are likely to capture the arrival of information (Brandt and Kavajecz, 2004; Pasquariello and Vega, 2007).[23] The variable $oflw$ is constructed as the aggregate volume of buyer-initiated orders minus that seller-initiated order during half-hour intervals.[24]

scrutinised (BIS, 1999): *tightness* is how far transaction prices diverge from mid-market prices, and can generally be measured by the bid-ask spread; *depth* is the volume of trades possible without affecting prevailing market prices or the amount of orders on the order-books of market-makers at a given time; *resiliency* is the speed with which imbalances in order flows are adjusted. Here we focus on tightness and depth, while the relationship between order flow imbalances and liquidity is extensively discussed in the following Section.

[23] Since MTS records inter-dealer trades, our measure represents inter-dealer order imbalances. It is highly likely, however, that inter-dealer order imbalances arise in response to customer imbalances as dealers lay off customer orders in the dealer market. See, on this, Chordia et al. (2002).

[24] Notice that we are able to identify the initiator of the trade explicitly in contrast to equity market studies where the calculation of order flows is commonly based on classification algorithms as the one proposed by Lee and Ready (1991).

Table 2 provides some descriptive statistics about our preferred measures of trading activity and liquidity.[25] For each bond, we report the mean (x_M), the median (x_{Me}) and the standard deviation (x_{SD}) of the two market characteristics along with their serial correlations up to the third lag (ρ_i, $i = 1,2,3$). Values in bold indicate statistically significant autocorrelation coefficients at the 5 percent level. Median values have concordant sign with the corresponding mean value (with the exception of DE0001135275). Although the sample means of average order flows vary sizably across bonds, the ratio $|x_M| / x_{SD}$ is bounded into a tight interval (less than 0.3), suggesting that market makers control their inventories so as to avoid excessive imbalances in either sides of the market. Sample means of quoted spreads are very similar for 5-year (around 2 cents) and 10-years (around 3 cents) fixed income instruments, while longer-dated securities exhibit higher average spreads, ranging from 9 cents for Germany and Italy to 11 cents for France. For all entities of reference, quoted spreads have lower serial correlation than order flow imbalances at all lags. As pointed out by D'Souza et al. (2007), this may arise from market making obligations for primary dealers as continuous quoting may induce them to adjust quote quickly and, thus, to reduce serial correlations for quoted spreads.

[Table 2 about here]

2.3 – How liquidity and trading activity evolve over time

[25] For all entities of reference, quoted spreads turn out to be positively and significantly correlated with $cliq$. By contrast, data reveal a negative correlation or weakly positive co-movements between $oflw$ and $tvol$ for the majority of securities. Pooling all available observations, the overall correlation (-0.01) is statistically not significant at the usual levels of significance. As pointed out in Chordia et al. (2002), this finding is not surprisingly, since a reported nominal trading volume of x might be entirely due to a sell ($-x$), to a buy ($+x$) or, more typically, to a split between sell and buy orders, with each possibility having its own unique implications for market makers' order imbalances.

We remove possible seasonal patterns from our variables (due to deterministic time-series variations or other possible institutional factors) using the two-step procedure proposed by Gallant et al. (1992).[26] The following adjustment variables are used: *i*) 11 monthly dummies, one for each from February to December; *ii*) 4 daily dummies, one for each from Monday to Thursday, *iii*) 17 half-hourly dummies, one for each of the hours from 9:00 (CET) and 17:30 (CET), *iv*) a dummy, $mrkt$, taking value 1, if trades take place on the domestic MTS platform, and 0, otherwise, as in Cheung et al. (2005), *v*) a dummy, $aggr$, taking value 1, if trades are initiated by a market maker, and 0, otherwise. Table 3 presents the regressions coefficients from the mean equation of quoted spreads (Panel-A) and order flows (Panel-B).[27]

There are common time-of-day and day-of-week patterns in liquidity as previously documented in Cheung et al. (2005): at the beginning market makers quote wider spreads, which drop as the trading day proceeds and then rise again before the market closes. Further, they are higher on Friday, in a way consistent with the notion that dealers want to protect themselves from liquidity risk (Lyons, 1997), due to the presence of few liquidity traders (for instance at the end of the trading week or at the extreme hours of the trading day) or to the increased (searching) cost needed to rebalance market makers' inventory (Reiss and Werner, 1998). By contrast, there are neither striking monthly effects nor intra-week patterns in trading activity, in a way consistent with the finding of Scalia (1998). Levels of order flows at

---

[26] Such a method guarantees that adjusted series have the same sample mean and variance as the unadjusted series, but the effect of seasonality on the mean and variance is eliminated. The first stage is to regress raw measures of trading activity and market liquidity on a series of j adjustment variables, γ, that is $\tilde{y}_t = \sum_{i=1}^{j} d_i \gamma_i + \varepsilon_t$ (mean equation), where $\tilde{y} = qspr, oflw$, alternatively, and t indexes time. Next, as to remove heteroschedasticity, the residuals ε_t are used in the regression $\ln(\varepsilon_t^2) = \sum_{i=1}^{j} f_i \gamma_i + \xi_t$ (variance equation). The adjusted series, y_t, are then calculated as $\tilde{y}_t = \alpha + [\beta \hat{\varepsilon}_t / \exp(\sum_{i=1}^{j} f_i \gamma_i / 2)]$, where $\hat{\varepsilon}_t$ are the estimated residuals and the parameters α and β are chosen so that the sample means and variances of the adjusted and the unadjusted series are the same.

[27] Results for the variance equation are suppressed for space consideration, but available upon request.

the beginning and at the end of the trading days are not statistically significant, suggesting higher imbalances during central hours of trading days. Furthermore, for a couple of bonds (DE0001135291 and IT0003934657), trades initiated by market makers reveal an excess of buys higher than the one recorded by market takers.[28] Finally, there are no clear regularities with respect to trading venues.

[Table 3 about here]

To formally test for stationarity, we check for the presence of a unit root in each series, allowing for an intercept as deterministic component. We employ the DF-GLS test, devised by Elliott et al. (1996), which is more efficient than usual unit-root tests. As reported in Table 4, the unit-root null can be rejected at conventional levels of significance in all cases. The KPSS stationarity tests (Kwiatkowski et al., 1992) corroborate these conclusions. Overall, order flows appear to be properly characterised by mean reverting processes, albeit quite persistent.

[Table 4 about here]

3 – Dynamic interactions between quoted spreads and order imbalances

In order to study how quoted spreads and order flows interact, simple correlation analyses are far from being beyond question because of a plurality of relevant aspects that cannot be properly taken into account.

3.1 – The empirical model

Standard market microstructure theory predicts that liquidity is influenced by inventory concerns about order flow imbalances. Irrespective of whether these order imbalances are originated by random shocks (Stoll, 1978) or by private information (Kyle, 1985), after a large imbalance of order flows on one side of the market, market makers' continuous quoting

[28] On the one hand, it may be the results of primary dealers' commitments to Treasuries as to ensure sufficiently high levels of depth. On the other hand, it may suggest heterogeneous dealers' preferences due to the existence of possible privileged information on those bonds.

activity is revised as to push trading on the other side of the market. On the other hand, since the feasibility of dynamic trading strategies is crucially affected by liquidity conditions, current investors' behaviour is likely to take into account the state of liquidity previously observed on the market. It is reasonable to expect a circular process where *past* values of a variable may affect *current* levels of the other market characteristic. This calls for resorting to a dynamic approach so as to analyse the interactions between levels of trading activity and market liquidity conditions, where either unidirectional or bi-directional interaction mechanisms may operate. Thus, it may be desirable to model endogenously both trading activity and liquidity dynamics. The standard Vector AutoRegressive (VAR) methodology is a natural candidate to accommodate these features.[29]

Furthermore, the empirical evidence documented in Brandt and Kavajecz (2004) suggests that the relationship between order flows and liquidity can differ depending on whether market liquidity is high or low.[30] In order to take into account the existence of different states of the world, we augment the VAR model by allowing for the (seasonally adjusted) endogenous variables ($oflw$ and $qspr$) to depend jointly on the state in which the system can be, each differing from the others according to the level of liquidity displayed by the market. In such a situation, the VAR process is modelled as time-invariant conditional on an unobservable regime (state) variable s_t, which indicates the regime prevailing at time t.

The general formulation of our econometric framework belongs to the class of Markov Switching VAR (MS-VAR, Krolzig, 1997) models.[31] For expositional purposes, we outline

[29] Such a route has been followed by D'Souza et al. (2007) for European and Canadian short-term Treasury securities.

[30] Other works indicate that liquidity dynamics may be non-linear, breaking down a linear relationship with trading activity measures. In the model of Pagano (1989) liquidity is intended as the average willingness of the market to accommodate trade at prevailing prices. However, this willingness may fluctuate as the underlying state of the economy changes. Eisfeldt (2004) studies instead why liquidity varies with economic conditions.

[31] The maximization of the likelihood function of an MS-VAR requires an iterative estimation of the parameters of

below the MS-VAR framework for the case of regime shifts in the mean alone, although shifts may be allowed for elsewhere. The MSM(m)-VAR(p) model, in the jargon of Krolzig (1997), can be written as:

$$y_t - \mu(s_t) = \sum_{i=1}^{k} A_i [y_{t-i} - \mu(s_{t-i})] + u_t \ , \ t = 1,...,T \tag{1}$$

where y_t is the vector collecting adjusted order flows and quoted spreads series, $\mu(s_t)$ is the vector of regime-dependent mean values, A's are matrices of autoregressive parameters, k is the truncation order of the autoregression, u_t is a vector of residuals and T is the effective number of observations used in estimation.

The regime s_t is assumed to be governed by a discrete time irreducible ergodic m-state stochastic Markov process with transition probabilities $p_{ij} = \Pr(s_{t+1} = j \mid s_t = i)$, $\sum_{j=1}^{m} p_{ij} = 1$, $i, j \in \{1,...,m\}$, collected in the transition matrix $P = \{p_{ij}\}_{m \times m}$.[32] In order to detect an adequate characterization of an m-regime k-th order VAR, we apply the "bottom-up" procedure (Krolzig, 1997). This approach allows to select both the number of regimes and the autoregressive order using the approximation provided by its VARMA representation

the autoregression and the transition probabilities governing the Markov chain of the unobserved states. Parameter estimation is usually obtained through the implementation of the expectation-maximization algorithm for maximum likelihood estimation (Dempster et al., 1977).

[32] Krolzig (1997) shows that, unlike the linear VAR model, the mean-adjusted form (1) is not equivalent to the intercept form MSI(m)-VAR(p) model, $y_t = \upsilon(s_t) + \sum_{l=1}^{p} A_l y_{t-l} + u_t$, since they produce different adjustment dynamics of the observed variables after a shift in regime. Following a regime shift in the mean $\mu(s_t)$ of model (1), indeed, the observed time series jumps immediately to its new level. By contrast, a regime shift of the intercept term $\upsilon(s_t)$ makes the process mean to adjust smoothly to the new level along the transition path. Since we are dealing with a spot financial market rather than, say, labour market, we consider it more plausible that the mean should quickly and abruptly shift to a new level rather than as a gradual swing. The data also strongly suggest mean over intercept dependency. Details are available upon request.

(Poskitt and Chung, 1996).[33] Furthermore, in terms of inference, we follow Nelson et al. (2001) who conclude that unit root tests remain robust in detecting stationarity in MS regressions.

3.2 – Assessing the interplay between liquidity and trading activity

After considerable experimentation, we select a specification of the MS-VAR models that allow for regime shifts in the deterministic component alone, keeping constant across states the autoregressive part of the system and the covariance matrix of residuals. The "bottom up" procedure indicates that all models are subject to (at least) two different regimes and a three-regime model is appropriate in seven out of nine entities of reference. The order of autoregression turns out to be one in six out of nine models and two in the remaining three cases (those relative to the Italian market).[34]

The main properties of the estimated regimes are reported in Table 5. The first three numerical columns report the estimated filtered probabilities of transition from regime j to regime j, p_{jj}, the j-th diagonal element of P. The p_{jj}'s are higher than 0.5 in 21 out 25 cases and reveal that the variables of the system switch across different states over time. The average duration of each regime j, dur_j, calculated as $dur_j = 1/(1-p_{jj})$, indicates that these

[33] Essentially, the bottom-up procedure consists of starting with a simple but statistically reliable Markov-switching model by restricting the effects of regime shifts on a limited number of parameters and checking the model against alternatives. For a technical discussion for such a procedure, see Krolzig (1997). Several other criteria are currently available in the literature. Psaradakis and Spagnolo (2006) provide some simulation results on the performance of various selection criteria within this class of models. However, it is not easy to implement these tests if the number of switching parameters increases or if the null is not a linear model.

[34] The analysis of the standardized residuals, not reported to save space, provide strong evidence of no serial correlation in any of the residual series. Furthermore, the coefficients of determination, adjusted both for the bias towards preferring a larger model relative to a smaller one and for the fact that the model allows for regime-dependence (Krolzig, 1997), suggests that an appreciable fraction of intra-day time-series variation in liquidity and trading activity measures is captured: the average explanatory power for the $oflw$ and the $qspr$ equations is 35 and 18 percent, respectively.

are meaningful regime switching findings, with average regime duration equals to 5.24 (i.e. lasting roughly three hours). Finally, the last column reports the upper bound of the LR tests (Davies, 1977), which shows that the null hypothesis of linearity is rejected, giving support to the choice of employing a MS-VAR specification rather than a linear model.

[Table 5 about here]

Having identified (at most) three regimes, we define them as follows: *i*) high liquidity regime (state 1): the state with lower mean than the whole-sample mean for $qspr$; *ii*) low liquidity regime (state 3): the state with higher mean than the whole-sample mean for $qspr$; *iii*) medium liquidity regime (state 2): an intermediate state with a higher mean than the one for high liquidity regime, but lower than the one for the low liquidity regime.

Panel-A of Table 6 provides the estimated regime dependent mean values (μ_i, $i = 1, 2, 3$) for the $oflw$ and the $qspr$ equations. Statistically significant coefficients at the 5 percent level are in bold. Panel-B presents the results from testing the symmetry between statistically positive and negative order flow imbalances and the equivalence of regime dependent mean values for quoted spreads. For each equation of our bivariate dynamic systems we also report the outcome of Granger-causality tests, with p-values in square brackets. The results are interesting in a number of respects.

First, according to our classification, not all government bonds display a normal liquidity regime: in the two-regime models (IT004026297 and IT0004019581), the states are associated to high and low liquidity conditions.[35] *Second*, sell orders exceed the buy-side trades in the presence of favourable liquidity conditions (with the exceptions of FR0010288357 and IT0004026297) and the other way around (excepting for DE0001141489 and, again, IT0004026297). A possible rationalization is the inability of market makers to adjust quotes during periods of large imbalances so as to induce trades on the other side of the market. An alternative explanation is that astute market participants buy securities from

[35] Notice that in the present framework liquidity regimes are endogenously determined by the maximum likelihood estimation procedure rather than *ex-ante* imposed as in Brandt and Kavajecz (2004).

the market when quoted spreads (and, thus, trading costs) are low and sell when quoted spreads get higher. This would imply that some dealers behave like informed investors (Fleming and Remolona, 1999) with their trading based on superior inventory and order flow information (Huang et al., 2002). Another possibility is that in the presence of heterogeneous private information (or heterogeneous interpretation of public information) trades occur on the basis of dealers' subjective valuations, which are updated monitoring the aggregate level of order flows (Brandt and Kavajecz, 2004).[36] According to this line of reasoning, our results reveal that when liquidity is an intermediate state market participants care about order flows to a lesser extent, consistently with the findings in Chordia et al. (2002) for the aggregate US equity market.

Third, each regime is characterised by a statistically distinctive level of liquidity as the null of equivalence of mean values for $qspr$ across regimes is rejected in eight out of nine entities of reference.[37] Furthermore, the symmetry assumption between the (absolute value of) means for order flows in extreme liquidity conditions is supported by the data in four entities of reference (DE0001135291, DE0001135275, FR0108354806, FR0010070060), while in the remaining models we find mixed results, with positive order imbalances exceeding (the absolute value of) negative order imbalances in three cases. *Fourth*, Granger-causality tests document bi-directional causality at the 5 percent level of significance in six models. For two 5-year bonds (FR0108354806 and IT004019581), causality runs from trading activity to quoted spreads, as predicted by standard paradigms of price formation. By contrast, for FR0010070060 there is evidence of a reverse causality going from liquidity conditions to trading activity.

[Table 6 about here]

[36] Thus, when an excess of buy-side orders occurs, dealers with a lower (higher) subjective valuation tend to revise them upward (downward). The opposite holds when aggregate order flows are negative.

[37] In the remaining case (FR0010070060), however, the regime-dependent mean values are quite close to the estimates for the other two very-long term bonds in our sample.

4 – Drivers behind the interactions between quoted spreads and order imbalances

We next move on investigating whether or not the probability of switching among regimes in *all* government securities we consider in the analysis is intimately related to common determinants.

Because most of the data on our candidate explanatory variables are not available at intra-day frequency, we follow Clarida et al. (2006) and convert the intra-day smoothed probabilities from the estimated MS-VAR models by daily averaging. In order to relate the probability of being in a specific regime to appropriate economic indicators, we define a variable, r, which is equal to 2, 1 and 0 when the average daily probability of being in the high, normal and low liquidity regime, respectively, is the highest as compared to the probabilities associated to the remaining states.

4.1 – Definition of the candidate explanatory variables

Building on the findings of previous works on equity markets (Chordia et al., 2005; Hasbrouck and Seppi, 2001; Korajczyk and Sadka, 2008), we supplement the MTS dataset with information on interest rates and other observable bond market characteristics, stock market developments, macroeconomic announcements and aggregate liquidity indicators. Below we present our set of covariates, whose construction is detailed in the Appendix.

I – Observable bond market characteristics. In keeping with standard microstructure models, liquidity is influenced by inventory concerns: a fall (rise) in short rates is expected to reduce (increase) the cost of financing inventories; market movements may affect investors' expectations and the composition of their optimal portfolio, while a rise of price volatility is likely to increase inventory risk. Thus, the first set of explanatory variables includes short interest rate, market movements and market volatility ($repo$, $mktr$ and $mktv$, respectively).

II – Stock market developments. A number of asset allocation strategies shift wealth between stock and bond markets. A negative information shock in the stock market often causes a "flight to quality" as investors substitute safe assets for risky assets. As pointed out by Beber et al. (2008), the resulting outflow from stocks into Treasury bonds markets may cause price pressures and also impact bond liquidity. Hence we introduce stock market volatility ($stkv$) as an additional regressor.

III – Macroeconomic announcements. Unexpected worsening of the economy or excessive inflationary pressures are likely to influence liquidity exacerbating inventory risk through an increase of inventory holding and order processing costs. Accordingly, macroeconomic releases on industrial production ($indp$) and inflation ($infl$) are employed. The cyclical conditions of the real economy may be relevant as well. Eisfeldt (2004) finds that economic booms lead to increased liquidity in the stock market: Treasury bond market liquidity, however, can be either pro-cyclical or counter-cyclical, depending on whether government bond and stock liquidity are complementary or substitute. We use unemployment ($unem$) as a proxy of the business cycle climate.[38]

IV – Liquidity management operations. We also consider a measure of aggregate market liquidity. A proper monetary policy may increase liquidity and foster trading activity by making margin loan requirements less costly, and by enhancing the ability of dealers to finance their positions (Garcia, 1989). To this aim we use the level of marginal lending facility ($malf$) as a proxy of liquidity supplied by the European Central Bank (ECB).[39]

V – Other controls. As further (time-invariant) regressors, we introduce three market dummies ($demm$ for Germany, $frfm$ for France and $mtsm$ for Italy) so as to capture possible unobservable country-specific patterns. Finally, we follow the classification in Dunne et al. (2007) to control for maturity effects: small-medium ($smty$) government bonds have

---

[38] Since most aggregate Euro area data releases are published after the Euro area countries have published their macro announcements, the informational value of Euro area macro news is small (Andersson et al., 2006). Accordingly, in the empirical model presented in this Section we use country-specific macroeconomic releases.

[39] To be rigorous, ECB's framework to manage liquidity operations comprises not only standing facilities but also open market operations and minimum requirements operations. See Bindseil (2004).

maturity (in terms of the difference between the maturity date and the issue date) less than 6.5 years; long- ($lmty$) and very-long ($vlmy$) securities refer, instead, to maturity between 6.6 and 13.5 years and more than 13.5 years, respectively.

4.2 – The econometric framework

Given the limited number of outcomes of the dependent variable, we use Ordered Regression Models (ORMs) rather standard OLS techniques. We dispose of the measure of r for each bond $i = 1,...,N$ over a number of trading days, indexed by $t = 1,...,T$. Considering pooling data, the basic notion underlying ORMs is the existence of a latent or unobserved continuous variable, r_{it}^*, ranging from -∞ to +∞, which is related to a set of explanatory variables by the standard linear relationship:

$$r_{it}^* = \beta' x_{it} + \gamma' z_i + u_{it} \qquad (2)$$

where x_{it} is a vector of time-varying regressors, z_i is a vector of time-invariant covariates, β and γ are the associated parameter vectors and u_{it} is a random error term.[40] Assuming a standard normal distribution yields the ordered probit model. The integer index r_{it} is observed and is related to (the unobserved) r_{it}^* by the relationship: $r_{it} = 0$ *iff* $r_{it}^* < \lambda_1$; $r_{it} = j$ *iff* $\lambda_{j-1} < r_{it}^* < \lambda_j$, $j = 2,...,J-1$; $r_{it} = J$ *iff* $r_{it}^* > J-1$; where λ_j are the unobserved thresholds defining the boundaries between different levels of r_{it}. They are free fixed parameters, with no significance to the unit distance between different observed values of r_{it}.[41]

---

[40] In order to control for possible endogeneity problems between the response variable and the explanatory variables we use lagged values for all regressors but for macroeconomic announcements, because macro releases in general become public at the very beginning of trading hours.

[41] The conditional cell probabilities (that is the probability of observing an individual as having a j value of r_{it}) can be formulated as $\Pr(r_{it} = j \mid x_{it}, z_i) = \Phi(\lambda_j - \beta' x_{it} - \gamma' z_i) - \Phi(\lambda_{j-1} - \beta' x_{it} - \gamma' z_i)$, where $\Phi(.)$ indicates the

An unattractive feature of pooled-ORMs (2) rests on their unsuitability to properly capture the effect of individual heterogeneity. The random effects (RE-ORM) approach assumes that both time-invariant, ν_i, and time-varying, ε_{it}, unobserved factors may contribute to determine liquidity conditions. If we express the random error term as $u_{it} = \nu_i + \varepsilon_{it}$, the latent model (2) modifies into $r_{it}^* = \beta' x_{it} + \gamma' z_i + \nu_i + \varepsilon_{it}$, where both error components are normally distributed and orthogonal to the set of predictors.[42]

Notice that both the standard pooled-ORM and the RE-ORM frameworks rely on the critical parallel regression assumption (PRA), according to which β's and γ's are identical across each regression. Following Boes and Winkelmann (2006), we resort to a generalized RE-ORM and introduce time-invariant individual effects to vary across ordinal categories, by making threshold parameters dependent on the predictors, so that the (implicit) restrictions embedded in the standard RE-ORM specification can be tested against the generalized threshold RE-ORM by means a standard χ^2-distributed LR test. Estimations are performed using maximum likelihood.[43]

4.3 – Commonality across government bonds in Europe

As a preliminary step, we use the Akaike Information Criterion (AIC) to select the most reliable specification among four competing nested and non-nested pooled-ORM models. Each specification includes time-invariant controls. Model [1] includes observable bond market characteristics and stock market volatility in order to assess whether inventory concerns

---

normal cumulative distribution function, with $\lambda_j > \lambda_{j-1}$, In turn, this set of equations can be used to compute the cumulative probabilites: $\Pr(r_{it} \le j \mid x_{it}, z_i) = \Phi(\lambda_j - \beta' x_{it} - \gamma' z_i)$.

[42] Since the underlying variance of the composite error, $\sigma_u^2 = \sigma_\nu^2 + \sigma_\varepsilon^2$, is not identified, we normalize $\sigma_\varepsilon^2 = 1$, so that $\rho_{u_{it},u_{is}} = \sigma_\nu^2(\sigma_\nu^2 + \sigma_\varepsilon^2)^{-1} = \sigma_\nu^2(\sigma_\nu^2 + 1)^{-1}$, and, thus, $\sigma_\nu = [\rho/(1-\rho)]^{1/2}$.

[43] In a generalized RE-ORM framework, the conditional probability model can be formulated as $\Pr(r_{it} = j \mid x_{it}, z_i; \beta_j, \gamma_j) = F(-\nu_{ij} - \beta_j' x_{it} - \gamma_j' z_i) - F(-\nu_{ij-1} - \beta_{j-1}' x_{it} - \gamma_{j-1}' z_i)$.

matter and whether investors flight to quality by rebalancing their portfolios toward less risky securities. Under the assumption of incomplete and heterogeneous information structure investors may react in a differentiated way to publicly available macroeconomic releases. Accordingly, Model [2] makes the response variable dependent on observable bond market characteristics controlling for macro releases. Model [3] embeds previous specifications. Finally, Model [4] is the richest variant, which takes account of aggregate liquidity conditions in the Euro Area as a further covariate. Table 7 reports the values of the AIC as well the log-likelihood and the χ^2-test statistics for the joint impact of the covariates on the response variable along with the corresponding p-values (in square brackets) and degrees of freedom (in parentheses). Maximum likelihood estimation results lead to favour Model [4], suggesting that the probability of being in a specific liquidity regime is the result of a wide range of overlapping forces.

[Table 7 about here]

The estimated coefficients for the pooled-ORM, the standard RE-ORM and the generalized RE-ORM based on Model [4] are presented in Columns (A), (B) and (C) of Table 8, respectively. Positive (negative) coefficients indicate a move toward a more (less) liquid state given an increase in the predictor.[44] Estimation results from the pooled-ORM (A) show that liquidity in European bond markets increases when the bond market grows; by contrast,

[44] The fixed thresholds (not reported in Table 8) in the pooled-ORM and in the RE-ORM specifications, λ_1 and λ_2, are statistically significant at the 5 percent level of significance (or better) and at least one is different from 1, implying that the J ordinal categories are not equally spaced. All estimates also include market dummies (with *mtsm* as reference category) and maturity dummies (with *smty* as reference category). In all specifications, these time-invariant regressors are statistically significant at the 1 percent level. Their signs suggest that in German and French spot markets for Treasury securities low liquidity conditions are more likely to occur than in the reference market. A possible explanation for this finding may be the depth of the Italian market due to manage the high level of Italian public debt. Furthermore, bonds with short-medium maturity turn out to be associated to higher liquidity states relative to long-term securities and lower liquidity conditions with respect to very-long Treasury fixed-income instruments.

increased bond market volatility reduces aggregate liquidity. As for macroeconomic announcements, unemployment news have a statistically significant and positive role in explaining switches across liquidity regimes. Finally, an increase of *mlf* exerts a statistically significant and positive effect on the response variable. Controlling for unobserved time-invariant heterogeneity [Column (B)] gives qualitatively similar results, with a sizable increase of the likelihood function. RE-ORM estimates, however, seem to leave scant room to a number of important covariates (such as refinancing costs, stock market volatility as well as macroeconomic announcements for industrial production and inflation) in explaining liquidity conditions in European bond markets.

A possible explanation of these findings may be a figment of a specification error in the empirical framework due to the PRA, which ensues problems, if in fact it does not hold. We assess empirically such a conjecture by relaxing the PRA for those covariates that turned out to be weakly significant or not statistically significant in the RE-ORM specification. Testing for PRA produces a LR test statistics (29.27) that failed at any conventional level of assessing significance when compared to critical values of a χ^2 distribution with 6 degrees of freedom. Column (C) presents the estimation results of the generalized RE-ORM, where the two numerical columns collect the estimated parameters for the probability that the response moves from category 0 to category 1 (*Equation 1*) and from category 1 to category 2 (*Equation 2*). While the effects of *mktr* and *mktv* remain unchanged with respect to previous specifications, refinancing costs have statistically significant detrimental effects on aggregate bond liquidity only when liquidity conditions move from low to medium levels. Stock market volatility has strong asymmetric effects as well: when bond market liquidity is low, a rise in stock market volatility exacerbates illiquidity conditions; in *Equation 2*, instead, it induces a positive response of the dependent variable. Estimated coefficients for macroeconomic announcements relative to industrial production and to unemployment suggest that liquidity conditions in European bond markets are counter-cyclical. Inflation affects negatively bond liquidity, albeit the coefficient is estimated with scant precision.

Finally, an increase of liquidity supplied by the ECB has a positive effect only when the dependent variable moves from medium to high levels.

[Table 8 about here]

4.4 – A closer look at the determinants: simulated probabilities

Since the parameters of a latent model do not have a direct interpretation *per se*, the most useful way to handle ORMs is to compute the marginal probability effects (mpe), that is the shift of the predicted discrete ordered distribution of the outcome variable as one (or more) of the predictors changes.[45] We focus below on the effect of time-varying variables that turned out to be statistically significant in (at least) one out of two equations of the generalized RE-ORM.

Figure 1 presents results from the generalized RE-ORM in a graphical format, by generating predicted probabilities that the response variable is put into each of the three probabilities $\Pr(r_{it}=0)$, $\Pr(r_{it}=1)$ and $\Pr(r_{it}=2)$, based on different predictor levels. This does allow for a better understanding of the effects of these different predictors as they move from their minimum to maximum.[46] In each graph, the vertical axis indicates the probability

[45] They can be obtained by simply taking first derivatives of a conditional model with respect to a (continuous) variable of interest. To do this in the case of a generalized RE-ORM framework, however, we need to impose further assumptions, since the time-invariant individual effects are realizations of a stochastic process. Following Boes and Winkelmann (2006), under the hypothesis of normally distributed ν_{ij}'s we can rescale the β's and the γ's parameters in the population-averaged coefficient vectors $\tilde{\beta}=\beta/(1+\sigma_{\nu}^{2})^{1/2}$ and $\tilde{\gamma}=\gamma/(1+\sigma_{\nu}^{2})^{1/2}$, respectively, and then take first derivatives.

[46] Once the β's and the γ's parameters are rescaled in the population-averaged coefficient vectors, the computation of simulated probabilities are obtained by using the cumulative model $\Pr(r_{it}\le j \mid x_{it},z_i;\beta_j,\gamma_j)=F(-\nu_{ij}-\beta_j' x_{it}-\gamma_j' z_i)$, in place of the conditional model as required for the computations of mpe's, by moving a predictor from its minimum to maximum sample value and keeping the other predictors evaluated at their sample means. Notice that each scenario portrayed in the graphs is conjectural, in the sense that there is no instance in the data where average levels of all other variables

associated to a certain state of liquidity. Black, grey and white bars refer to $\Pr(r_{it}=0)$, $\Pr(r_{it}=1)$ and $\Pr(r_{it}=2)$, respectively. The horizontal axis reports these probabilities, computed at the minimum as well as at the first quartile, the median, the third quartile and at the maximum values of the distribution of each predictor, *ceteris paribus*.

[Figure 1 about here]

When refinancing costs get higher, we observe an increased probability of low liquidity states along with a progressive reduction of $\Pr(r_{it}=1)$. As a result, at very high levels of $repo$ we find an increased likelihood for the occurrence of extreme liquidity conditions and of inventory concerns (Chordia et al., 2002). A maximum change in government bond market volatility has a detrimental effects on aggregate Treasury bond liquidity by rising $\Pr(r_{it}=0)$ and reducing $\Pr(r_{it}=2)$. Simulations for bond market developments indicate that moving from very low to very high levels of $mktr$ induces a monotonic decline in $\Pr(r_{it}=0)$ along with an unambiguous raise of $\Pr(r_{it}=2)$, in a way consistent with momentum strategies argumentations. The probability associated to intermediate liquidity conditions in government bond markets evaporates as stock market turmoil becomes harsher: thus, stock market volatility appears to lead rebalancing investors' portfolios through changes in order flows. The overall relationship between macro announcements on industrial production and the response variable is negative: a maximum (positive) surprise in $indp$ generates a sizable jump of $\Pr(r_{it}=0)$. The opposite holds for favourable macroeconomic releases concerning unemployment levels. On the grounds of the conclusions in Eisfeldt (2004), where increasing liquidity in the stock market arises when economy grows, our findings point out that bond and stock market liquidity are likely to be substitute rather than complement along the business cycle. Finally, a sizable increase $\Pr(r_{it}=2)$ can be observed only after a certain

coincide with the maximum level of refinancing costs, for instance. This caveat notwithstanding, simulated probabilities are a useful tool to directly asses the importance of the estimated coefficient of the latent model in explaining shifts of the response variable across its categories.

threshold of mlf , corresponding to values beyond the third quartile of the distribution of our measure of liquidity supplied by the ECB.

4.5 – A further step ahead: disentangling temporary and permanent effects

What are the effects on the aggregate Treasury bond liquidity of a temporary worsening of refinancing conditions faced by dealers? To what extent does bond liquidity react to permanent changes in the management of liquidity operations by monetary authorities? What happens after a long-lasting turmoil in the stock market?

We seek to provide an answer by discussing these issues in the light of the ongoing turmoil that international financial markets have been experiencing. To do this, we distinguish for some of the explanatory variables x_{it} a permanent and a transitory effect, by including both their daily value and their mean over the sample span. Consider the refinancing costs for the i-th bond at time t, $repo_{it}$, for instance: in this more flexible framework, it enters the model as $\beta_{temp}(repo_{it} - \overline{repo}_i) + \beta_{perm}\overline{repo}_i$, where the upper bar stands for the average over time. We perform the same decomposition for $stkv$ and $malf$ as well. The deviations from the averages per individual identify *shock* effects (*within*-effect), while the means identify *level* effects (i.e. the differences *between* individuals). Including those within and between effects aims at introducing dynamics in the model, because the mean value changes gradually when days pass by (Van Praag et al., 2003). For the sake of brevity, in Figure 2 we focus on the simulated probabilities relative to the permanent/temporary decompositions of the selected variables.[47]

[Figure 2 about here]

[47] Outcomes from the other covariates in all three different specifications of the augmented generalized RE-ORM framework are qualitatively and quantitatively very similar to those reported in Figure 1. Complete results are available on request. We have tried a specification of the generalized RE-ORM including all three decompositions contemporaneously, but various optimization algorithms of the likelihood functions all failed to converge.

Refinancing inventories: any role for investment managers' behaviour (Panel A)? The permanent/transitory decomposition allows to better assess the effects of soaring refinancing costs. When changes in the repo rate are temporary in nature, low levels of *repo* stimulate portfolio rebalancing, while moving to higher refinancing costs induces a decline of $\Pr(r_{it}=2)$ and a rise of $\Pr(r_{it}=1)$. With permanent increases in the level of interest rates, we obtain similar results to those from the baseline specification: a monotonic growth for $\Pr(r_{it}=0)$ and decline of $\Pr(r_{it}=1)$. Portfolio rebalancing with permanently high refinancing costs would be consistent with the explanation put forward by Rajan (2006) and tested by Manganelli and Wolswijk (2007), according to which trading in risk free assets is stimulated by investment managers' compensation schemes rather than argumentations based on reduced costs of financing inventories.

Is liquidity management an effective policy instrument (Panel B)? The main rationale behind changes in liquidity interventions by monetary authorities during financial distress is that interest rates may be no longer necessarily linked to liquidity conditions. Our simulations indicate that if these policy measures are perceived as being temporary in nature, the overall impact on government bond markets is very similar to the findings from the baseline generalized RE-ORM discussed in the previous sub-Section. Remarkably different implications arise when participants in the market for Treasury securities interpret liquidity supply policies as long-term changes in the liquidity management: a strong positive effect on the response variable emerges.

Contagion or safe heaven (Panel C)? With declining stock prices and/or increasing volatility in stock markets, investors are likely to revise their risk/return profiles. Treasury fixed income instruments appear as a natural landing when turbulence in riskier financial segments takes place. Temporary stress in stock markets increases the probability of extreme liquidity conditions only when the magnitude of the shock is sufficiently large, in a way consistent with the results from the baseline generalized RE-ORM. When stock market turmoil is long-lasting, instead, our results provide unambiguous evidence that investors perceive the market of government securities as a safe heaven, so that funds move from equities to relatively less risky financial instruments.

Summary and discussions of results. Our sample span ends a few weeks before the first symptoms of contraction in the degree of liquidity in several financial segments and corresponds to the latest information available *before* such an exceptional episode of financial distress. In view of that, the above-discussed empirical evidence may be of relevance to evaluate whether the ECB has been conducting a proper strategy in order to cushion the impact of financial distress, *conditional* on the information set up to the first half of 2007. Our results point out a clear link between communication policies and effectiveness of interventions: when investors interpret monetary authorities' management liquidity as long-lasting measures, marginal lending facilities are more effective in alleviating the occurrence of illiquidity conditions in the European market for Treasury securities. Hence, a transparent communication strategy by the ECB and a fuller confidence by the banking system in using marginal lending facilities could be beneficial in fostering liquidity in such a financial segment.

5 – Conclusions

Using transaction-based data for Treasury bonds with maturities of 5, 10 and 32 years for the three largest European markets, namely Italy, France and Germany, over the period July, 3 2006 – June, 29 2007, this work is a contribution to the growing body of research focused on the functioning of the secondary Treasury bond market in Europe. The empirical investigation explores in sequence: i) how liquidity and trading activity evolve over time; ii) to what extent their dynamics interact and iii) whether liquidity and trading activity dynamics exhibit some common patterns across bonds.

We find common time-of-day and day-of-week patterns in liquidity: at the intraday frequency it is U-shaped, while the intraweek path suggests that market makers quote wider spreads on Friday, in a way consistent with the notion that dealers want to protect themselves from liquidity risk. By contrast, we are not able to find clear monthly effects nor intraweek patterns in trading activity. MS-VAR estimation results reveal that abnormal (i.e. very high or very low) liquidity conditions lead dealers to pay attention to the information revealed by order flows; when liquidity is an intermediate state, instead, market participants care about order flows to a lesser extent. As a final point, ordered probit estimates for longitudinal data indicate that extreme liquidity conditions are likely to occur when refinancing costs are temporary low (according to standard portfolio rebalancing argumentations) and permanently high (coherently with explanations based on investment managers' compensation schemes). By exacerbating inventory risk, bond market volatility has a detrimental effect on aggregate liquidity, while bond market returns induce changes in the composition of portfolios. Our estimates also point out that liquidity states evolve counter-cyclically relative to analysts' sentiment on the business climate. Temporary stock market volatility shocks increase the probability of observing extreme liquidity conditions; by contrast, when stock market turmoil is long-lasting, investors perceive the European government bond market as a safe heaven. Finally, bond market liquidity reacts positively to an increase of the volume of marginal lending facilities, with a stronger response if those policy measures are interpreted as being permanent in nature. On the grounds of the ongoing financial turmoil, we argue that ECB has been conducting a proper liquidity management strategy given the information set available before such a crisis in international capital markets.

A fuller understanding of the spillovers across financial segments and across countries is an empirical question that calls for further analysis. Possible improvements of the research agenda may include updating the sample span so as to have a closer look at the effects of the financial turmoil on the European Treasury securities market. An alternative way of asses how government bond liquidity evolves over time may be a joint modelling approach of various measures of market liquidity, such as quoted spreads *and* depths or price impact measures. Another venue for further advances may take account of a richer modelling strategy for shifts across liquidity regimes for *individual* bonds. For instance, since liquidity and trading activity are likely to be affected by issuance calendars published by Euro area countries' Treasuries, exploiting such a source of information would be of interest. In this respect, endogenizing MS-VAR estimated transition probabilities making them dependent on market characteristics as well as on institutional factors could be fruitful to increase market participants' confidence on trading that specific security. These issues are left for future research.

References

Amihud Y. and H. Mendelson (1991), Liquidity, Maturity, and the Yields on U.S. Treasury Securities, Journal of Finance, 46, pp. 1411-1425.

Andersson M., L.J. Hansen and S. Sebestyén (2006), Which News Moves the Euro Area Bond Market?, ECB Working Paper, 631.

Bank for International Settlements (1999), Market Liquidity: Research Findings and Selected Policy Implications, http://www.bis.org/publ/cgfs11.htm.

Beber A., M. W. Brandt and K. A. Kavajecz (2008), Flight-to-Quality or Flight-to-Liquidity? Evidence From the Euro-Area Bond Market, Review of Financial Studies, forthcoming.

Bindseil U. (2004), Monetary Policy Implementation: Theory, Past and Present, Oxford, Oxford University Press.

Boes, S. and R. Winkelmann (2006), The Effect of Income on Positive and Negative Subjective Well-Being, mimeo, University of Zurich.

Brandt M. W. and K. A. Kavajecz (2004), Price Discovery in the U.S. Treasury Market: The Impact of Order flow and Liquidity on the Yield Curve, Journal of Finance, 59, pp. 2623-2654.

Cheung C., F. de Jong and B. Rindi (2005), Trading European Sovereign Bonds: The Microstructure of the MTS Trading Platforms, ECB Working Paper, 432.

Chordia T., R. Roll and A. Subrahmanyam (2001), Market Liquidity and Trading Activity, Journal of Finance, 56, pp. 501–530.

Chordia T., R. Roll and A. Subrahmanyam (2002), Order Imbalance, Liquidity and Market

Returns, Journal of Financial Economics, 65, pp. 111-130.

Chordia T., A. Sarkar and A. Subrahmanyam (2005), An Empirical Analysis of Stock and Bond Market Liquidity, Review of Financial Studies, 18, p. 85-129.

Clarida R. H., L. Sarno, M. P. Taylor and G. Valente (2006), The Role of Asymmetries and Regime Shifts in the Term Structure of Interest Rates, Journal of Business, 79, pp. 1193-1224.

Davies R. (1977), Hypothesis Testing when a Nuisance Parameter is Present only under the Alternative, Biometrika, 64, pp. 247-254.

Dempster A. P., N. M. Laird and D. B.Rubin (1977), Maximum Likelihood Estimation from Incomplete Data via the EM Algorithm, Journal of the Royal Statistical Society, 39, Series B, pp. 1-38.

D'Souza C., I. Lo and S. Sapp (2007), Price Formation and Liquidity Provision in Short-Term Fixed Income Markets, Bank of Canada Working Paper, 2007-27.

Dunne P. G., M. J. Moore and R. Portes (2007), Benchmark Status in Fixed-Income Asset Markets, Journal of Business Finance and Accounting, 34, pp. 1615-1634.

Eisfeldt, A., 2004, Endogenous Liquidity in Asset Markets, Journal of Finance, 59, pp. 1-30.

Elliott G., T. Rothenberg and J. H. Stock (1996), Efficient Tests for an Autoregressive Unit Root, Econometrica, 64, pp. 813-836.

Fleming M. and E. Remolona (1999), Price Formation and Liquidity in the U.S. Treasury Market: The Response to Public Information, Journal of Finance, 54, pp. 1901-1915.

Galati G. and K. Tsatsaronis (2003), The Impact of the Euro on Europe's Financial Markets, Financial Markets, Institutions and Instruments, 12, pp. 165-221.

Gallant A., P. Rossi and G. Tauchen (1992), Stock Prices and Volume, Review of Financial Studies, 5, pp. 199-242.

Garcia G. (1989), The Lender of Last Resort in the Wake of the Crash, American Economic Review, 79, pp. 151-155.

Girardi A. (2008), The Informational Content of Trades on the EuroMTS Platform, Documenti di Lavoro ISAE, 97.

Goldreich D., B. Hanke, and P. Nath (2005), The Price of Future Liquidity: Time-Varying Liquidity in the US Treasury Market, Review of Finance, 9, pp. 1-32.

Hasbrouck J. and D. Seppi (2001), Common Factors in Prices, Order Flows, and Liquidity, Journal of Financial Economics, 59, pp. 383-411.

Huang R., J. Cai and X. Wang (2002), Inventory Risk-sharing and Public Information-based Trading in the Treasury Note Interdealer Broker Market, working paper, Journal of Financial Intermediation, 11, pp. 269-296.

International Monetary Fund and World Bank (2000), Draft Guidelines for Public Debt Management, http://www.imf.org/external/np/mae/pdebt/2000/eng/index.htm.

Johnson T. C. (2008), Volume, Liquidity, and Liquidity Risk, Journal of Financial Economics, 87, pp. 388-417.

Jones C., G. Kaul and M. Lipson (1994), Transactions, Volume, and Volatility, Review of Financial Studies, 7, pp. 631-651.

Korajczyk R. A. and R. Sadka (2008), Pricing the Commonality across Alternative Measures of Liquidity, Journal of Financial Economics, 87, pp. 45-72.

Krolzig H. M. (1997), Markov-Switching Vector Autoregressions. Modelling, Statistical Inference and Application to Business Cycle Analysis, Springer Verlag, Berlin.

Kyle A. (1985), Continuous Auctions and Insider Trading, Econometrica, 53, pp. 131-1335.

Kwiatkowski D., P. C. B. Phillips, P. Schmidt and Y. Shin (1992), Testing the Null Hypothesis of Stationary against the Alternative of a Unit Root, Journal of Econometrics, 54, pp. 159-178.

Lee C. and M. Ready (1991), Inferring Trade Direction from Intraday Data, Journal of Finance, 46, pp. 733–747.

Lyons R. (1997), A Simultaneous Trade Model of the Foreign Exchange Hot Potato, Journal of International Economics, 42, pp. 275-298.

Manganelli S. and G. Wolswijk (2007), Market Discipline, Financial Integration and Fiscal Rules: What Drives Spreads in the Euro Area Government Bond Market?, ECB Working Paper, 745.

Menkveld A. J., Y. C. Cheung and F. de Jong (2004), Euro Area Sovereign Yield Dynamics: The Role of Order Imbalance, ECB Working Paper, 385.

Nelson C. R., J. Piger and E. Zivot (2001), Markov Regime Switching and Unit-Root Tests, Journal of Business and Economic Statistics, 19, pp. 404-415.

Paesani P. and G. Piga (2007), Transparency in the European Bond Market, Transition Studies Review, 14, pp. 3-21.

Pagano M. (1989), Trading Volume and Asset Liquidity, Quarterly Journal of Economics, 104, pp. 255-274.

Pagano M. and E. L. Von Thadden (2004), The European Bond Markets under EMU, Oxford Review of Economic Policy, 20, pp. 531-554.

Pasquariello P. and C. Vega (2007), The On-The-Run Liquidity Phenomenon, paper presented at The Fourth MTS Conference on Financial Markets, 13-14 December, Rome.

Persaud A.D. (2006), Improving Efficiency in the European Government Bond Market, Discussion Paper ICAP plc.

Poskitt D. S. and S. H. Chung (1996), Markov-chain Models, Time Series Analysis and Extreme Value Theory, Advances in Applied Probability, 28, pp. 405–425.

Psaradakis Z. and N. Spagnolo (2006), Joint Determination of the State Dimension and Autoregressive Order for Models with Markov Switching, Journal of Time Series Analysis, 27, pp. 753-766.

Rajan R. (2006), Has Financial Development made the World Riskier?, European Financial Management, 12, pp. 499-533.

Reiss P. and I. Werner (1998), Does Risk Sharing Motivate Inter-dealer Trading?, Journal of Finance, 53, pp. 1657-1703.

Scalia A. (1998), Periodic Information Asymmetry and Intraday Market Behaviour: An Empirical Analysis, European Finance Review, 1, pp. 307-335.

Schwert G. W. (1989), Tests for Unit Roots: A Monte Carlo Investigation, Journal of Business and Economic Statistics, 7, pp. 147-159.

Stoll H. (1978), The Pricing of Security Dealer Services: An Empirical Study of NASDAQ Stocks, Journal of Finance, 33, pp. 1153-1172.

Upper C. and T. Werner (2002), How Resilient Are Financial Markets to Stress? Bund Futures and Bonds during the 1998 Turbulence, BIS Papers, 12, pp. 110-123.

Van Praag B. M. S., P. Frijters and A. Ferrer-i-Carbonell (2003), The anatomy of subjective well-being, Journal of Economic Behavior and Organization, 51, pp. 29-49.

Appendix. Construction of time-varying drivers of liquidity states

Observable bond market characteristics and stock market developments. In order to control for possible trend patterns in the covariates over the chosen sample span, we define *relative* quantities with respect to European averages values. All variables are constructed by using daily data. *repo* is defined as the difference between bond specific spot next repo rates and the Euro short term repo (middle rate) by the ECB. Repo rates are from MTS database, while is taken from Datastream. *mktr* is defined as the difference between HP-filtered log-prices of the country-specific EuroMTS index for the relevant maturity of a bond and the European aggregate EuroMTS index for the same maturity. *mktv* is defined as the absolute value of the difference between the first differences of the log-prices of the country-specific EuroMTS index for the relevant maturity of a bond and the European aggregate EuroMTS index for the same maturity. Data for the construction of *mktr* and *mktv* are disseminated by the EuroMTS website (http://www.euromtsindex.com/). *stkv* is defined as the absolute value of the difference between the first differences of the log-prices of the country-specific stock index and the Eurostoxx index. Data are retrieved *via* Datastream.

Macroeconomic announcements and liquidity management operations. For each announcement, we construct the standardized scheduled news, given by the difference between the value announced and the median of survey expectation of announcement divided by the sample standard deviation of that difference. We set the standardized scheduled news equal to zero on days without macroeconomic announcements. Country-specific announcement data as well as the survey expectation of the announcements on year-on-year changes of inflation (*infl*), industrial production (*indp*) and unemployment (*unem*) are taken from Bloomberg. Finally, *malf* is the standardized value (i.e. the difference between actual values and the sample average divided by the sample standard deviation) of the amount (in EUR millions) of volumes for marginal lending facilities published on the ECB website (http://www.ecb.eu/stats/monetary/res/html/index.en.html#data).

Tables and Figures

Table 1 – Bond codes

Market code	Bond code	Issue date	Maturity date	Maturity (years)	Trades on domestic MTS (%)	Trades by market makers (%)
DEM	DE0001141489	22/03/06	08/04/11	5.05	84.31	98.04
	DE0001135291	23/11/05	04/01/16	10.12	56.31	89.08
	DE0001135275	04/01/05	04/01/37	32.02	73.81	97.81
FRF	FR0108354806	19/01/06	12/01/11	4.98	79.49	99.36
	FR0010288357	02/02/06	25/04/16	10.23	47.21	98.83
	FR0010070060	25/04/03	25/04/35	32.02	81.64	100.00
MTS	IT0004026297	13/03/06	15/03/11	5.01	91.59	99.70
	IT0004019581	27/02/06	01/08/16	10.43	86.60	97.73
	IT0003934657	01/08/05	01/02/37	31.53	90.61	98.06

Note. Market codes are DEM for Germany, FRF for France and MTS for Italy. See Section 2.1 of the paper for details on the criteria for inclusion in the sample.

Table 2 – Summary statistics for liquidity and trading activity measures

	Quoted Spreads						Order Flow Imbalances						Correlation
Bond code	x_M	x_{Me}	x_{SD}	ρ_1	ρ_2	ρ_3	x_M	x_{Me}	x_{SD}	ρ_1	ρ_2	ρ_3	$r_{qspr,oflw}$
DE0001141489	0.0245	0.0251	0.0069	**0.2644**	**0.1795**	0.1357	-5.9444	-7.5000	21.6496	**0.7096**	**0.5126**	**0.3962**	-0.1089
DE0001135291	0.0322	0.0313	0.0114	**0.4118**	**0.2410**	**0.1806**	-4.8242	-2.5000	25.0892	**0.8139**	**0.6692**	**0.5391**	-0.0131
DE0001135275	0.0916	0.0872	0.0330	**0.6099**	**0.4144**	**0.3107**	-0.0690	0.0000	16.9896	**0.8496**	**0.7128**	**0.5902**	-0.0605
FR0108354806	0.0266	0.0277	0.0072	**0.3835**	**0.1842**	0.0535	2.6795	-10.0000	32.5309	**0.8898**	**0.7860**	**0.6943**	-0.2458
FR0010288357	0.0347	0.0318	0.0188	**0.5939**	**0.2876**	0.0377	-11.0499	-5.0000	39.3023	**0.8856**	**0.7803**	**0.6830**	-0.0583
FR0010070060	0.1123	0.1131	0.0318	**0.1791**	0.1359	0.0690	3.5507	5.0000	12.9371	**0.8371**	**0.7178**	**0.6197**	-0.0216
IT0004026297	0.0194	0.0202	0.0055	**0.5719**	**0.3937**	**0.2629**	-13.0589	-5.0000	63.3699	**0.9551**	**0.9128**	**0.8749**	-0.1339
IT0004019581	0.0259	0.0254	0.0076	**0.7916**	**0.6588**	**0.5543**	3.8499	5.0000	80.2379	**0.9567**	**0.9135**	**0.8705**	0.0370
IT0003934657	0.0926	0.0925	0.0307	**0.6638**	**0.5170**	**0.4256**	4.8121	2.5000	38.9936	**0.9581**	**0.9147**	**0.8729**	-0.0415

Note. Quoted spreads are defined as the difference between the best bid and best ask divided by midquote prices, (equally weighted) averaged during half-hour time intervals. Order flows are constructed as the aggregate volume of buyer-initiated orders minus that seller-initiated order during half-hour intervals. For each bond, we report the mean (x_M), the median (x_{Me}) and the standard deviation (x_{SD}) of the two market characteristics along with their serial correlations up to the third lag (ρ_i , $i = 1, 2, 3$). Values in bold indicate statistically significant autocorrelation coefficients at the 5 percent level.

Table 3a – Seasonal adjustment for liquidity measures

	Panel A - Quoted Spreads								
	DE0001141489	DE0001135291	DE0001135275	FR0108354806	FR0010288357	FR0010070060	IT0004026297	IT0004019581	IT0003934657
February	0.0022	0.0021	0.0040	-0.0006	-0.0195 **	0.0024	-0.0009	0.0011 *	0.0180 **
March	-0.0042	0.0056	0.0248 **	0.0051	-0.0067	-0.0083	0.0009	0.0001	0.0207 **
April	-0.0005	0.0054	0.0106 *	0.0084 *	-0.0031	-0.0058	-0.0010	0.0000	-0.0106 **
May	-0.0025	-0.0034	0.0038	0.0119	0.0057	0.0187	-0.0016 **	-0.0022 **	0.0102 *
June	-0.0062 *	0.0003	0.0350 **	0.0104 **	0.0046	0.0504 **	-0.0017 **	0.0016 **	0.0164 **
July	0.0040	-0.0063	0.0164 **	0.0104 **	0.0070	-0.0069	-0.0006	-0.0010 *	0.0133 **
August	-0.0041	-0.0023	0.0105 *	0.0067	-0.0071	0.0265 *	-0.0013	-0.0041 **	0.0170 **
September	-0.0023	-0.0055	0.0071	0.0058	-0.0109	-0.0107	-0.0008	-0.0049 **	0.0069 **
October	-0.0054	-0.0001	0.0117 *	0.0070 *	-0.0036	-0.0067	-0.0009	-0.0027 **	0.0157 **
November	0.0037	-0.0082 *	0.0095	0.0088 *	-0.0023	0.0024	-0.0007	-0.0024 **	0.0141 **
December	-0.0063	0.0025	0.0189 **	0.0086 *	-0.0050	0.0047	-0.0017 **	-0.0014 **	0.0022
Monday	0.0025	0.0026	0.0009	-0.0032	0.0066	0.0034	-0.0009 *	-0.0017 **	-0.0049 *
Tuesday	0.0005	0.0027	-0.0112 **	-0.0038	-0.0040	-0.0094	-0.0001	-0.0012 **	0.0033
Wednesday	0.0006	-0.0014	-0.0069 *	-0.0046	-0.0003	-0.0051	0.0004	-0.0021 **	0.0012
Thursday	-0.0009	0.0002	-0.0079 *	0.0001	-0.0006	0.0037	-0.0008 *	-0.0017 **	-0.0026
9:00-9:30	-0.0111	0.0015	-0.0379 **	-0.0017	-0.0029	-0.0227	-0.0005	-0.0090 **	-0.0262 **
9:30-10:00	-0.0123	-0.0018	-0.0405 **	-0.0088	-0.0033	-0.0228	0.0004	-0.0091 **	-0.0358 **
10:00-10:30	-0.0085	0.0030	-0.0380 **	-0.0027	-0.0048	-0.0286	0.0000	-0.0101 **	-0.0321 **
10:30-11:00	-0.0076	0.0009	-0.0537 **	-0.0036	-0.0046	-0.0171	0.0000	-0.0102 **	-0.0293 **
11:00-11:30	-0.0087	-0.0003	-0.0412 **	0.0017	-0.0084	-0.0154	-0.0005	-0.0090 **	-0.0273 **
11:30-12:00	-0.0070	0.0023	-0.0410 **	-0.0055	-0.0028	-0.0301	-0.0009	-0.0102 **	-0.0313 **
12:00-12:30	-0.0021	0.0001	-0.0484 **	0.0004	0.0409 **	-0.0101	-0.0011	-0.0108 **	-0.0324 **
12:30-13:00	-0.0131	-0.0044	-0.0377 **	-0.0012	-0.0064	-0.0130	0.0003	-0.0091 **	-0.0090
13:00-13:30	-0.0050	0.0075	-0.0390 **	-0.0038	-0.0072	-0.0236	-0.0005	-0.0093 **	-0.0202 **
13:30-14:00	-0.0062	-0.0099	-0.0539 **	-0.0084	-0.0040	-0.0355 *	-0.0011	-0.0094 **	-0.0263 **
14:00-14:30	-0.0065	0.0050	-0.0327 **	-0.0059	-0.0067	-0.0319	-0.0011	-0.0089 **	-0.0184 **
14:30-15:00	-0.0121	0.0060	-0.0206 **	-0.0066	0.0039	0.0143	-0.0010	-0.0077 **	-0.0149 **
15:00-15:30	-0.0040	0.0019	-0.0221 **	0.0011	-0.0032	-0.0138	0.0002	-0.0084 **	-0.0279 **
15:30-16:00	-0.0154 *	0.0071	-0.0449 **	-0.0026	-0.0053	-0.0060	0.0023 **	-0.0080 **	-0.0157 **
16:00-16:30	-0.0083	0.0072	-0.0345 **	0.0112	0.0033	0.0105	0.0022 *	-0.0048 **	-0.0130 **
16:30-17:00	-0.0019	0.0049	-0.0409 **	0.0071	0.0024	0.0215	0.0039 **	-0.0032 **	-0.0161 **
17:00-17:30	-0.0167 *	0.0205 *	-0.0228 **	0.0080	-0.0088	0.0430	0.0043 **	-0.0021 *	-0.0095
Aggressor	-0.0043	-0.0030	-0.0017	-0.0082	0.0101	.	-0.0009	-0.0008	0.0043
Market	0.0041 *	-0.0030	-0.0012	0.0012	-0.0001	0.0139 *	0.0002	-0.0008 **	-0.0019
Intercept	0.0363 **	0.0353 **	0.1270 **	0.0326 **	0.0296 *	0.1164 **	0.0210 **	0.0388 **	0.1052 **

Table 3b – Seasonal adjustment for trading activity measures

	Panel B - Order Flow Imbalances								
	DE0001141489	DE0001135291	DE0001135275	FR0108354806	FR0010288357	FR0010070060	IT0004026297	IT0004019581	IT0003934657
February	20.8078	1.2853	2.0297	4.4121	13.4925	-13.7792 **	-6.9166	-13.1349 **	-5.0916
March	15.9849 *	-2.9352	5.3518 *	11.4735	-8.3904	-15.7133 **	-51.6786 **	-20.7736 **	-2.8594
April	37.4977 **	-9.4441	6.6176 **	-17.5814	12.8413	-3.9014	-13.3937 *	-50.8364 **	6.4778
May	7.6175	-17.8102	4.9710	4.6952	16.3762	-6.0085	20.3377 **	-14.7276 **	0.7191
June	23.2759 **	-0.6394	3.4102	-5.1432	25.0602	-8.8610	-6.8063	-26.4379 **	-6.5045 *
July	49.1016 **	-6.1197	-0.1007	22.6057 *	9.2035	-12.8413 *	5.6954	-17.0430 **	23.5071 **
August	31.0505 **	17.2768 *	0.7389	36.8646 **	-9.7139	3.6617	0.2182	-15.7484 **	13.7432 **
September	37.5078 **	2.6928	-2.6537	4.3113	5.8165	-5.8040	-16.5870 **	-28.9414 **	-3.9217
October	35.8664 **	0.8172	0.2650	18.8647	8.8422	-8.1886	0.6986	13.3716 **	2.1083
November	38.0921 **	3.2759	0.3011	8.3133	-24.2460 *	-8.4900	-13.6754 *	-18.4665 **	-10.2894 **
December	23.6972 *	0.4972	2.5453	3.6586	3.8468	-10.7147 **	10.8008	-3.9244	-5.7751
Monday	-11.5280	6.9363	2.6566	5.2098	-21.9735 **	8.7223 **	-0.2589	-16.1196 **	-10.8968 **
Tuesday	3.2134	0.0913	9.5098 **	18.7858 *	-9.6657	7.2694 *	1.1196	0.4641	-9.2537 **
Wednesday	-5.8079	-5.2307	4.0615 *	4.2688	-3.0757	0.6743	-23.0534 **	-11.4871 **	-15.2268 **
Thursday	-7.4094	-2.3945	5.0945 **	-11.7943	13.9095	4.6647	-10.0850 **	-10.2672 **	0.4037
9:00-9:30	5.0266	-0.0986	-3.6337	-7.1075	13.1274	-8.5056	-28.0229 **	24.8367 **	3.8819
9:30-10:00	13.0706	-0.0150	-9.6012 **	-7.2694	2.4758	-13.8679 *	-13.8303	28.8305 **	8.8227
10:00-10:30	-9.6775	-7.7570	-9.5296 **	-1.0125	7.2927	-2.9953	-82.3033 **	44.0877 **	4.3174
10:30-11:00	-8.3622	4.8703	-4.7151	-19.8017	-2.3675	-0.2005	-19.5747 *	19.7091 **	47.3946 **
11:00-11:30	5.1043	0.1728	5.0911	-6.5344	-5.4213	-2.5213	-34.0171 **	77.8661 **	7.1543
11:30-12:00	-20.4650	-32.8005 **	-3.0833	7.6911	-42.0608 **	-7.6421	-33.0020 **	18.6237 **	5.9743
12:00-12:30	-10.6230	-3.9018	-1.6108	-16.2788	7.9965	-9.5733	-26.2195 **	9.7842	-6.4168
12:30-13:00	-14.0860	-1.1449	2.0776	-17.0419	10.9847	-4.4565	-2.9841	30.6836 **	-9.3761
13:00-13:30	2.6625	-18.6703	11.9748 **	-2.2704	-9.6046	-4.4538	-13.0067	-11.7389	-15.9896 **
13:30-14:00	-11.7540	-10.6496	-5.2537	47.2626 *	0.4315	8.9336	-13.4170	-16.7941 *	1.1727
14:00-14:30	-1.8317	-2.2450	-0.1021	-0.5569	1.3663	0.2474	-11.2014	33.1370 **	11.2590 *
14:30-15:00	-5.3764	4.4927	-1.7235	7.7528	-34.6980 **	-4.8123	-25.2041 **	28.8009 **	1.9367
15:00-15:30	1.6420	4.7215	-2.5586	-15.2911	-1.3540	-5.5629	-3.6300	34.4221 **	-1.2585
15:30-16:00	17.0254	-4.0949	6.9065 *	-9.0891	-12.6181	-10.6468	-0.4458	21.91966 *	6.1329
16:00-16:30	4.0462	-6.2888	-0.7874	9.4348	-13.5276	-10.5341	-9.5835	32.5824 **	2.6626
16:30-17:00	-11.1000	-5.9464	-10.2307 **	-5.5085	9.1644	-7.7718	-15.3226	20.9428 *	0.8002
17:00-17:30	-8.9643	7.0656	-0.2472	-21.0851	21.1606	-5.8543	-15.5539	18.3277	2.6084
Aggressor	-12.0760	22.5516 **	4.9201	5.8180	5.4855	.	15.5456	-3.7432	25.4430 **
Market	5.9237	-1.2406	-1.2315	-2.6679	-11.0895 *	2.5131	20.5419 **	4.1881	-1.5714
Intercept	-14.6390	-18.4095	-7.8299	-15.5461	3.2361	6.9765	-9.4660	-1.0439	-22.4793 **

Note. Estimated coefficients from the mean equation of quoted spreads (Panel A) and order flows (Panel B) according to the procedure by Gallant et al. (1992). The following adjustment variables are used: *i*) 11 monthly dummies, one for each from February to December; *ii*) 4 daily dummies, one for each from Monday to Thursday, *iii*) 17 half-hourly dummies, one for each of the hours from 9:00 (CET) and 17:30 (CET), *iv*) a dummy, $mrkt$, taking value 1, if trades take place on the domestic MTS platform, and 0, otherwise, as in Cheung et al. (2005), *v*) a dummy, $aggr$, taking value 1, if trades are initiated by a market maker, and 0, otherwise. Asterisk and double asterisk indicate statistically significant coefficients at the 10 and the 5 percent levels, respectively.

Table 4 – Unit root test results

	Quoted Spreads			Order Flow Imbalances		
Bond code	Lags	DF-GLS	KPSS	Lags	DF-GLS	KPSS
DE0001141489	1	-6.53	0.12	1	-7.60	0.10
DE0001135291	2	-2.73	0.15	1	-9.67	0.16
DE0001135275	2	-14.64	0.16	1	-13.54	0.46
FR0108354806	1	-2.43	0.05	1	-5.04	0.12
FR0010288357	3	-3.63	0.17	1	-8.05	0.25
FR0010070060	2	-3.34	0.07	1	-5.86	0.18
IT0004026297	1	-24.03	0.12	2	-9.09	0.29
IT0004019581	3	-26.79	0.08	1	-19.07	0.34
IT0003934657	3	-17.10	0.05	1	-10.63	0.63

Note. Unit root test statistics in the version proposed by Elliot et al. (1996) for the null of a unit root process for the variables in the levels are reported in the column "DF-GLS". Critical values at the 10, 5 and 1 percent levels of significance are -2.62, -2.03 and -1.73, respectively, if a constant is included in the regression. The order of autoregression is chosen according to the modified Akaike Information Critoerion and reported in the column "Lags". Test statistics for the test by Kwiatkowski et al. (1992) for null of a stationarity process for the variables in the levels are reported in the column "KPSS". Critical values at the 10, 5 and 1 percent levels of significance are 0.35, 0.46 and 0.74, respectively, if a constant is included in the regression. The order of autoregression is chosen according to the rule provided by Schwert (1989) and reported in the column "Lags".

Table 5 – Properties of Markov switching regimes

	Lags	p_{11}	p_{22}	p_{33}	dur_1	dur_2	dur_3	*Davies*
DE0001141489	1	0.1849	0.4000	0.8408	1.23	1.67	6.28	[0.0000]
DE0001135291	1	0.4128	0.7819	0.5986	1.70	4.58	2.49	[0.0000]
DE0001135275	1	0.7918	0.8317	0.6908	4.80	5.94	3.23	[0.0000]
FR0108354806	1	0.8044	0.8818	0.4751	5.11	8.46	1.91	[0.0025]
FR0010288357	1	0.6624	0.7307	0.5894	2.96	3.71	2.44	[0.0000]
FR0010070060	1	0.5245	0.7348	0.7861	2.10	3.77	4.68	[0.0104]
IT0004026297	2	0.9285	.	0.8827	13.98	.	8.52	[0.0000]
IT0004019581	2	0.9266	.	0.8995	13.63	.	9.95	[0.0000]
IT0003934657	2	0.8371	0.8530	0.7972	6.14	6.80	4.93	[0.0000]

Note. The order of autoregression chosen according to the general-to-specific procedure is reported in the column "Lags". p_{jj}'s ($j = 1, 2, 3$) are the estimated filtered probabilities of transition from regime j to regime j. The average duration of each regime j, dur_j, is calculated as $dur_j = 1/(1 - p_{jj})$. *Davies* is the upper bound of the LR tests for the null of a linear VAR. p-values are in squared brackets.

Table 6 - MS-VAR estimation results

	Equation: Quoted Spreads			Equation: Order Flow Imbalances		
Panel A	μ_1	μ_2	μ_3	μ_1	μ_2	μ_3
DE0001141489	**0.0154**	**0.0248**	**0.0260**	6.8105	**78.8751**	**-11.4183**
	(0.0036)	(0.0036)	(0.0022)	(4.4775)	(5.7629)	(2.0671)
DE0001135291	**0.0154**	**0.0352**	**0.0375**	-0.0813	**-3.4387**	**7.5881**
	(0.0034)	(0.0032)	(0.0030)	(1.8170)	(1.6569)	(1.8988)
DE0001135275	**0.0858**	**0.0901**	**0.1194**	**-15.1009**	5.5157	**24.6818**
	(0.0052)	(0.0048)	(0.0060)	(3.8545)	(3.8350)	(3.9071)
FR0108354806	**0.0252**	**0.0275**	**0.0296**	**-8.0508**	0.2807	**13.7744**
	(0.0028)	(0.0029)	(0.0040)	(2.4969)	(2.6262)	(4.0889)
FR0010288357	**0.0265**	**0.0312**	**0.0613**	**20.6449**	**-48.4495**	7.9136
	(0.0032)	(0.0034)	(0.0030)	(6.8392)	(7.0203)	(8.3280)
FR0010070060	**0.0858**	**0.1086**	**0.1286**	**-10.5542**	3.4779	**10.7240**
	(0.0078)	(0.0079)	(0.0094)	(3.5817)	(3.6260)	(3.7159)
IT0004026297	**0.0187**	.	**0.0206**	**23.6405**	.	**-72.3159**
	(0.0006)		(0.0007)	(7.2633)		(7.5152)
IT0004019581	**0.0211**	.	**0.0324**	**-17.5754**	.	**32.9866**
	(0.0007)		(0.0007)	(9.7688)		(9.3437)
IT0003934657	**0.0646**	**0.0912**	**0.1267**	**-23.9607**	9.3981	**29.2129**
	(0.0035)	(0.0036)	(0.0037)	(9.1934)	(9.2237)	(9.1457)
Panel B	Restriction on the mean		Granger Causality	Restriction on the mean		Granger Causality
DE0001141489	$\mu_1 = \mu_2 = \mu_3$	[0.0070]	[0.0390]	$\mu_2 = -\mu_3$	[0.0000]	[0.0000]
DE0001135291	$\mu_1 = \mu_2 = \mu_3$	[0.0000]	[0.0000]	$\mu_2 = -\mu_3$	[0.2122]	[0.0358]
DE0001135275	$\mu_1 = \mu_2 = \mu_3$	[0.0000]	[0.0461]	$\mu_1 = -\mu_3$	[0.2112]	[0.0000]
FR0108354806	$\mu_1 = \mu_2 = \mu_3$	[0.1985]	[0.0441]	$\mu_1 = -\mu_3$	[0.3335]	[0.2563]
FR0010288357	$\mu_1 = \mu_2 = \mu_3$	[0.0000]	[0.0000]	$\mu_1 = -\mu_2$	[0.0000]	[0.0000]
FR0010070060	$\mu_1 = \mu_2 = \mu_3$	[0.0000]	[0.8480]	$\mu_1 = -\mu_3$	[0.9800]	[0.0109]
IT0004026297	$\mu_1 = \mu_3$	[0.0000]	[0.0091]	$\mu_1 = -\mu_3$	[0.0000]	[0.2457]
IT0004019581	$\mu_1 = \mu_3$	[0.0000]	[0.0000]	$\mu_1 = -\mu_3$	[0.0000]	[0.0000]
IT0003934657	$\mu_1 = \mu_2 = \mu_3$	[0.0000]	[0.0000]	$\mu_1 = -\mu_3$	[0.0000]	[0.0000]

Note. In Panel A, regime-dependent mean values (μ_j, $j = 1,2,3$) statistically significant at the 5 percent level of significance (or better) are reported in bold. Estimated standard errors are in parentheses. In Panel B, restriction on the mean in the quoted spread (order flow) equation tests the null of equal mean (in absolute values) across regimes. Granger Causality in the quoted spread (order flow) equation tests the null that past values of order flows (quoted spreads) do not affect current values of the dependent variable. p-values are in squared brackets.

Table 7 – Alternative specifications for ordered regression models

	Model [1]	Model [2]	Model [3]	Model [4]
I - Observable bond market characteristics	X	X	X	X
II - Stock market developments	X	.	X	X
III - Macroeconomic announcements	.	X	X	X
IV - Liquidity management operations	.	.	.	X
LL	-1529.48	-1527.55	-1527.21	-1525.20
χ^2	29.91 (8) [0.0002]	33.77 (10) [0.0002]	34.44 (11) [0.0003]	38.47 (12) [0.0001]
AIC	3078.95	3079.09	3080.42	3078.40

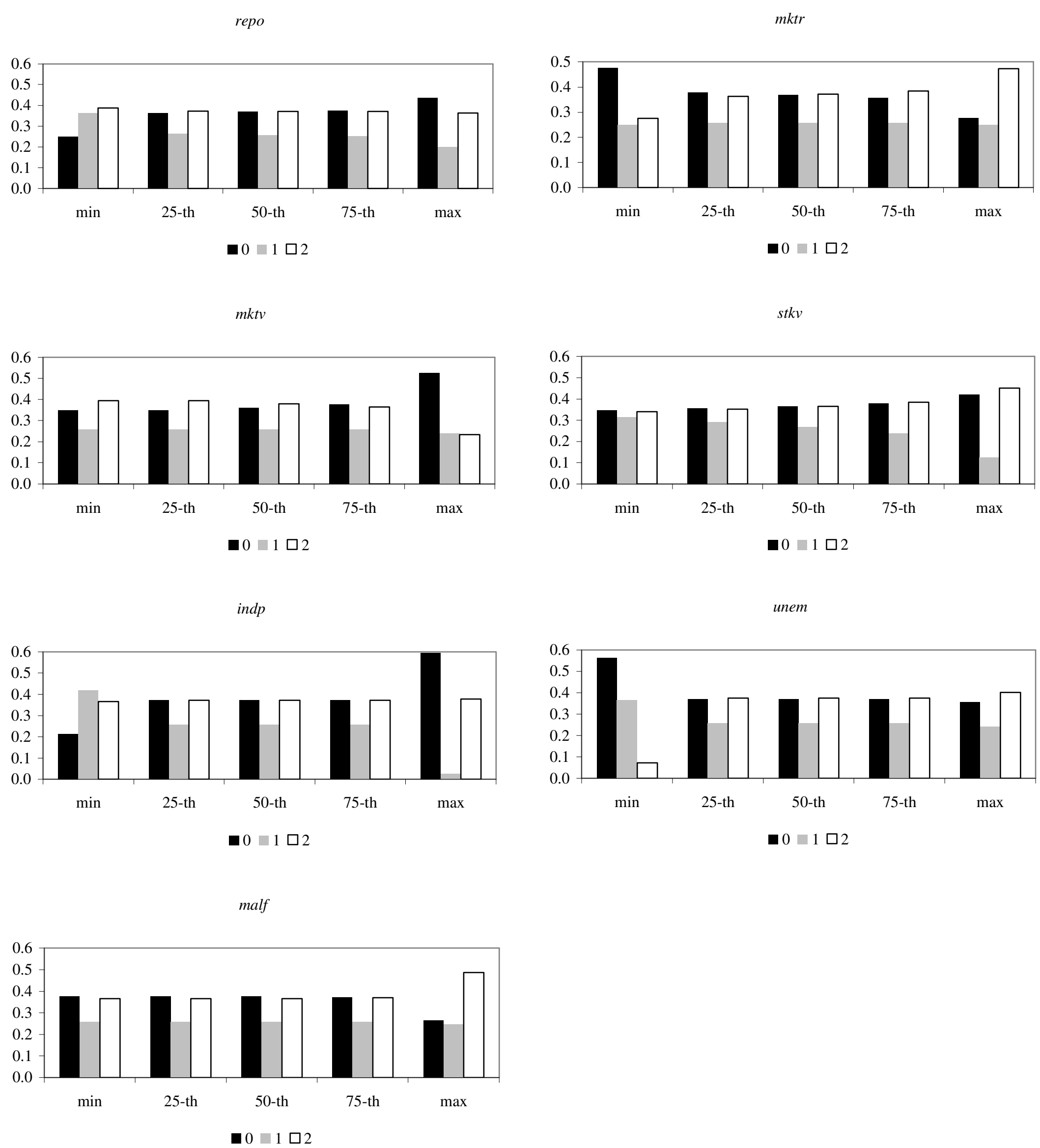
Note. LL and AIC indicate the value of the log-likelihood function and the Akaike Information Criteria, respectively. χ^2 is the test statistics for the joint impact of the covariates on the dependent variable. Degrees of freedom are in parentheses, while p-values in square brackets.

Table 8 – Ordered probit estimation results

	Pooled-ORM (A)	RE-ORM (B)	Generalized RE-ORM (C)	
			Equation 1	*Equation 2*
repo	-0.3758	-0.4321	-0.7313*	-0.1277
	(0.3694)	(0.3754)	(0.4282)	(0.4287)
mktr	0.2454**	0.3024**	0.2971**	
	(0.1176)	(0.1191)	(0.1197)	
mktv	-0.9869**	-1.0058**	-1.0130**	
	(0.4165)	(0.4186)	(0.4191)	
stkv	0.1305	0.1473	-0.3555*	0.5234***
	(0.1664)	(0.1695)	(0.1957)	(0.1869)
indp	-0.1806	-0.1642	-0.3118*	0.0063
	(0.1349)	(0.1350)	(0.1635)	(0.1743)
infl	-0.0695	-0.0436	-0.0835	-0.0179
	(0.1470)	(0.1525)	(0.1999)	(0.1662)
unem	0.0742*	0.0733*	0.0497	0.1154*
	(0.0443)	(0.0440)	(0.0475)	(0.0688)
malf	0.0712**	0.0622*	0.0445	0.0732*
	(0.0357)	(0.0362)	(0.0441)	(0.0397)
ρ	.	0.4298***	0.4341***	
		(0.0440)	(0.0437)	
Observations	1417	1417	1417	
LL	-1525.20	-1465.236	-1450.603	
χ^2	38.47 (12) [0.0001]	42.65 (12) [0.0000]	102.53 (18) [0.0000]	
AIC	3078.40	2960.47	2943.21	
χ^2-PRA	.	.	29.27 (6) [0.0000]	

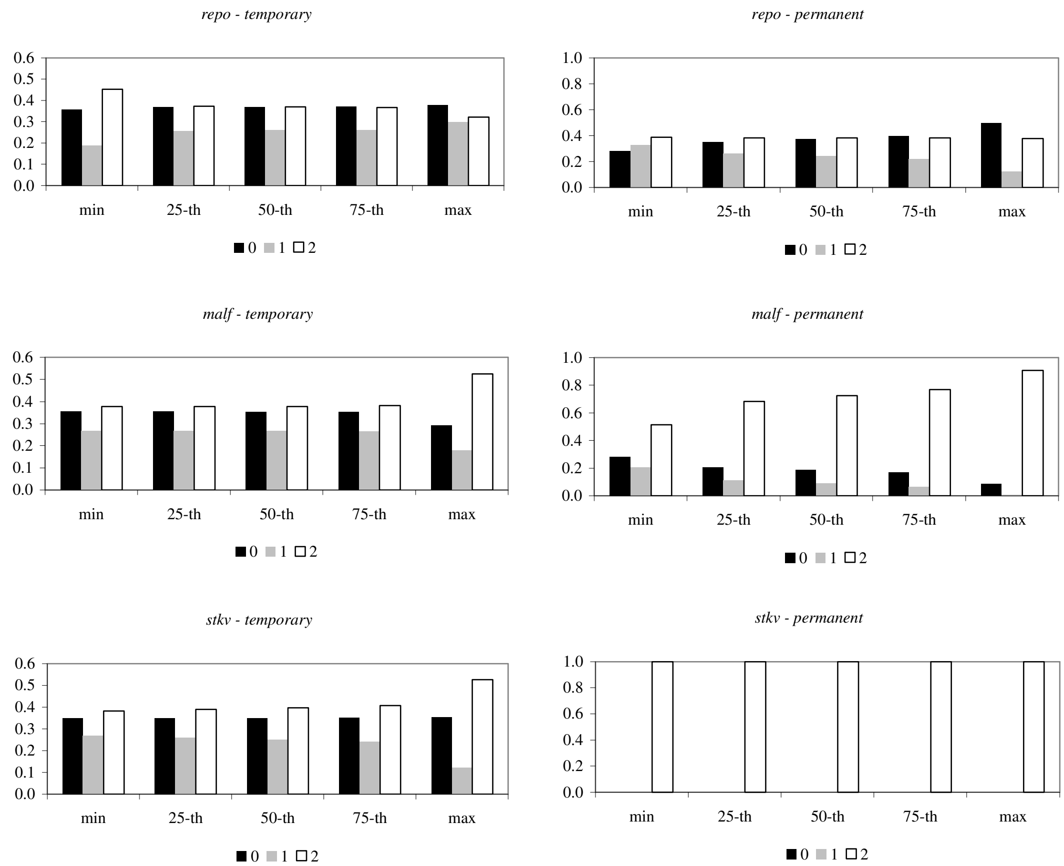
Note. The dependent variable is an ordinal indicator which is equal to 2, 1 and 0 when the average daily probability of being in the high, normal and low liquidity regime, respectively, is the highest as compared to the probabilities associated to the remaining states by daily averaging. See Section 4 of the paper for the definition of the covariates. Country and maturity dummies, albeit included among the regressors, are omitted for ease of exposition. Single, double and triple asterisks indicate significance at the 10, 5 and 1 percent levels, respectively. Standard errors are in parentheses. LL and AIC indicate the value of the log-likelihood function and the Akaike Information Criteria, respectively. χ^2 is the test statistics for the joint impact of the covariates on the dependent variable. χ^2-PRA is the test statistics for symmetric impact of the covariates on the dependent variable across categories. Degrees of freedom are in parentheses, while p-values in square brackets.

Figure 1 – Simulated probabilities: baseline generalized RE-ORM



Note. The dependent variable is an ordinal indicator which is equal to 2, 1 and 0 when the average daily probability of being in the high, normal and low liquidity regime, respectively, is the highest as compared to the probabilities associated to the remaining states by daily averaging. See Section 4.1 of the paper for the definition of the covariates. Country and maturity dummies, albeit included among the regressors, are omitted for ease of exposition. In each graph, the vertical axis indicates the probability associated to a certain state of liquidity. Black, grey and white bars refer to $\Pr(r_{it} = 0)$, $\Pr(r_{it} = 1)$ and $\Pr(r_{it} = 2)$, respectively. The horizontal axis reports these probabilities, computed at the minimum as well as at the first quartile, the median, the third quartile and at the maximum values of the distribution of each predictor, *ceteris paribus*.

Figure 2 – Simulated probabilities: disentangling temporary and permanent effects



Note. The dependent variable is an ordinal indicator which is equal to 2, 1 and 0 when the average daily probability of being in the high, normal and low liquidity regime, respectively, is the highest as compared to the probabilities associated to the remaining states by daily averaging. See Section 4.5 of the paper for the definition of the covariates. Country and maturity dummies, albeit included among the regressors, are omitted for ease of exposition. In each graph, the vertical axis indicates the probability associated to a certain state of liquidity. Black, grey and white bars refer to $\Pr(r_{it} = 0)$, $\Pr(r_{it} = 1)$ and $\Pr(r_{it} = 2)$, respectively. The horizontal axis reports these probabilities, computed at the minimum as well as at the first quartile, the median, the third quartile and at the maximum values of the distribution of each predictor, *ceteris paribus*.

The Contribution of Domestic, Regional, and International Factors to Latin America's Business Cycle[†]

[†] This is a joint paper with Melisso Boschi (University of Essex, University of Perugia, and Centre for Applied Macroeconomic Analysis, mboschi@stat.unipg.it). Though this paper is the result of the joint research of the authors, Introduction, Section 2 and the Appendix can be attributed to Melisso Boschi; Section 3, Section 4 and Conclusions to Alessandro Girardi.

Abstract

This paper quantifies the relative contribution of domestic, regional and international factors to the fluctuation of domestic output in six key Latin American (LA) countries: Argentina, Bolivia, Brazil, Chile, Mexico and Peru. Using quarterly data over the period 1980:1-2003:4, a multivariate, multi-country time series model was estimated to study the economic interdependence among LA countries and, in addition, between each of them and the three world largest industrial economies: the US, the Euro Area and Japan. Falsifying a common suspicion, it is shown that the proportion of LA countries domestic output variability explained by industrial countries factors is modest. By contrast, domestic and regional factors account for the main share of output variability at all simulation horizons. The implications for the choice of the exchange rate regime are also discussed.

Keywords: International business cycle, Latin America, exchange rate regimes, Global VAR methodology, VEC models.

JEL Classification: C32, E32, F31, F41.

1 – Introduction

In keeping with the central message of the Optimal Currency Areas (OCAs) literature initiated by Mundell (1961) and McKinnon (1963), detecting the sources of business cycle has important implications for the choice of exchange rate regimes. If, in fact, one economy is hit by shocks dissimilar to those hitting its trading partner countries, the cost of adopting a fixed exchange rate regime, and thus giving up monetary policy, can be correspondingly large. The canonical criteria suggested by early contributions to OCAs (e.g. Artis (2003), HM Treasury (2003)) also state that if the standard pre-requisites for successful currency area hold, a fixed exchange rate regime may gain stability before adverse shocks make it fail. In many academic and policy circles, these criteria, although more than forty-years-old, are still considered to be a useful framework to consult when deciding upon the adoption of a common currency.

Following the currency and financial crises of the nineties, and especially the Argentine turmoil of 2001-2002, a wide debate has concerned the choice among available currency regimes options for Latin American countries (e.g. Edwards (2002), Berg et al. (2002)). This work aims to analyse to what extent domestic, regional and international economic conditions affect domestic output fluctuations in six key Latin American (LA) countries - namely Argentina, Bolivia, Brazil, Chile, Mexico and Peru - and the implications for the choice of the exchange rate regime. This country sample is chosen mainly to compare more easily our results to those of the existing literature to be reviewed below, and especially Ahmed (2003) and Canova (2005). Our analysis is naturally related to the strand of research studying the comovement of LA countries' business cycles with each other and with developed economies'. Hoffmaister and Roldos (1997) document that domestic country-specific aggregate supply shocks are by far the most important source of output fluctuations in LA countries. Aiolfi et al. (2006) uncover a sizeable common component in LA countries' business cycles using common dynamic factors techniques, thus suggesting the existence of a regional cycle. On the other hand, Agénor et al. (2000) point out that the business cycle in

12 developing countries is positively related to the output and real interest rate fluctuations in industrial economies, albeit they do not try to quantify the importance of external shocks compared to domestic ones. Employing a Bayesian dynamic latent factor model, Kose et al. (2003) and Kose et al. (2008) estimate the world, region and country-specific components in output, consumption and investment of sixty countries covering seven regions. As far as concerns Latin America, Kose et al. (2003) find that country-specific factors explain the largest part of the variance of output in all LA countries considered in this study, with the exception of Bolivia, for which the regional world component is more important than the region and country-specific one.

From a wider perspective, our analysis is also related to the literature on the link between international business cycle and the choice of a proper exchange rate regime for a small open economy. Berg et al. (2002) find that supply shocks in LA countries are weakly correlated among them and, most importantly, with the US ones, providing evidence against the adoption of a common currency in the region or against straight "dollarisation". Ahmed (2003) focuses on the existence of the prerequisites for six LA countries to adopt a fixed exchange rate regime with their main trading partners (the US). While domestic business cycle seems to be driven by US monetary policy rather than by foreign output shocks, external shocks taken as a whole (foreign output, US interest rates, terms of trade) explain a smaller component of LA business cycle than domestic shocks (output, real exchange rate, inflation); this results points towards the adoption of a freely floating exchange rate. By contrast, Canova (2005) finds that US monetary policy shocks, magnified by the interest rates transmission channel, are a relevant source of fluctuations of LA countries' inflation and output.

The critical difference between the papers cited above and our study is three-fold. First, besides the US we also consider the Euro Area and Japan as possible sources of external shocks to domestic business cycle in LA countries. This is partly motivated by the trade relationship between LA and Euro Area countries. But, as it will become apparent below, this is not the entire story since financial linkages - through NFA and short-term interest rates - play a determinant role. Second, we examine the role exerted by neighbour countries on each LA country's business cycle in order to assess the existence of the pre-requisites for the adoption of a common currency area. Third, our empirical framework is explicitly designed to identify shocks according to their geographical origin. The latter point is particularly important when comparing our results to those obtained by Kose et al. (2003) and Kose et al. (2008). In fact, while they can only recover the different components of the variables of interest, using the GVAR methodology it is possible to identify the role played by specific foreign economies to domestic business cycle.

The econometric methodology consists of a procedure for aggregating a number of VEC systems in a Global Vector Auto Regressive (GVAR) model describing the world economy (Pesaran et al. (2004a)) in order to perform dynamic simulation exercises. Using quarterly data over the period 1980:1-2003:4, nine country/region-specific Vector Error Correction (VEC) models were estimated, each containing four endogenous domestic variables (output, real interest rate, real exchange rate, net foreign assets), two foreign variables (foreign output and foreign real interest rate) and the price of oil. This is consistent with a parsimonious, reduced form, small open economy model such as that presented in Boschi (2007). Country-specific foreign variables, constructed as weighted averages of the endogenous variables of the other countries/regions, and the real oil price are modelled as weakly exogenous.

The main findings can be summarised as follows. First, domestic factors explain by far the largest share of domestic output variability over all simulation horizons in all LA countries. Second, regional factors, though much less important than domestic ones, contribute to the variability of domestic output more than industrial countries' ones. This is true for all LA countries except Mexico. Third, in all LA countries the proportion of the forecast error variance of output explained by industrial countries factors is overall modest. These results should inform the choice between freely floating and fixed exchange rate regimes. Also, they should be taken into account when choosing a reference currency in a fixed exchange rate arrangement: "dollarisation" does not appear an obvious option. Aside from their scientific merits and policy implications, our findings that international risk sharing could be problematic at a regional level but it is still viable when capital crosses continents is consistent with the conclusions in Aiolfi et al. (2006) and may also be of benefit to international investors.

The remainder of the paper is structured as follows. Section 2 reviews the inter-regional macro-econometric framework. Section 3 presents preliminary analysis on the individual series as well as the main estimation results relative to country/region VEC systems and the properties of the GVAR model. The quantitative assessment of the geographical sources affecting output fluctuations in LA countries is discussed in Section 4 along with the main policy implications. Concluding remarks follow.

2 – Modelling Latin American economies in a multi-country framework

The empirical framework we use to model LA economies in the international context relies on the GVAR approach (Pesaran et al. (2004a)). As customary in the VEC modelling framework, the GVAR methodology builds on the association between the economic concept of long-run and the statistical concept of stationarity through the identification of stationary linear combinations of the data, known as cointegration vectors. These vectors describe the steady-state configuration which the model tends to revert to in the long-run. The advantages of the GVAR over panel cointegration techniques are well-known (Baltagi (2004) and Pesaran et al. (2004b)) and relate to the possible distortion of within-group cointegration test results caused by the existence of between-group cointegration, as shown by Banerjee et al. (2004). Also, the GVAR allows for a coherent analysis of short-run dynamics of the systems through scenario simulations.

Specifically, the GVAR methodology consists of a procedure for stacking in a single coherent model of the world economy a number of country-specific VEC systems and explicitly allows for interdependences across economies in a true multi-country setting. The crucial advantage of this methodology is that although the shocks hitting the variables of the global system are unidentified according to their economic nature (for instance, supply, demand or policy disturbances), nevertheless they are identified basing on their geographic origin. This is because each country/region-specific system in the multi-country model is estimated conditionally on foreign variables, thus leaving only modest correlation among cross-country shocks to endogenous factors. Thus, our empirical framework makes it possible to distinguish and identify the shocks which originated in the three industrial countries/regions (US, Euro Area and Japan), in addition to those which originated in each LA country, rather than considering only one country (commonly the US in the previous literature) or an ambiguous "rest of the world" as the main source of external shocks.

2.1 – The GVAR model

Adopting the same notation as in Pesaran et al. (2004a), there is benefit in reviewing the econometic setup employed in this work. There are $N+1$ countries/regions in the world economy indexed by $i = 0,1,...,N$.[48] For each country the following VEC model is estimated:[49]

$$\Delta \mathbf{x}_{it} = \mathbf{a}_{i0} + \mathbf{a}_{i2}\mathbf{D}_{it} + \mathbf{\Pi}_i \boldsymbol{\kappa}_i - \mathbf{\Pi}_i[\mathbf{v}_{i,t-1} - \boldsymbol{\kappa}_i(t-1)] + \mathbf{\Lambda}_{i0}\Delta \mathbf{x}^*_{it} + \mathbf{\Psi}_{i0}\Delta \mathbf{d}_t + \boldsymbol{\varepsilon}_{it} \tag{1}$$

where $\mathbf{x}_{it}$ is a $(k_i \times 1)$ vector of country i domestic variables, $\mathbf{x}^*_{it}$ is a $(k^*_i \times 1)$ vector of foreign variables specific to country i (to be defined below), $\mathbf{d}_t$ is a $(k_d \times 1)$ vector of $I(1)$ variables common to all country-specific models and exogenous to the global economy (such as oil prices), $\mathbf{v}_{i,t-1} \equiv (\mathbf{z}'_{i,t-1}, \mathbf{d}'_{t-1})'$, $\mathbf{z}_{it} \equiv (\mathbf{x}'_{it}, \mathbf{x}'^*_{it})'$, $\mathbf{a}_{i0}$ is a $(k_i \times 1)$ vector of fixed intercepts, $\mathbf{a}_{i2}$ is a $(k_i \times m)$ matrix of coefficients of the exogenous deterministic components included in the $(m \times 1)$ vector $\mathbf{D}_{it}$, $\mathbf{\Lambda}_{i0}$ is a $(k_i \times k^*_i)$ matrix of coefficients associated to the foreign variables, $\mathbf{\Psi}_{i0}$ is a $(k_i \times k_d)$ vector associated to the global variables, $\boldsymbol{\varepsilon}_{it}$ is a $(k_i \times 1)$ vector of country-specific shocks, with $\boldsymbol{\varepsilon}_{it} \sim N(\mathbf{0}, \mathbf{\Sigma}_{ii})$, where $\mathbf{\Sigma}_{ii}$ is a non-singular variance-covariance matrix, and where $t = 1,2,...,T$ indexes time. The number of long-run relations is

---

[48] $N = 8$ in this paper. $i = 0$ is the reference country (the US).

[49] The exposition refers to a VARX* of order one, as suggested by the standard information criteria and by the diagnostic tests discussed below.

given by the rank $r_i \le k_i$ of the $k_i \times (k_i + k_i^* + k_d)$ matrix $\mathbf{\Pi}_i$. Finally, in order to avoid introducing quadratic trends in the levels of the variables when $\mathbf{\Pi}_i$ is rank-deficient, $k_i - r_i$ restrictions $\mathbf{a}_{i1} = \mathbf{\Pi}_i \boldsymbol{\kappa}_i$ are imposed on the trend coefficients, where $\mathbf{a}_{i1}$ is the coefficient of the time trend term in the isomorphic level VAR form of (1) and $\boldsymbol{\kappa}_i$ is a $(k_i + k_i^* + k_d) \times 1$ vector of fixed constants.

The foreign variables $\mathbf{x}_{it}^*$ are weighted averages of the variables of the rest of the world with country/region-specific weights, w_{ij}, given by trade shares, i.e. the share of country j in the total trade of country i over the years 1995-2001, measured in 1995 US dollars. Thus a generic foreign variable x_{it}^* is given by:

$$x_{it}^* = \sum_{j=0}^{N} w_{ij} x_{jt} \tag{2}$$

where $w_{ii} = 0$, $\forall i = 0,1,...,N$ and $\sum_{j=0}^{N} w_{ij} = 1$, $\forall i, j = 0,1,...,N$. In our set-up, all foreign variables collected in the vector $\mathbf{x}_{it}^*$ as well as the global exogenous variables, $\mathbf{d}_t$, are treated as long-run forcing variables.

Rather than estimating directly the complete system composed by the $N+1$ country-specific models (1) together with the relations (2), we followed Pesaran et al. (2004a) and estimate the parameters of each country-specific model separately and then stack the coefficients estimates in a GVAR model. All country/region-specific endogenous variables are collected in the $(k \times 1)$ global vector $\mathbf{x}_t = (\mathbf{x}'_{0t}, \mathbf{x}'_{1t}, ..., \mathbf{x}'_{Nt})'$ where $k = \sum_{i=0}^{N} k_i$. Then we have that $\mathbf{z}_{it} = \mathbf{W}_i \mathbf{x}_t$, where $\mathbf{W}_i$ is the $(k_i + k_i^*) \times k$ matrix collecting the trade weights w_{ij}, $\forall i, j = 0,1,...,N$.

Therefore, for each country/region the following VAR form of model (1) is obtained:

$$\mathbf{A}_i \mathbf{W}_i \mathbf{x}_t = \mathbf{a}_{i0} + \mathbf{a}_{i1} t + \mathbf{a}_{i2} \mathbf{D}_{it} + \mathbf{B}_i \mathbf{W}_i \mathbf{x}_{t-1} + \mathbf{\Psi}_{i0} \mathbf{d}_t + \mathbf{\Psi}_{i1} \mathbf{d}_{t-1} + \boldsymbol{\varepsilon}_{it} \tag{3}$$

where $\mathbf{A}_i$ and $\mathbf{B}_i$ are matrices of dimension $k_i \times (k_i + k_i^*)$ and matrix $\mathbf{A}_i$ has full row rank. Stacking the $N+1$ systems (3) yields the following GVAR in level form:

$$\mathbf{G}\mathbf{x}_t = \mathbf{a}_0 + \mathbf{a}_1 t + \mathbf{a}_2 \mathbf{D}_t + \mathbf{H}\mathbf{x}_{t-1} + \mathbf{\Psi}_0 \mathbf{d}_t + \mathbf{\Psi}_1 \mathbf{d}_{t-1} + \boldsymbol{\varepsilon}_t \qquad (4)$$

where $\mathbf{G}$ is a $k \times k$ full rank matrix, $\mathbf{a}_h = (\mathbf{a}_{0h}, ..., \mathbf{a}_{Nh})'$ for $h = 0,1,2$, $\mathbf{G} = (\mathbf{A}_0\mathbf{W}_0, ..., \mathbf{A}_N\mathbf{W}_N)'$, $\mathbf{H} = (\mathbf{B}_0\mathbf{W}_0, ..., \mathbf{B}_N\mathbf{W}_N)'$, for $h = 0,1$, $\mathbf{\Psi}_h = (\mathbf{\Psi}_{0h}, ..., \mathbf{\Psi}_{Nh})'$, for $h = 0,1$, $\mathbf{D}_t = (\mathbf{\Psi}_{0t}, ..., \mathbf{\Psi}_{Nt})'$. The GVAR has the reduced form:

$$\mathbf{x}_t = \mathbf{b}_0 + \mathbf{b}_1 t + \mathbf{b}_2 \mathbf{D}_t + \mathcal{F}\mathbf{x}_{t-1} + \mathbf{\Upsilon}_0 \mathbf{d}_t + \mathbf{\Upsilon}_1 \mathbf{d}_{t-1} + \mathbf{u}_t \qquad (5)$$

where $\mathbf{b}_h = \mathbf{G}^{-1}\mathbf{a}_h$ for $h = 0,1,2$, $\mathcal{F} = \mathbf{G}^{-1}\mathbf{H}$, $\mathbf{\Upsilon}_h = \mathbf{G}^{-1}\mathbf{\Psi}_h$ for $h = 0,1$, and $\mathbf{u}_t = \mathbf{G}^{-1}\boldsymbol{\varepsilon}_t$.[50]

2.2 – Generalised Forecast Error Variance Decomposition

The bulk of our empirical investigation is conducted using the Generalised Forecast Error Variance Decomposition (GFEVD) developed by Koop et al. (1996) and Pesaran and Shin (1998). The GFEVD considers the proportion of the variance of the n-step ahead forecast error of the variable of interest which is explained by conditioning on the non-orthogonalised shocks u_{jt}, $u_{j,t+1}$, ..., $u_{j,t+n}$ for $j = 1,...,k$, while explicitly allowing for the contemporaneous correlations between these shocks and the shocks to the other equations in the system.[51]

[50] As pointed out by Pesaran et al. (2004a), three conditions need to be fullfilled so as to ensure that the GVAR estimation procedure is indeed equivalent to the simultaneous estimation of the VAR model of the world economy. First, the global model must be dynamically stable, i.e. the eigenvalues of matrix $\mathcal{F}$ in equation (5) lie either on or inside the unit circle. Second, trade weights must be such small that $\sum_{j=0}^{N} w_{ij}^2 \to 0$ as $N \to \infty$, $\forall i$. Third, the cross-dependence of the idiosyncratic shocks must be sufficiently small, so that $\frac{1}{N}\sum_{j=0}^{N} \sigma_{ij,ls} \to \infty$, $\forall i,l,s$, where $\sigma_{ij,ls} = \mathrm{cov}(\varepsilon_{ilt}, \varepsilon_{jst})$ is the covariance of the l^{th} variable in country i with the s^{th} variable in country j. These conditions amount to an econometric formalisation of the economic concept of "small open economy" and are discussed in details in Section 3 below.

[51] It is worth emphasising that this is the reason why the GFEVD encompasses simpler methods traditionally used to assess cross-country business cycle asymmetry such as the correlation analysis of shocks (e.g. Berg et al.

Although this methodology prevents a structural interpretation of the impulses, it overcomes the identification problem by providing a meaningful characterisation of the dynamic responses of variables of interest to typically observable shocks.[52] One useful feature of the GFEVD is its invariance to the ordering of the variables. Formally, the proportion of the n-step ahead forecast error variance of the l^{th} element of $\mathbf{x}_t$ accounted for by the innovations in the j^{th} element of $\mathbf{x}_t$ can be expressed as:

$$\text{GFEVD}(\mathbf{x}_{(l)t};\mathbf{u}_{(j)t};n) = \frac{\sigma_{jj}^{-1}\sum_{l=0}^{n}(\mathbf{s}_l'\boldsymbol{F}^n\mathbf{G}^{-1}\boldsymbol{\Sigma}\mathbf{s}_j)^2}{\sum_{l=0}^{n}\boldsymbol{F}^n\mathbf{G}^{-1}\boldsymbol{\Sigma}\mathbf{G}'^{-1}\boldsymbol{F}'^n\mathbf{s}_l} \tag{6}$$

$n = 0,1,2,...$; $l = 1,...,k$; $j = 1,...,k$

where all symbols are defined above.[53]

3 – Preliminary analyses and estimation results

Data description. Time series data for the following countries/regions were considered: Argentina, Bolivia, Chile, Brazil, Mexico, Peru, the US, Japan and the Euro Area. We use quarterly seasonally adjusted series covering the period 1980:1-2003:4.[54] The Euro Area

(2002)).

[52] We resort to GFEVD because it is impossible to recover the structural shocks from the GVAR residuals due to the large number of variables whose contemporaneous relationship is ignored. In the GVAR estimated in this paper, including $k_i = 4$ endogenous variables for each of the $N+1=9$ country models, exact identification of shocks would require 108 (i.e. $\sum_{i=0}^{N} k_i(k_i - 1)$) restrictions derived by economic theory, which seems an impossible task to undertake. Dees et al. (2007a) identify the shocks to US monetary policy by imposing a recursive structure on the US block of the variance-covariance matrix of the GVAR. However, this exercise is beyond the scope of this paper.

[53] Notice that due to the possible non-diagonal form of matrix $\boldsymbol{\Sigma}$, the elements of GFEVD across j need not sum to unity since shocks are not orthogonal. However, in order to facilitate cross-country comparisons and interpretation of results, the sum of variance decompositions are normalised to 100.

[54] Note that the 1980s mark the beginning of the modern wave of international capital flows to Latin America and thus analysing the role of this factor in domestic business cycle prior to the sample start makes little sense.

variables were constructed as weighted averages of the corresponding time series of the following countries in the region, with weights given by the *per capita* PPP-GDP share of the period 1995-2000: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain.[55] For each country/region, a VEC model (1) was estimated, where the vector of endogenous variables, $\mathbf{x}_{it}$, includes y_t, sr_t, q_t and nfa_t, denoting real per-capita output, short-term real interest rate, real exchange rate and the net foreign asset/nominal GDP ratio respectively; the vector of country-specific foreign variables, $\mathbf{x}_{it}^*$, includes y_t^* and sr_t^*, representing the rest of the world real per-capita output and short-term interest rate, respectively; finally, the vector $\mathbf{d}_t$ includes the oil price in real terms, oil_t, as a global weakly exogenous variable.[56] The matrix of trade weights used to construct the country/region-specific foreign variables is reported in Table 1, where the 1995 - 2001 trade shares are displayed in column by country/region. The Appendix indicates in detail data sources and variables construction.

[Table 1 about here]

Unit root tests. As a preliminary exercise, we carried out standard ADF unit root tests on the time series involved. Panel [A] of Table 2 reports results based on AIC order selection, while statistics shown in Panel [B] use the modified AIC method proposed by Ng and Perron (2001) to correct the size distortion ofordinary ADF test statistics.

[Table 2 about here]

[55] On the validity of the aggregating expedient to construct synthetic time-series for the Euro Area economy as a whole see Girardi and Paesani (2008) among others.

[56] Boschi (2007) motivates the inclusion of these variables in the GVAR basing on a small open economy model of net foreign assets and real exchange rate determination. Furthermore, we follow Dees et al. (2007b) in treating the real exchange rate as an endogenous variable. As for net foreign assets, a number of studies (Girardi and Paesani (2008), Lane and Milesi-Ferretti (2004) among others) suggest that it is driven by both domestic and foreign factors, giving support to our modelling strategy.

Furthermore, in order to take into account the possibility of structural breaks due to financial crises and recessions, we performed the ADF unit root test with breaks proposed by Saikkonen and Lütkepohl (2002) and Lanne et al. (2002, 2003). The results are reported in Table 3, Panels [A] and [B]. Since the distribution under the null hypothesis is non-standard, we use the critical values provided by Lanne et al. (2002).

[Table 3 about here]

Overall, the combination of both types of tests (standard and with breaks), indicate that all variables can be reasonably considered to be driven by I(1) stochastic trends. On the other hand, differencing the series appears to induce stationarity.[57]

Determination of the autoregressive order. We chose the lag length of the endogenous variables, p_i, by combining standard selection criteria; namely the Akaike information criterion (AIC), the Schwarz Bayesian criterion (SBC) and the log-likelihood ratio statistic (LR). These criteria were adjusted to take into account the potential small sample problems, starting from a maximum lag order of four. The results, reported in Table 4, indicate that the SBC suggests order one for all models except Bolivia, Mexico and US, the AIC selects order four for Chile, Mexico and the Euro Area, order three for Peru, order two for Argentina, Bolivia, Japan and the US, and order one for Brazil, while the LR favours an order of autoregression higher than four for Mexico, three for Chile, Peru, and Euro Area, two for Bolivia, Japan, and US, one for Argentina and Brazil.

[Table 4 about here]

[57] The only exceptions are the real exchange rate of Mexico that seems to be stationary, and the net foreign assets of Bolivia, which appear to be $I(2)$. We choose to model these variables as realizations of $I(1)$ processes since the actual integration properties of the real exchange rate series of Mexico are likely to depend on the composition of its trading partners prices and exchange rates. For example, using a different basket of trading partners, Boschi (2007) finds that the real exchange rate of Mexico is $I(1)$. The net foreign assets of Bolivia were treated as $I(1)$ since this hypothesis is rejected at the 5 percent confidence level but not at the 10 percent.

Given the alternatives, and taking into account the limited sample size compared to the number of unknown parameters in each VARX* model, where X* indicates foreign exogenous variables, the lag order p_i is set equal to 1. This choice is comforted by the fact that the SBC estimates the lag order consistently, while the AIC does not (Lütkepohl (2006), p. 151). In order to choose the lag order of the foreign specific variables, q_i, an unrestricted VAR was run for each country/region in which the foreign variables are treated as endogenous, obtaining similar results.[58] Basing on this evidence and considering data limitations, we set q_i equal to one in all models.

Misspecification tests. The selected lag order and the inclusion of dummy variables corresponding to residual values larger than 3.5 times the standard error is sufficient to obtain a satisfactory specification of the models, giving support to our model specification strategy. Univariate specification tests, reported in Table 5, show that the null hypothesis of no serial correlation is rejected only in 5 out of 36 equations at the standard confidence level, while the null of normality is rejected only in 3 equations. Finally, the univariate F test rejects the null of homoschedasticity only for Japanese output and US real exchange rate at 5 percent level.

[Table 5 about here]

In order to detect possible parameters instability due to structural breaks conventional CUSUM and CUSUMSQ tests at single equation level for each model were undertaken. The results, unreported here to preserve space, were comforting since episodes of parameters instability emerge only for a limited number of equations and only for very short periods of time.[59]

[58] These results are unreported to save space, but are available on request.

[59] These are the beginning of the nineties for the Argentinean, Chilean, Peruvian, and US net foreign assets, for the Chilean, Mexican, and Peruvian real interest rate, and for the Mexican and US real exchange rate; the beginning of the eighties for the Chilean and US output. Complete CUSUM and CUSUMSQ tests results are available on request.

Cointegration tests. Table 6 reports the maximum eigenvalue and trace tests statistics together with their associated 90 and 95 percent critical values. Both tests select unambiguously a cointegration rank equal to 1 for Brazil, Mexico, Peru, and Japan, and 4 for the US. For the other models, where the results were less clear cut, we favoured the conclusion of the trace test comforted by Johansen (1992), according to which the maximum eigenvalue test may produce a non-coherent testing strategy. Thus, we set a cointegration rank of 1 for Argentina, and 2 for Bolivia and the Euro Area. As for Chile, after considerable experimentation, a rank of 2 was chosen in order to have a more stable Global VAR.[60]

[Table 6 about here]

Properties of the Global VAR. Since in the GVAR the total number of endogenous variables is 36 and that of cointegrating relations is at most 15,[61] it then follows that matrix $\boldsymbol{F}$ in equation (5) must have at least 36-15=21 eigenvalues that fall on the unit circle in order to ensure stability of the global model. Our results confirm this; the matrix $\boldsymbol{F}$ estimated from the country-specific models has exactly 21 eigenvalues falling on the unit circle, while the remaining 15 are all less than one (in modulus).

A second key assumption of the GVAR approach is that idiosyncratic shocks are cross-sectionally weakly correlated. The basic idea is that conditioning the estimation of country/region-specific VEC models on foreign variables considered as proxies of "common" global factors will leave only a modest degree of correlation of the remaining shocks across countries/regions. This is also important if we were to interpret the disturbances in the GFEVD analysis as "geographically structural": an external shock is truly external if its contemporaneous correlation with internal shocks is weak. In order to verify these claims,

[60] Notice that the long-run structure defined by the cointegration space of each country/region specific model could be restricted according to the implications of a small open economy model (e.g. Boschi (2007) and Dees et al. (2007b)), but given the explicit focus of this paper on the relationship among economies at a business cycle frequency, we limited our exercise to unrestricted models.

[61] That is the sum of the ranks of matrix $\mathbf{\Pi}_i$ in equation (1) for each country $i = 0,..., N+1$ (Pesaran et al. (2004a)).

contemporaneous correlations of residuals across different country-specific models for each equation were computed. Table 7 reports such correlation coefficients, computed as averages of the correlation coefficients between the residuals of each equation (variable) with all other countries/regions equations residuals. A two-tailed t-test rejects the hypothesis that these coefficients are significantly different from zero at the conventional level. Thus, the model seems to be successful in capturing the effect of common factors driving domestic variables.

[Table 7 about here]

A third econometric concern refers to the assumption that foreign variables and oil price are weakly exogenous in the country/region-specific VEC models. Along the lines described by Johansen (1992) and followed by Pesaran et al. (2004a), we examined the weak exogeneity of these variables by testing the joint significance of the error correction terms in auxiliary equations of the country/region-specific foreign variables, $\mathbf{x}_{it}^{*}$ and the oil price. Specifically, we carried out the following regression for each lth element of country i vector of foreign variables, $\mathbf{x}_{it}^{*}$ and for the oil price:

$$\Delta x_{il,t}^{*} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ijl} ECM_{i,t-1}^{j} + \varphi' \Delta \mathbf{v}_{i,t-1} + \zeta_{il,t}$$

where μ_{il} is a constant, $ECM_{i,t-1}^{j}$, $j = 1,...,r_i$, are the estimated error correction terms corresponding to the r_i cointegrating relations found in the i^{th} model, $\varphi_{il,k}$ are coefficients, $\Delta \mathbf{v}_{i,t-1}$ is defined by (1), and $\zeta_{il,t}$ is the residual. Then an F test of the joint hypotheses that $\gamma_{ijl} = 0$, $j = 1,...,r_i$, is carried out. Table 8 reports the results.

[Table 8 about here]

Most of the test statistics are not significant at the 5 percent level.[62] Given the overall statistical support and the strong theoretical prior in favour of the weak exogeneity hypothesis, foreign variables and the oil price were treated as weakly exogenous.

[62] The weak exogeneity assumption is rejected at the 1 percent level only in the model of Peru for the short-term rates and in the Euro Area model for oil prices, while it is rejected at the 5 percent level in the models of

4 – Assessing the geographical origin of business cycle fluctuations in Latin America

As discussed above, the modest degree of cross-country correlation of reduced form residuals allows for an approximated identification of disturbances according to their geographical origin. Given the focus of the present study, we confined our analysis to output fluctuations. Table 9 reports the GFEVD of each LA country's domestic output over a simulation horizon of 40 quarters. Panel [A] refers to the contribution to domestic output forecast error variance of domestic shocks, i. e. y, sr, q, and nfa. Panel [B] summarises the contribution of external shocks classified according to whether their origin is regional, i.e. from other LA countries, or from one of the three industrial economies we consider in the analysis. Finally, Panel [C] reports an overall comparison of domestic versus foreign contribution to each country's domestic output fluctuations.

[Table 9 about here]

Domestic shocks. A mixed picture of the local determinants of output variability emerged. Real factors (output itself) are neatly predominant over the whole forecast horizon only in Argentina and, especially, Brazil, while this is true only up to the 12th quarter for Bolivia, Chile and Mexico, and up to the 20th quarter for Peru. Financial factors seem to play a significant role in all countries apart from Argentina and Brazil (and even here still play a role).[63] This is consistent with Canova's (2005) findings that financial factors are an important channel of transmission of foreign shocks; or it could be interpreted as idiosyncratic sources of variability. However, this first block of results should be taken with caution since, as detailed above, the GFEVD tool does not allow for an *economic* identification of shocks, but rather it provides a meaningful characterisation of disturbances

Mexico and US for output.

[63] Specifically, net foreign assets are the main source of variability in Chile (from the second simulation year on) and Peru (at all horizons), while the real interest rate is the main source of output variability for some quarters in Bolivia, Mexico, and Peru.

according to their geographical origin, tracing out the dynamic responses of variables to *typical* (i.e. historically observed) shocks. Therefore, the rest of this Section will focus on the contribution of shocks having different geographical origin to LA countries' domestic output fluctuations.

Regional vs domestic shocks. Over the entire forecast horizon, regional factors contribute approximately 20 percent of domestic output variability in Argentina, Bolivia and Chile but drops to approximately 10 percent in Brazil and Mexico. This pattern is somehow more variegated in Peru where the contribution of regional shocks ranges from 13 to 42 percent. Overall this result supports evidence of a sizeable regional business cycle component in Latin America. Aiolfi *et al*. (2006) attribute this feature to the role of common global factors on the grounds of limited trade and financial linkages among these economies. However, the breakdown (unreported) of the figures in column 5 of Table 9 show that regional factors affect domestic business cycle through financial channels (short-term rates and net foreign assets) in a non-negligible way. Thus, since the main common global real and financial factors were controlled for in this study in a coherent model of the world economy, the findings are interpreted as due to similarities in the economic structure of the LA countries examined.

Industrial countries' vs regional and domestic shocks. In *all* Latin American countries considered here, domestic factors contribute far more than industrial countries' factors to the variability of domestic output.[64] Overall, industrial countries explain a small fraction of output fluctuation, ranging from 7 percent in Bolivia to almost 13 percent in Mexico. Specifically, the US economy is the most important contributor to domestic output forecast variability at all horizons for Argentina and Peru. The role of Euro Area is never very large on impact, but tends to increase over time. Japan gives an important contribution to output variability in all countries, and especially in Argentina, Bolivia, Brazil and Chile. This

[64] This is true for all countries at all horizons, with an average difference between the percentage contribution of domestic shocks and that of industrial ones stretching from 53 percentage points for Chile to 74 percentage points for Brazil.

central finding disputes the other relevant literature on international business cycles, most of which concentrate on the role of US macroeconomic variables and implicitly assume that the US role in the global economy and its trade and financial links with Latin America (the US "backyard") are the main driving force behind business cycles co-movements in this region (Ahmed (2003), Canova (2005)). Falsifying a common suspicion, estimates show that the proportion of LA countries' domestic output variability explained by the US (and by the other industrial countries) is modest when compared to the contribution of regional shocks.

Robustness checks. In order to gain some insights on the reasons why our results differ from those studies where the US role seems bigger, a number of alternative models were estimated.[65] In particular, we estimated first a VEC model including only output of all countries/regions considered in the GVAR - i.e. Argentina, Bolivia, Brazil, Chile, Mexico, Peru, the US, Euro Area and Japan. The results show that the role of the US and regional shocks are larger than in the GVAR, especially at longer forecast horizons, with the exception of Mexico for which the importance of US shocks decreases over time. In addition, six VEC models, one for each LA country — each model including the relevant LA country's factors, i.e. y_t, sr_t, q_t and nfa_t, along with the US counterparts — were estimated. As expected, in these six models the US factors play an even bigger role than in the VEC model containing only output of all countries/regions. The US explain on average more than 20 percent of domestic output forecast error variance in all LA countries, with the only exception of Brazil.

All in all, considering the evidence provided by the simple VEC models, the reason why in the GVAR the influence exerted by the US is smaller seems to be related more to the inclusion of a larger set of countries/regions than to the larger number of factors. This helps to understand why previous literature - where the US is the only external economy taken into account - overestimated the contribution of the US shocks to LA business cycle. In this

[65] Results of these additional estimations are unreported to save space, but they can be provided by the authors upon request.

respect, the paper by Kose *et al.* (2003) goes along the right direction since it considers a large group of countries. They find, like in this study, that country-specific factors are the main determinant of output fluctuations in Latin America, but they reserve a smaller role to the regional factors compared to this paper. However, the methodology in their paper, namely a Bayesian dynamic latent factor model, does not allow to recover the geographical origin of factors affecting domestic business cycle, but rather identifies the generic components of a series as divided in world, region and country-specific.[66] For this reason the GVAR appears a more suitable methodology to address the problem of choosing the proper exchange rate regime for an emerging market basing on the main geographical determinants of its business cycle.

Which exchange rate regime for Latin American countries? The findindgs of this paper have important implications for the choice among such alternative extreme exchange rate regimes, i.e. hard pegs (currency board or unilateral "dollarisation"), the formation of an independent common currency area and the freely floating exchange rate. *First*, as long as "dollarisation" requires a large degree of business cycle synchronisation among the country adopting the dollar and the US economy, the GFEVD analysis shows that in the LA countries this regime may be subject to strong destabilising shocks originated in countries other than the US, either developed or developing. A sensible way to take into account this fact could be pegging the domestic currency to a "synthetic" foreign currency built as a weighted average of the currencies of the main industrial and developing countries affecting domestic business cycle. *Second*, although the contribution of regional factors to domestic business cycle in LA countries is noticeable, and indeed larger than industrial countries influence, nevertheless idyosincratic shocks play a dominant role in all LA countries' economies. This result cast doubts on the viability of a common currency area along the path

---

[66] Notice that from a more technical perspective, the methodology used in Kose et al. (2003) differs from ours because they compute the variance decomposition of the raw series of interest, while in this paper the forecast error variance decomposition is derived. Then, while we analyse the innovation (or unsystematic) part of the series as recovered from the residual of the estimated model, they decompose the systematic part of it.

set by the European Monetary Union. Idiosyncratic shocks could destabilise such a monetary arrangement well before it could enhance the required real and financial integration necessary to make it work. All results above suggest that a freely floating exchange rate might be the most viable option to be pursued in LA countries, in line with what argued by Ahmed (2003) and Berg *et al.* (2002).

Implications for portfolio diversification. Aside from the academic and policy implications, our results may be of interest for international investors as well. The large contribution of regional factors to domestic business cycle suggests that economic conditions are highly correlated in LA countries. However, the GFEVD analysis show that this does not result from a sizeable regional business cycle component in LA as found by Aiolfi et al. (2006), but rather from the relevant role of all neighbour countries' factors – real and financial - for domestic output fluctuations. This caveat notwithstanding, the evidence here reported should discourage investors to engage in regional risk-sharing. By contrast, portfolio diversification may still be a viable option when capital crosses continents.

5 – Conclusions

Over recent years, the increasing international economic integration driven by the liberalisation of current and capital accounts has stimulated a growing number of studies on the causative determinants of macroeconomic fluctuations in emerging markets. The vast majority of existing contributions implicitly assume that US are the main origin country of external shocks. In this paper we have demonstrated that this is not the case, at least not in LA countries.

To quantify the relative contribution of domestic, regional and international shocks in explaining domestic output fluctuations, quarterly data over the period 1980:1-2003:4 was used and a multi-variate time series model was estimated to include six key LA countries (Argentina, Bolivia, Brazil, Chile, Mexico and Peru) as well as three major industrial economies (the US, Euro Area and Japan). The main findings can be summarised as follows. Domestic and regional factors account for the main share of output variability at all horizons, while the proportion explained by industrial countries factors is modest. All in all, assessing the relevant contribution of shocks originating in other neighbour countries and in countries/regions other than the US will provide a better understanding of the actual geographical origin of external drivers of output variability in LA countries.

From a macro-econometric research perspective, our findings suggest that presuming the US are the main source of external shocks can lead to misleading results. Other industrial countries and, especially, neighbour developing countries are largely influential on LA domestic economic conditions. Furthermore, admitting both real and financial channels of transmission of shocks across economies helps to avoid over-estimating the effects exerted by individual variables (for instance GDP) in explaining ouput fluctuation in LA countries. This result, in turn, should inform the choice of a reference currency when adopting a fixed exchange rate arrangement. “Dollarisation” does not appear an obvious option. Analogously, the formation of a common currency area in LA may be subject to excessively large destabilising shocks before the region economy is homogenous enough to make the arrangement work. In a nutshell, freely floating exchange rates remain a sensible option. On a more practical level, investors willing to diversify their portfolios’ risk could benefit from broadening their international composition, while concentration of asset acquisition in the same region appears inadequate given the large contribution of neighbouring countries’ factors to domestic output fluctuations.

Appendix

A.1 Data sources

Net Foreign Assets (*NFA*). The NFA series is obtained for each country as the sum, period-by-period, of foreign assets and liabilities given by the following quarterly time series taken from the IFS database: *DIA* (Direct Investment Abroad - code 78...BDDZF), *PIA* (Portfolio Investment Assets - code 78...BFDZF), *OIA* (Other Investment Assets - code 78...BHDZF), *DIL* (Direct Investment Liabilities - code 78...BEDZF), *PIL* (Portfolio

Investment Liabilities - code 78...BGDZF), and OIL (Other Investment Liabilities - code 78...BIDZF). Therefore: $NFA = DIA + PIA + OIA - DIL - PIL - OIL$.

Population (*POP*). The source is the IFS database. The code is 99Z..ZF.... Available annual data are interpolated linearly.

Nominal Output (*YNC*). The series is the volume of GDP in billions of national currency. It is taken from IFS for all countries except for Brazil. The code is 99B./CZF.... The series for Brazil is obtained from IPEADATA.

Output (*YCC*). The source for all countries, except Brazil, is the IFS database. The code is ..99BVP/RZF.. (2000=100). The quarterly data for Argentina's GDP volume index are only available from 1993:1; the series is extended backward using the rates of growth of the GDP index series provided by Oxford Economic Forecasting. The GDP index of Brazil is obtained by deflating (with the CPI) the GDP volume in billions of national currency provided by IPEADATA.

Price index (*CPI*). The source is the IFS' Consumer Prices Index (CPI), which code is 64...ZF.. (2000=100).

Exchange rates (*NER*). The source is the IFS' series of National Currency per US Dollar, with code 17 .RF.ZF... except fo Mexico for which the series ..WF.ZF... is used.

Nominal short-term interest rates (*SR*). The series is the Money Market Rate or equivalent (code 60B..ZF...) from the IFS.

Oil price (*OILP*). The series is the price of Brent from IFS, with code 11276AAZZF....

A.2 Variables construction

The Euro Area variables are constructed as weighted averages of the corresponding series of Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. The weights are each country's mean shares of the Euro Area's real GDP in PPP over the period 1995-2000. The real GDP in PPP series are obtained from the World Bank's World Development Indicators 2002. Following Pesaran et al. (2004a), the variables used in the estimation of each country/region-specific VEC model are constructed from the series above as follows:

$y = \ln[100 \cdot (YCC / POP) / POP_{2000}]$;

$sr = 0.25 \cdot \ln(1 + SR/100) - \ln(CPI_{+1} / CPI)$;

$q = \ln(100 \cdot NER / NER_{2000}) - \ln(CPI)$;

$nfa = NFA / (YNC / NER)$;

$y_i^* = \sum_{j=0}^{N} w_{ij} y_j$;

$sr_i^* = \sum_{j=0}^{N} w_{ij} sr_j$;

$oil = \ln(100 \cdot OILP / OILP_{2000})$.

References

Agenor, P. R., C. J. McDermott, and E. S. Prasad (2000) “Macroeconomic Fluctuations in Developing Countries: Some Stylized Facts” World Bank Economic Review, 14, 251-285.

Ahmed, S. (2003) “Sources of Economic Fluctuations in Latin America and Implications for Choice of Exchange Rate Regime”, Journal of Development Economics, 72, 181-202.

Aiolfi, M., L. Catão, and A. Timmermann (2006) “Common Factors in Latin America's Business Cycles”, IMF Working Paper, 06/49.

Artis, M. J. (2003) “Reflections on the Optimal Currency Area (OCA) Criteria in the Light of EMU”, International Journal of Finance and Economics, 8, 297-307.

Baltagi, B. H. (2004) “Comment”, Journal of Business Economics and Statistics, 2, 163-164.

Banerjee, A., M. Marcellino, and C. Osbat (2004) “Some Cautions on the Use of Panel Methods for Integrated Series of Macro-economic Data”, Econometrics Journal, 7, 322-340.

Berg, A., E. Borensztein, and P. Mauro (2002) “An Evaluation of Monetary Policy Regime Options for Latin America”, North American Journal of Economics and Finance, 13, 213-235.

Boschi, M. (2007) “Foreign Capital in Latin America: A Long-run Structural Global VAR Perspective”, University of Essex, Department of Economics Discussion Paper, n. 647.

Canova, F. (2005) “The Transmission of US Shocks to Latin America”, Journal of Applied Econometrics, 20, 229-251.

Dees, S., F. di Mauro, M. H. Pesaran, and L. V. Smith (2007a) “Exploring the International Linkages of the Euro Area: A Global VAR Analysis”, Journal of Applied Econometrics, 22, 1-38.

Dees, S., S. Holly, M. H. Pesaran, and L. V. Smith (2007b) “Long-run Macroeconomic Relations in the Global Economy”, Economics - The Open-Access, Open-Assessment E-Journal, 2007-3.

Edwards, S. (2002) "The Great Exchange Rate Debate after Argentina", North American Journal of Economics and Finance, 13, 237-252.

Girardi, A. and P. Paesani (2008) "The Transfer Problem in the Euro Area: A Cointegration Analysis", Open Economies Review, forthcoming.

HM Treasury (2003) "Analysis of European and UK Business Cycles and Shocks", available at www.hmtrasury.gov.uk.

Hoffmaister, A. W. and J. F. Roldos (1997) "Are Business Cycles Different in Asia and Latin America?", IMF Working Paper, n. 97/9.

Johansen, S. (1992) "Determination of the Cointegration Rank in the Presence of a Linear Trend", Oxford Bullettin of Economics and Statistics, 54, 383-397.

Koop, G., M. H. Pesaran, and S. M. Potter (1996) "Impulse Response Analysis in Nonlinear Multivariate Models", Journal of Econometrics, 74, 119-147.

Kose, M. A., C. Otrok, and E. Prasad (2008) "Global Business Cycles: Convergence or Decoupling?", IZA Discussion Papers, n. 3442.

Kose, M. A., C. Otrok, and C. Whiteman (2003) "International Business Cycles: World, Region, and Country Specific Factors", American Economic Review, 93, 1216-1239.

Lane, P. R. and G. M. Milesi-Ferretti (2004) "The Transfer Problem Revisited: Net Foreign Assets and Real Exchange Rates", Review of Economics and Statistics, 86, 841-857.

Lanne, M., H. Lütkepohl, and P. Saikkonen (2002) "Comparison of Unit Root Tests for Time Series with Level Shifts", Journal of Time Series Analysis, 23, 667-685.

Lanne, M., H. Lütkepohl, and P. Saikkonen (2003) "Test Procedures for Unit Roots in Time Series with Level Shifts at Unknown Time", Oxford Bulletin of Economics and Statistics, 65, 91-155.

Lütkepohl, H. (2006) New Introduction to Multiple Time Series Analysis, Springer Verlag, Berlin.

McKinnon, R. I. (1963) "Optimum Currency Areas", American Economic Review, 53, 717-725.

Mundell, R. A. (1961) “A Theory of Optimum Currency Areas”, American Economic Review, 51, 657-665.

Ng, S. and P. Perron (2001) “Lag Lenght Selection and the Construction of Unit Root Tests with Good Size and Power”, Econometrica, 69, 1519-1554.

Pesaran, M. H., T. Schuermann, and S. M. Weiner (2004a) “Modelling Regional Interdependencies using a Global Error-Correcting Macroeconometric Model”, Journal of Business Economics and Statistics, 2, 126-162.

Pesaran, M. H., T. Schuermann, and S. M. Weiner (2004b) “Rejoinder to Comments on Modelling Regional Interdependencies using a Global Error-Correcting Macro-econometric Model”, Journal of Business Economics and Statistics, 2, 175-181.

Pesaran, M. H. and Y. Shin (1998) “Generalised Impulse Response Analysis in Linear Multivariate Models”, Economics Letters, 58, 17-29.

Saikkonen, P. and H. Lutkepohl (2002) “Testing for a Unit Root in a Time Series with a Level Shift at Unknown Time”, Econometric Theory, 18, 313-348.

Table 1 – Trade weights

	Argentina	Bolivia	Brazil	Chile	Mexico	Peru	Euro Area	Japan	US
Argentina	0	0.158	0.178	0.126	0.003	0.033	0.026	0.004	0.012
Bolivia	0.011	0	0.008	0.010	0.000	0.023	0.001	0.000	0.001
Brazil	0.358	0.149	0	0.094	0.009	0.064	0.067	0.020	0.041
Chile	0.075	0.077	0.029	0	0.006	0.080	0.015	0.012	0.011
Mexico	0.025	0.020	0.028	0.054	0	0.041	0.031	0.020	0.283
Peru	0.010	0.093	0.008	0.026	0.002	0	0.005	0.002	0.006
Euro Area	0.273	0.077	0.334	0.248	0.060	0.219	0	0.272	0.342
Japan	0.042	0.091	0.081	0.149	0.027	0.083	0.224	0	0.305
US	0.207	0.335	0.334	0.293	0.894	0.458	0.631	0.670	0

Notes: Trade weights, computed as shares of exports and imports in 1995-2001, are displayed in column by country/region. Each column, but not row, sums to one. Source: Direction of Trade Statistics Yearbook, IMF, 2002.

Table 2 – ADF unit root test statistics

Panel [A]. AIC order selection

	Argentina	Bolivia	Brazil	Chile	Mexico	Peru	Euro Area	Japan	US
y	-1.92	-1.33	-1.74	-2.57	-2.28	-1.67	-3.25	-1.49	-2.84
Δy	-3.90	-2.87	-9.44	-5.22	-4.86	-6.53	-2.30	-3.24	-4.80
sr	-1.69	-2.28	-4.13	-2.18	-2.68	-0.90	-2.38	-1.20	-2.27
Δsr	-8.05	-5.14	-7.61	-3.62	-8.89	-4.59	-5.33	-7.85	-4.27
q	-2.65	-1.19	-1.97	-1.53	-3.70	-1.66	-2.98	-2.30	-2.70
Δq	-4.54	-6.90	-8.35	-4.32	-4.33	-4.94	-6.55	-4.19	-3.40
nfa	-1.86	-2.71	-1.06	-4.41	-3.03	-3.90	-5.14	-1.20	-3.04
Δnfa	-7.82	-2.67	-4.88	-2.96	-5.02	-5.24	-3.45	-5.60	-3.18
y^*	-2.12	-2.80	-2.05	-3.64	-2.92	-3.19	-3.49	-4.32	-2.65
Δy^*	-9.30	-8.02	-5.44	-4.76	-4.74	-4.91	-3.70	-4.96	-5.42
sr^*	-2.04	-2.79	-6.02	-7.78	-2.62	-3.84	-3.27	-3.53	-2.53
Δsr^*	-2.70	-2.96	-4.98	-7.55	-6.32	-7.41	-4.61	-12.42	-6.57
oil	-	-	-	-	-	-	-	-	-1.85
Δoil	-	-	-	-	-	-	-	-	-5.87

Panel [B]. Modified AIC order selection

	Argentina	Bolivia	Brazil	Chile	Mexico	Peru	Euro Area	Japan	US
y	-1.92	-1.33	-1.74	-2.57	-2.28	-1.67	-1.96	-1.49	-2.88
Δy	-4.54	-2.79	-2.59	-3.24	-4.02	-2.56	-2.76	-3.24	-4.39
sr	-1.69	-2.32	-3.39	-1.25	-2.68	-0.90	-1.87	-1.20	-0.85
Δsr	-16.65	-11.40	-7.74	-5.30	-5.71	-5.20	-14.66	-18.48	-12.48
q	-2.65	-1.19	-1.48	-1.76	-4.07	-1.58	-2.47	-1.58	-2.31
Δq	-3.73	-1.98	-6.32	-1.86	-4.59	-3.58	-4.10	-4.19	-2.25
nfa	-1.15	-3.10	-1.06	-2.42	-1.61	-2.31	-3.78	-1.20	-3.19
Δnfa	-2.34	-1.72	-1.95	-1.61	-4.33	-4.85	-2.37	-4.02	-1.83
y^*	-2.12	-1.98	-1.51	-2.25	-2.92	-2.78	-2.24	-3.02	-1.84
Δy^*	-2.80	-5.03	-3.84	-4.90	-4.02	-5.02	-5.93	-3.22	-4.87
sr^*	-1.16	-2.11	-4.64	-1.49	-0.79	-2.61	-2.26	0.08	-2.06
Δsr^*	-2.37	-2.57	-19.04	-15.77	-12.60	-13.20	-18.86	-12.42	-4.53
oil	-	-	-	-	-	-	-	-	-1.85
Δoil	-	-	-	-	-	-	-	-	-6.27

Notes: The ADF statistics are based on univariate AR(p) models in the levels with p chosen according to the modified AIC, with a maximum lag order of 11. The sample period is 1980:1-2003:4. The regressions for all variables in the levels include an intercept and a linear trend with the exception of interest rates whose underlying regressions include only an intercept. The 95 percent critical value for regressions with trend is -3.46 and for regressions without trend -2.89.

Table 3 – ADF unit root tests with breaks statistics

Panel [A]. Level variables

	y	*sr*	*q*	*nfa*	*y**	*sr**	*oil*
Argentina							
Suggested break date	1994 Q2	1991 Q2	1984 Q2	1984 Q4	1985 Q1	1990 Q3	-
Test statistic	-2.23 [8]	-3.61 [3]	-1.52 [2]	-1.83 [3]	-1.37 [0]	-2.58 [7]	-
Bolivia							
Suggested break date	1985 Q2	1991 Q1	1984 Q3	1988 Q4	1994 Q2	1994 Q2	-
Test statistic	-1.04 [10]	-1.07 [7]	-1.34 [2]	-3.52 [10]	-2.56 [1]	-5.83 [7]	-
Brazil							
Suggested break date	1995 Q1	1988 Q4	1994 Q4	1989 Q2	1991 Q2	1982 Q2	-
Test statistic	-1.88 [0]	-1.63 [1]	-2.03 [5]	-2.30 [5]	-1.87 [9]	-4.85 [4]	-
Chile							
Suggested break date	1995 Q1	1991 Q2	2003 Q1	1987 Q1	1985 Q1	1990 Q3	-
Test statistic	-1.11 [4]	-2.56 [10]	-2.29 [4]	-2.02 [3]	-2.70 [2]	-2.99 [0]	-
Mexico							
Suggested break date	1982 Q1	1988 Q4	1982 Q1	1982 Q2	1982 Q2	1986 Q2	-
Test statistic	-3.43 [2]	-3.79 [0]	-4.19 [3]	-2.84 [2]	-2.43 [3]	-2.82 [2]	-
Peru							
Suggested break date	1992 Q2	1984 Q4	1991 Q1	1989 Q1	1984 Q1	1990 Q3	-
Test statistic	-1.92 [1]	-0.90 [8]	-1.94 [3]	-3.45 [2]	-1.83 [1]	-1.80 [2]	-
Euro Area							
Suggested break date	1984 Q2	1993 Q2	1991 Q2	1999 Q4	1990 Q2	2002 Q1	-
Test statistic	-2.27 [6]	-2.64 [3]	-2.11 [1]	-2.86 [9]	-2.18 [7]	-3.34 [3]	-
Japan							
Suggested break date	2001 Q3	1986 Q4	1995 Q3	2000 Q2	1982 Q1	1986 Q4	-
Test statistic	-1.73 [3]	-1.70 [4]	-2.88 [3]	-1.67 [4]	-2.86 [3]	-3.93 [0]	-
US							
Suggested break date	1981 Q4	1986 Q4	1988 Q4	2000 Q3	1995 Q2	1991 Q4	2000 Q3
Test statistic	-2.34 [2]	-3.04 [2]	-2.72 [7]	-2.28 [9]	-2.21 [2]	-2.90 [4]	-2.33 [4]
Crit. value at 5% (1%)	-3.03 (-3.55)	-2.88 (-3.48)	-3.03 (-3.55)	-3.03 (-3.55)	-3.03 (-3.55)	-2.88 (-3.48)	-3.03 (-3.55)

Panel [B]. Differenced variables

	Δy	*Δsr*	*Δq*	*Δnfa*	*Δy**	*Δsr**	*Δoil*
Argentina							
Suggested break date	1991 Q3	1992 Q1	1988 Q3	1985 Q3	1991 Q2	1991 Q2	-
Test statistic	-2.19 [7]	-2.96 [5]	-3.04 [1]	-2.50 [2]	-3.37 [0]	-1.54 [3]	-
Bolivia							
Suggested break date	1984 Q1	1984 Q2	1983 Q1	2003 Q1	1994 Q2	1993 Q4	-
Test statistic	-3.42 [4]	-2.94 [6]	-3.60 [0]	-2.59 [4]	-2.06 [1]	-1.76 [10]	-
Brazil							
Suggested break date	1991 Q2	1989 Q2	1990 Q2	2003 Q1	2002 Q2	1988 Q4	-
Test statistic	-3.54 [0]	-2.30 [1]	-1.35 [4]	-2.59 [4]	-4.06 [7]	-3.11 [7]	-
Chile							
Suggested break date	1988 Q3	1991 Q1	1982 Q2	2002 Q4	2002 Q2	1982 Q3	-
Test statistic	-3.37 [0]	-1.03 [10]	-3.72 [2]	-2.97 [10]	-3.66 [7]	-6.45 [4]	-
Mexico							
Suggested break date	1987 Q1	1985 Q1	1982 Q1	1982 Q3	1983 Q1	1986 Q2	-
Test statistic	-4.12 [1]	-4.26 [0]	-4.30 [3]	-5.75 [4]	-5.79 [2]	-2.68 [5]	-
Peru							
Suggested break date	1989 Q2	1988 Q3	1990 Q2	1986 Q1	1985 Q3	1990 Q1	-
Test statistic	-2.47 [3]	-1.80 [7]	-1.80 [2]	-2.39 [3]	-6.05 [9]	-2.72 [4]	-
Euro Area							
Suggested break date	1984 Q3	1992 Q4	1988 Q4	1989 Q4	1990 Q2	1988 Q2	-
Test statistic	-3.89 [3]	-1.70 [7]	-3.38 [0]	-2.80 [9]	-2.75 [6]	-3.18 [3]	-
Japan							
Suggested break date	2002 Q2	1987 Q2	1995 Q3	2000 Q3	1990 Q2	1986 Q2	-
Test statistic	-2.50 [2]	-2.41 [3]	-1.57 [3]	-1.93 [5]	-3.49 [9]	-3.11 [10]	-
US							
Suggested break date	1981 Q3	1998 Q1	1988 Q3	1991 Q1	1995 Q1	1982 Q3	1986 Q3
Test statistic	-3.18 [2]	-2.29 [10]	-2.36 [3]	-3.23 [7]	-1.64 [2]	-4.88 [3]	-2.34 [3]
Crit. value at 5% (1%)	-2.88 (-3.48)	-2.88 (-3.48)	-2.88 (-3.48)	-2.88 (-3.48)	-2.88 (-3.48)	-2.88 (-3.48)	-2.88 (-3.48)

Notes: the regressions for all variables in the levels include an intercept and a linear trend with the exception of interest rates whose underlying regression include only an intercept. For differenced variables the regressions do not include an intercept and a linear trend. The lag order, selected according to the AIC with a maximum lag order of 10, is reported in square brackets.

Table 4 – Test statistics for selecting the lag order of the endogenous (domestic) variables in the VARX(pi,qi) model*

Order (p_i)	AIC	SBC		Adjusted LR test
		Argentina		
Order (p_i)	AIC	SBC		Adjusted LR test
4	750.1	629.1		
3	760.7	659.8	$\chi2(16)$ =	8.0098[.949]
2	**761.8**	681.1	$\chi2(32)$ =	30.0748[.564]
1	757.3	**696.7**	$\chi2(48)$ =	**60.3741[.108]**
0	354.6	314.2	$\chi2(64)$ =	679.3204[.000]
		Bolivia		
Order (p_i)	AIC	SBC		Adjusted LR test
4	1108.0	987.0		
3	1111.5	1010.7	$\chi2(16)$ =	18.4464[.298]
2	**1118.8**	**1038.1**	$\chi2(32)$ =	**31.3951[.497]**
1	1072.1	1011.5	$\chi2(48)$ =	124.1005[.000]
0	529.1	488.8	$\chi2(64)$ =	950.3084[.000]
		Brazil		
Order (p_i)	AIC	SBC		Adjusted LR test
4	676.7	560.7		
3	682.5	586.6	$\chi2(16)$ =	15.3189[.501]
2	690.2	614.6	$\chi2(32)$ =	27.6889[.685]
1	**694.9**	**639.4**	$\chi2(48)$ =	**44.6904[.609]**
0	241.1	205.8	$\chi2(64)$ =	749.4294[.000]
		Chile		
Order (p_i)	AIC	SBC		Adjusted LR test
4	**970.4**	854.4		
3	970.2	874.3	$\chi2(16)$ =	**24.3738[.082]**
2	961.1	885.5	$\chi2(32)$ =	61.8960[.001]
1	942.6	**887.1**	$\chi2(48)$ =	113.7365[.000]
0	450.9	415.6	$\chi2(64)$ =	875.3154[.000]
		Mexico		
Order (p_i)	AIC	SBC		Adjusted LR test
4	**979.0**	868.1		
3	974.1	883.3	$\chi2(16)$ =	31.8997[.010]
2	973.4	**902.8**	$\chi2(32)$ =	57.2928[.004]
1	950.4	900.0	$\chi2(48)$ =	116.5151[.000]
0	552.1	521.9	$\chi2(64)$ =	747.0024[.000]
		Peru		
Order (p_i)	AIC	SBC		Adjusted LR test
4	814.2	693.1		
3	**820.8**	720.0	$\chi2(25)$ =	**13.8210[.612]**
2	797.7	717.0	$\chi2(50)$ =	71.6619[.000]
1	800.5	**740.0**	$\chi2(75)$ =	91.1393[.000]
0	291.1	250.7	$\chi2(100)$ =	867.8986[.000]
		Euro Area		
Order (p_i)	AIC	SBC		Adjusted LR test
4	**1423.5**	1307.5		
3	1423.4	1327.6	$\chi2(25)$ =	**24.1098[.087]**
2	1423.1	1347.5	$\chi2(50)$ =	48.5555[.031]
1	1408.5	**1353.1**	$\chi2(75)$ =	94.4301[.000]
0	846.9	811.6	$\chi2(100)$ =	960.8257[.000]
		Japan		
Order (p_i)	AIC	SBC		Adjusted LR test
4	1156.6	1040.6		
3	1155.6	1059.8	$\chi2(25)$ =	25.5334[.061]
2	**1164.0**	1088.3	$\chi2(50)$ =	**37.0023[.249]**
1	1155.6	**1100.1**	$\chi2(75)$ =	73.5455[.010]
0	801.8	766.5	$\chi2(100)$ =	628.2555[.000]
		US		
Order (p_i)	AIC	SBC		Adjusted LR test
4	1359.1	1253.2		
3	1361.7	1275.9	$\chi2(25)$ =	20.8059[.186]
2	**1367.4**	**1301.9**	$\chi2(50)$ =	**36.5831[.264]**
1	1305.6	1260.3	$\chi2(75)$ =	156.6580[.000]
0	797.0	771.8	$\chi2(100)$ =	966.4766[.000]

Notes: statistics in bold indicate the order selected by the relevant criterion/test. Unrestricted VARs are estimated with foreign variables treated as exogenous.

Table 5 – Univariate specification tests statistics

	Δy	Δsr	Δq	Δnfa
Argentina				
Serial Correlation F(4,83)	1.87 [0.123]	2.39 [0.057]	2.27 [0.069]	1.58 [0.187]
Normality χ^2(2)	67.18 [0.000]**	1.36 [0.506]	2.00 [0.369]	17.08 [0.000]**
Heteroscedasticity F(1,93)	0.14 [0.709]	5.44 [0.022]*	4.47 [0.037]*	1.55 [0.217]
Bolivia				
Serial Correlation F(4,82)	1.63 [0.174]	1.59 [0.184]	1.96 [0.108]	33.30 [0.000]**
Normality χ^2(2)	0.00 [0.998]	0.64 [0.725]	0.88 [0.645]	2.02 [0.365]
Heteroscedasticity F(1,93)	5.36 [0.023]*	3.78 [0.055]	4.54 [0.036]*	2.63 [0.108]
Brazil				
Serial Correlation F(4,84)	0.41 [0.803]	1.38 [0.247]	0.61 [0.654]	1.84 [0.129]
Normality χ^2(2)	1.48 [0.476]	2.36 [0.308]	0.64 [0.725]	0.19 [0.911]
Heteroscedasticity F(1,93)	0.65 [0.423]	4.16 [0.044]*	4.51 [0.036]*	0.58 [0.450]
Chile				
Serial Correlation F(4,83)	1.11 [0.357]	6.09 [0.000]**	3.60 [0.009]**	1.76 [0.145]
Normality χ^2(2)	1.52 [0.468]	0.86 [0.652]	2.87 [0.238]	1.69 [0.430]
Heteroscedasticity F(1,93)	3.09 [0.082]	0.34 [0.559]	0.34 [0.559]	0.39 [0.535]
Mexico				
Serial Correlation F(4,85)	4.45 [0.003]**	0.79 [0.537]	0.73 [0.575]	0.90 [0.469]
Normality χ^2(2)	0.98 [0.612]	1.01 [0.605]	35.25 [0.000]**	0.19 [0.909]
Heteroscedasticity F(1,93)	2.06 [0.155]	0.19 [0.668]	0.20 [0.658]	3.68 [0.058]
Peru				
Serial Correlation F(4,83)	0.75 [0.559]	1.16 [0.336]	0.42 [0.795]	1.67 [0.164]
Normality χ^2(2)	0.75 [0.686]	1.25 [0.535]	2.22 [0.330]	1.14 [0.564]
Heteroscedasticity F(1,93)	1.16 [0.285]	1.95 [0.166]	0.25 [0.617]	0.79 [0.376]
Euro Area				
Serial Correlation F(4,83)	1.02 [0.401]	2.08 [0.091]	3.14 [0.019]*	1.57 [0.190]
Normality χ^2(2)	3.22 [0.199]	2.77 [0.250]	2.01 [0.367]	3.73 [0.155]
Heteroscedasticity F(1,93)	2.09 [0.152]	0.17 [0.681]	2.37 [0.127]	0.10 [0.753]
Japan				
Serial Correlation F(4,84)	0.39 [0.812]	0.82 [0.514]	3.00 [0.023]*	1.28 [0.284]
Normality χ^2(2)	0.49 [0.782]	0.39 [0.824]	0.46 [0.794]	0.03 [0.984]
Heteroscedasticity F(1,93)	7.12 [0.009]**	0.90 [0.345]	2.05 [0.155]	2.68 [0.105]
US				
Serial Correlation F(4,83)	3.55 [0.010]*	1.77 [0.142]	2.56 [0.045]*	16.18 [0.000]**
Normality χ^2(2)	5.96 [0.051]	1.37 [0.503]	1.96 [0.375]	0.65 [0.721]
Heteroscedasticity F(1,93)	1.26 [0.265]	0.29 [0.592]	10.30 [0.002]**	0.03 [0.867]

Notes: the figures in square brackets are probability values associated with test statistics. The symbols "*" and "**" denote statistical significance at the 5 percent and the 1 percent respectively.

Table 6 – Cointegration rank statistics

H_0	H_1				95%	90%
Maximum eigenvalue test						
H_0	H_1	**Argentina**	**Bolivia**	**Brazil**	**95%**	**90%**
r = 0	r = 1	277.51	111.90	85.90	40.98	38.04
r ≤ 1	r = 2	40.01	**31.34**	**22.60**	34.65	31.89
r ≤ 2	r = 3	**16.25**	24.98	10.52	27.80	25.28
r ≤ 3	r = 4	4.93	12.37	3.81	20.47	18.19
H_0	H_1	**Chile**	**Mexico**	**Peru**	**95%**	**90%**
r = 0	r = 1	147.11	91.07	94.82	40.98	38.04
r ≤ 1	r = 2	35.62	**19.69**	**16.64**	34.65	31.89
r ≤ 2	r = 3	**14.66**	16.69	10.23	27.80	25.28
r ≤ 3	r = 4	9.55	6.89	7.43	20.47	18.19
H_0	H_1	**Euro Area**	**Japan**	**US**	**95%**	**90%**
r = 0	r = 1	249.61	91.77	192.20	40.98	38.04
r ≤ 1	r = 2	76.30	**24.11**	50.44	34.65	31.89
r ≤ 2	r = 3	33.93	16.93	34.16	27.80	25.28
r ≤ 3	r = 4	**2.81**	3.79	28.39	20.47	18.19
Trace test						
H_0	H_1	**Argentina**	**Bolivia**	**Brazil**	**95%**	**90%**
r = 0	r = 1	338.70	180.60	122.84	90.02	85.59
r ≤ 1	r = 2	**61.19**	68.70	**36.94**	63.54	59.39
r ≤ 2	r = 3	21.18	**37.36**	14.33	40.37	37.07
r ≤ 3	r = 4	4.93	12.37	3.81	20.47	18.19
H_0	H_1	**Chile**	**Mexico**	**Peru**	**95%**	**90%**
r = 0	r = 1	206.94	134.33	129.12	90.02	85.59
r ≤ 1	r = 2	**59.83**	**43.26**	**34.30**	63.54	59.39
r ≤ 2	r = 3	24.21	23.58	17.66	40.37	37.07
r ≤ 3	r ≤ 3	9.55	6.89	7.43	20.47	18.19
H_0	H_1	**Euro Area**	**Japan**	**US**	**95%**	**90%**
r = 0	r = 1	362.64	136.60	305.18	90.02	85.59
r ≤ 1	r = 2	113.03	**44.83**	112.98	63.54	59.39
r ≤ 2	r = 3	**36.73**	20.72	62.55	40.37	37.07
r ≤ 3	r = 4	2.81	3.79	28.39	20.47	18.19

Notes: the last two columns report the critical values at the 95 percent and 90 percent significance level. Statistics in bold indicate acceptance of the null hypothesis at the 5 percent significance level.

Table 7 – Average cross-section correlations of residuals

	Argentina	Bolivia	Brazil	Chile	Mexico	Peru	Euro Area	Japan	US
y	0.02	0.02	0.00	-0.03	-0.02	0.00	-0.04	-0.02	0.01
	[0.17]	[0.22]	[0.01]	[-0.28]	[-0.19]	[-0.01]	[-0.38]	[-0.24]	[0.07]
sr	0.04	-0.02	0.01	0.00	0.03	0.00	0.01	0.03	0.00
	[0.37]	[-0.19]	[0.13]	[-0.02]	[0.30]	[-0.01]	[0.12]	[0.30]	[0.04]
q	0.01	0.01	0.02	0.01	0.02	0.02	-0.01	-0.06	-0.03
	[0.09]	[0.13]	[0.16]	[0.14]	[0.21]	[0.19]	[-0.10]	[-0.53]	[-0.34]
nfa	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	[0.13]	[0.44]	[0.31]	[0.25]	[-0.05]	[-0.00]	[-0.15]	[0.13]	[-0.05]

Notes: each entry is the average correlation of the residual of the equation on the corresponding row for the country/region on the corresponding column with all other countries/regions endogenous variables residuals. Two-tailed t-test statistics with 93 d.o.f. are in square brackets. The null hypothesis is no correlation. The 5 percent critical value is 1.98.

Table 8 – F statistics for testing the weak exogeneity of the country-specific foreign variables and oil prices

Country		Foreign variables and oil prices		
		*y**	*sr**	*oil*
Argentina	F(1,85)	0.58 [0.450]	1.11 [0.296]	0.08 [0.772]
Bolivia	F(2,84)	0.49 [0.613]	0.04 [0.965]	2.79 [0.067]
Brazil	F(1,85)	0.16 [0.693]	1.92 [0.170]	0.25 [0.618]
Chile	F(2,84)	1.47 [0.237]	2.20 [0.117]	0.09 [0.911]
Mexico	F(1,85)	6.47 [0.013]*	0.14 [0.706]	0.39 [0.534]
Peru	F(1,85)	0.07 [0.799]	16.44 [0.000]**	0.43 [0.512]
Euro Area	F(2,84)	1.07 [0.349]	0.40 [0.669]	5.36 [0.006]**
Japan	F(1,85)	0.05 [0.822]	3.78 [0.055]	0.66 [0.420]
US	F(4,82)	3.13 [0.019]*	0.91 [0.464]	2.39 [0.058]

Notes: the figures in square brackets are probability values associated with test statistics. The symbols "*" and "**" denote statistical significance at the 5 percent and the 1 percent respectively.

Table 9 – Generalized variance decomposition of the forecast error of output

Horizon	Panel [A] Domestic factors *y*	*sr*	*rer*	*nfa*	Panel [B] Regional factors	Industrial countries factors US	EA	JAP	Panel [C] All domestic factors	All foreign factors
					Argentina					
0	62.76	2.10	0.01	0.60	20.48	6.38	3.90	3.76	65.47	34.53
4	60.97	5.13	0.03	0.43	20.93	5.53	3.14	3.84	66.56	33.44
8	61.29	5.32	0.03	0.39	20.93	5.30	3.03	3.70	67.04	32.96
12	61.55	5.40	0.03	0.37	20.94	5.13	2.99	3.60	67.34	32.66
20	61.83	5.46	0.03	0.33	20.97	4.92	2.96	3.49	67.66	32.34
40	61.98	5.52	0.03	0.29	21.06	4.75	2.93	3.42	67.83	32.17
					Bolivia					
0	69.16	6.44	0.68	0.33	19.73	0.80	0.98	1.89	76.61	23.39
4	53.71	22.71	1.81	0.06	15.48	1.69	2.19	2.35	78.30	21.70
8	41.11	30.35	5.76	0.02	15.56	1.83	3.21	2.17	77.23	22.77
12	33.42	32.58	10.33	0.01	16.18	1.74	3.85	1.90	76.34	23.66
20	24.34	29.79	20.55	0.09	17.51	1.80	4.30	1.61	74.77	25.23
40	12.00	14.31	42.63	1.22	19.79	4.32	2.92	2.83	70.15	29.86
					Brazil					
0	75.54	0.26	0.65	5.24	9.05	3.55	0.74	4.96	81.69	18.31
4	76.18	0.25	1.35	4.46	9.58	3.54	0.67	3.98	82.23	17.77
8	75.99	0.15	2.18	3.78	10.19	3.56	0.77	3.38	82.10	17.90
12	75.48	0.12	2.97	3.26	10.71	3.59	0.91	2.96	81.83	18.17
20	74.28	0.15	4.28	2.56	11.49	3.66	1.16	2.42	81.27	18.73
40	72.19	0.28	6.13	1.75	12.52	3.74	1.57	1.81	80.35	19.65
					Chile					
0	56.83	4.51	0.34	0.20	24.54	8.53	1.70	3.36	61.87	38.13
4	55.98	5.36	1.34	0.32	24.07	8.02	1.07	3.83	63.00	37.00
8	49.69	3.52	7.78	2.34	24.94	7.01	0.93	3.79	63.33	36.67
12	39.10	2.43	17.25	5.78	24.79	5.90	1.37	3.38	64.56	35.44
20	20.17	3.50	32.08	11.71	22.74	4.52	2.91	2.36	67.47	32.53
40	4.80	7.47	41.46	16.12	19.78	4.17	4.93	1.28	69.85	30.15
					Mexico					
0	69.31	0.06	1.00	1.09	15.83	8.50	2.14	2.07	71.46	28.54
4	54.31	6.79	6.26	3.41	14.00	9.70	3.40	2.12	70.77	29.23
8	40.27	15.99	11.48	5.57	12.36	8.04	3.79	2.51	73.31	26.69
12	30.34	23.18	15.01	6.95	11.28	6.48	3.85	2.91	75.48	24.52
20	19.47	31.74	18.63	8.28	10.22	4.58	3.66	3.42	78.13	21.87
40	11.00	39.49	21.21	9.17	9.36	2.98	3.13	3.67	80.87	19.13
					Peru					
0	58.42	4.21	0.03	18.06	13.29	2.40	1.67	1.91	80.72	19.28
4	55.27	1.87	0.36	20.83	14.46	4.30	1.01	1.91	78.33	21.67
8	45.75	3.84	1.39	20.33	20.21	5.45	1.14	1.88	71.31	28.69
12	35.71	7.66	2.54	18.33	26.73	5.54	1.60	1.89	64.24	35.76
20	22.36	14.12	4.25	14.69	35.52	4.61	2.57	1.88	55.41	44.59
40	10.92	20.55	6.26	11.29	41.88	3.84	3.55	1.71	49.01	50.99

Notes: share of the k-step ahead forecast error variance of domestic output explained by the shocks on the corresponding column. Entries have been normalized so that they sum to 100. Each entry in columns "All domestic factors" and "All foreign factors" are the sum of the corresponding percentages in columns 2, 3, 4, 5 and in columns 6, 7, 8, 9, respectively.