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Asymmetric Network Effects

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Abstract

When platforms compete for consumers, two types of consumer heterogeneity will matter: consumers value the presence of other consumers on a platform differently, and consumers contribute to the value of the platform differently. The optimal discriminatory pricing policy for platforms will depend on whether those two dimensions of consumer heterogeneity are positively or negatively correlated, which is an empirical question. In a companion paper (Cantillon & Yin, 2008), we study membership decisions of trading firms for two competing exchanges: LIFFE and DTB. Our analysis shows that different traders care about liquidity differently. In this paper, we estimate the heterogeneous contribution to liquidity by different types. We combine the estimates from both papers of heterogeneous preferences and contributions to liquidity. (*JEL* L1, G15; *keywords* derivatives exchange; network effects; heterogeneity; entry strategy; adoption; liquidity; platform competition)

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1 Introduction

Individual heterogeneity in terms of value and contribution to network effects has a potentially great impact on firms' optimal strategies in terms of pricing and customer targeting. Individuals may value network size differently but may also contribute to network effects differently, and those who value the network size most may not be those who contribute to the network the most. The optimal discriminatory pricing policy for platforms will depend on whether those two dimensions of consumer heterogeneity are positively or negatively correlated, which is an empirical question. If heavy contributors are correlated with those who derive utility from a larger network, then a smaller network will need to subsidize those heavy contributors to induce them to adopt its platform. That same firm should de-emphasize subsidies for heavy contributors who may have a preference for somewhat illiquid markets, and even more so for weak contributors.

Financial exchanges are a good example of an industry where network effects matter: traders value liquidity and markets attracting more traders are usually more liquid. Financial exchanges are also a good example of an industry where user heterogeneity is likely to be important: users (traders) differ in their business models, trading motives, trading behavior, and so on. Their needs for liquidity and contributions to trading volume vary along those same dimensions. Understanding the role of heterogeneous traders in choosing platforms based on different liquidity preferences and contributing to liquidity differently are all the more important in the current financial exchange context of consolidation, global competition and differentiated pricing.

In a companion paper (Cantillon & Yin, 2008), we study membership decisions of trading firms for two competing exchanges: the London International Financial Futures and Options Exchange (LIFFE) and Deutsche Terminbörse (DTB). Our analysis shows that different traders care about liquidity in the Bund futures market differently; as a result, different types of traders became members of LIFFE or DTB at different times.

Variation in volume and open interest[1] per member across the exchanges and over time suggest that either (1) traders of different types contributing differently to liquidity, or (2) the different *mix* of traders resulting in different levels of liquidity (in other words, contributions to liquidity are not solely a function of a trader type but of interactions with other traders), or both. In this paper, we estimate the heterogeneous contribution to liquidity by different types on LIFFE and DTB. These estimates take into account the relative mix of heterogeneous traders on the liquidity of an exchange. We then combine the estimates from both papers of heterogeneous preferences and heterogeneous contributions to liquidity. Only by combining estimates of the contribution of traders to liquidity and their heterogeneous valuation of liquidity can we derive optimal pricing policies by exchanges. We find that valuations of liquidity tend to be correlated with contributions to liquidity in this setting, which suggests that subsidies are necessary to induce high liquidity contributors to trade on a less liquid exchange.

Given its emphasis on user heterogeneity and pricing, the two-sided (or more appropriately, multi-sided) market literature has recently explored implications of user heterogeneity on pricing and competition theoretically (e.g. Jullien, 2001, Caillaud and Jullien, 2003 and Jullien, 2006). The empirical literature on network effects and individual heterogeneity has been limited by the high data requirement for evaluating the sources of individual heterogeneity. The few papers that allow for user heterogeneity have focused on adoption (e.g. Gowrisankaran and Stavins, 2004, Ackerberg and Gowrisankaran, 2006, Tucker, 2005) and thus only on heterogeneity in terms of valuation of network effects. The two exceptions to our knowledge are the work of Ryan & Tucker (2008) and Tucker (2008), who consider the importance of key individuals in the adoption by other potential users of a technology (video conferencing) exhibiting network effects. The work in these papers takes advantage of individual level data on the social networks that influence adoption. In our setting, volume

[1] Open interest in a derivatives market records the number of open positions. It is used as a proxy of liquidity because it captures the potential number of trades that are active (since traders will close their positions at some time or the other before maturity).

of trades generates value as opposed to specific social interactions between individuals. In this sense, our findings are divorced from the social network structure underlying economic interactions, and thus our findings should be considered as more appropriately generalizable to many agent, market level settings where social networks may be less prominent drivers of activity as opposed to within-firm settings. Moreover, our work puts together value of and contributions to liquidity.

By design, financial markets are institutions created to foster exchange among people with different needs. Thus, the financial literature has long recognized the heterogeneity of traders and the implications for liquidity. Research has focused on several different dimensions of heterogeneity, attempting to model the interactions between different types of traders and the resulting effect on contributions to liquidity. Black (1986) theoretically explains the necessity of uninformed, noise traders as trading partners for more informed traders to generate trading volume in a market. A number of papers examine the drivers for some traders to be liquidity providers and liquidity takers. (Grossman & Miller, 1987, Biais 1993) Others focus on risk sharing. (Cuny, 1993) A few papers focus specifically on the differential behavior of scalpers (speculative day traders). (Silber, 1984, Kuserk & Locke, 1993) The empirical work on examining the relationship between trader types on liquidity has generally involved micro level data on traders, where the type of the trader is well known to the researcher. This research has show that trading behavior by different types of traders is influenced by factors such as volatility. For example, Locke & Sarkar (2001) find that depending on the volatility in the market, customers may trade more with each other than market makers. Bloomfield, O'Hara, & Saar (2003) employ experiments to test various theories about differences in trader types along the dimensions mentioned in the literature and the resulting trading behavior. They find that depending on the volatility in the market, informed and noise traders may switch positions from being liquidity providers to liquidity takers. As a result of these findings, we include controls for the volatility of the instrument being traded. (Reiss & Werner, 2004) We will ultimately try to construct types based on observable characteristics of our traders that reflect the various dimensions studied in this literature. We believe that we are the first paper to empirically match trader preferences for liquidity with trader contributions to liquidity.

Section 2 presents our model of liquidity production. Section 3 describes our data and presents descriptive statistics. Section 4 presents the empirical model, and Section 5 results from our estimation of volume production by different trader types. Section 6 and combines the results from Cantillon & Yin (2008) with these estimates to examine how heterogeneous valuations to liquidity are correlated with heterogeneous contributions to liquidity. Section 7 concludes.

2 Model

The model will essentially build on Jullien (2001 and 2006).

We model liquidity as follows:

$$\text{liquidity}_{et} = f(n_{1et}, n_{2et,} ...; Z_{et}) \tag{1}$$

where liquidity_{et} is a measure of liquidity of exchange e in time t, n_{1et}, $n_{2et}, ...$ records the number of traders of type 1, type 2, etc. that are members of exchange e in month t, and Z_{et} is a vector of various other variables that attract liquidity.

Equation (1) can be seen as a production function, and we will draw on the production function literature as we examine different specifications for the $f(.)$ function in Equation (1) (for a survey, see e.g. Fuss, McFadden and Mundlak, 1978). We borrow functional forms from the productivity literature in order to decompose our aggregate volume data into the marginal contributions of different types of traders interacting with each other. The empirical productivity literature provides a nice guide for our exercise: capital, labor, and other inputs of interest are mapped into aggregate output (typically U.S. manufacturing) (for a survey of this work, see Chung 1994). The empirical productivity literature has grappled with several issues which will also be relevant to our setting (see Walters, 1963, for a survey of generic issues in the production function literature). A primary topic of research has been the design of more flexible functional forms for the production function. (Arrow et al., 1961, Heady & Dillon, 1961, Christensen et al., 1973, Pollak et al., 1984)) Several studies examine the flexibility and robustness of various production functions (Appelbaum, 1979, Berndt & Khaled, 1979, Caves &Christensen, 1980, Guilkey et al., 1983), and we utilize their findings to narrow our set of candidate production functions. Another issue has been the inclusion of disembodied technical progress in the production function. Typically, the literature has included a time regressor to control for changes in productivity that are not tied to the particular combination of inputs at a given point in time. (Berndt and Wood, 1982) We will also employ several controls for time and other characteristics in Z_{et} which we believe may drive volume separately from the interaction of trader types.

2.1 Cobb-Douglas Production Function (CD)

In this paper, we employ the Cobb-Douglas production function. The canonical CD production function (Cobb & Douglas, 1928) can be written as follows:

$$y = \alpha_0 \prod_{k=1}^{K} x_k^{\alpha_k}, 0 < \alpha_k \forall k \tag{2}$$

$$\ln y = \ln \alpha_0 + \sum_{k=1}^{K} \alpha_k \ln x_k, 0 < \alpha_k \forall k \tag{3}$$

The CD is an attractive functional form since it allows for heterogeneity in how different types of traders contribute to liquidity and flexibility in terms of how different types of traders complement or substitute one another in producing liquidity. Since traders find their counterpart to a transaction amongst all the other traders (including those of its own type), the CD functional form appropriately allows the marginal effect of an additional type to be a function of the number of all other types trading. If we ignore the restriction that $0 < \alpha_k$ for all k, then there is no restriction on the sign of the first and second derivatives. This means that the model permits trader types to be complements or substitutes for each other, since the cross-partial effect of an extra trader can be positive or negative. Otherwise, the model imposes both increasing marginal contributions to all additional trader types and complementarity between all trader types.

Note that the marginal effect of each trader is a function of the number of other types. For example:

$$\frac{\partial y}{\partial x_i} = \frac{\alpha_i}{x_i} \alpha_0 \prod_{k=1}^{K} x_k^{\alpha_k} \tag{4}$$

and

$$\frac{\partial y}{\partial x_i \partial x_j} = \frac{\alpha_i \alpha_j}{x_i x_j} \alpha_0 \prod_{k=1}^{K} x_k^{\alpha_k}. \tag{5}$$

As a result, the marginal effect of a type of trader will change in magnitude over time as the mix of other traders changes. The interaction effect of one type of trader with another type will also vary in magnitude with the mix of other traders. However, the Cobb-Douglas functional form imposes that the signs on these derivatives will remain constant over time, as clear from the examples in Equations 4 and 5.

3 Data

Our data comes from the competition between LIFFE and DTB that played out during the 1990s. Both exchanges offered trading in the Bund future, a future on the German government bond, and they competed fiercely to attract members and trading volumes. For the purposes of this paper, we focus on the period between November 1990 and April 1998. During this period, both exchanges attracted substantial trading volumes and different sets of traders. The number of traders that were members of at least one exchange grew from to 172 to 222. At the same time, trading volumes of the Bund grew more than tenfold during the 1990s. Several factors contributed to this. First, German reunification in 1990 increased Germany's borrowing needs. The resulting increase in the public debt fueled interest in the future contract. Second, interest rates in the eurozone progressively converged as monetary union took shape (the euro - which fixed exchange rates among participating countries - was introduced on 1 January 1999). As a result, the Bund contract, which was the biggest future on a government bond in Europe progressively attracted traders from other government bond futures. Third, futures went from exotic financial instruments to instruments used routinely by banks, asset management funds and corporations. The ensuing pool of liquidity attracted speculators and arbitrageurs of all kinds.[2]

3.1 Firm data

We have obtained from each exchange a list of past and current members. The original dataset from DTB contains information on 493 individual establishments that held a membership any time during the 1 January 1990 - 31 December 1999 period. The original dataset from LIFFE contains information on 305 individual establishments that held a membership allowing them to trade interest rate instruments (including the Bund) any time over the same period.

We use the collected information on group ownership and mergers and acquisitions to match establishments to groups (procedure described in Cantillon & Yin, 2008). With this convention, our dataset covers 578 groups. On average, 362.64 groups are present in any

[2] Speculators trade on the basis of their forecasts about future movements of prices: they take positions, hoping that prices will move in a direction favorable to them. Arbitrageurs speculate on the basis of price co-movements between similar securities.

given month (min = 315, max = 433, std deviation = 32.66).

Types will be defined on the basis of business lines only for now. Business lines proxy for trading motives and sources of revenue.[3] We partitioned the groups in our dataset into seven business lines: universal bank, investment bank, retail bank, specialized trading firm, asset management, brokerage, and proprietary trading firm. We distinguished banks by the type of customers they serve. Retail banks serve primarily individual customers as well as small and medium enterprises. Investment banks serve corporate clients as well as, often, wealthy individuals. Universal banks serve all types of customers.

For most of their activities, investment banks compete with more focused financial firms. Table 1 summarizes the main activities of an investment bank (IB): underwriting and mergers & acquisitions, market making, brokerage services, asset management and proprietary trading. Specialized trading firms compete with investment banks by making markets, offering execution and/or clearing for institutional clients, and trading on their own account. Asset management firms sometimes offer brokerage services to a retail clientele and trade on their own account on top of their core asset management activity. Brokerages offer execution services and sometimes also offer some funds. Proprietary trading firms are firms that focus on trading on their own account. Table 1 compares the activities covered by these firms. In categorizing our firms, we have assigned the smallest encompassing category for each group. Thus a group active in market making, proprietary trading and asset management would be classified as an IB, but a group active in asset management and proprietary trading would be classified as an asset management firm and a group active in proprietary trading and market making would be classified as a specialized trading firm. Evaluated at the time a group first appears in our dataset, our data contain 64 universal banks, 28 retail banks, 102 investment banks, 48 asset management firms, 95 specialized trading firms, 110 brokerages and 131 proprietary trading firms.

[3] Business types also proxy for scope of products traded and size, because universal banks tend to be larger than retail banks and investment banks on average, and investment banks tend to be bigger than more specialized financial firms.

Table 1: Investment banks and their competitors

Activities\Business types	IB	Specialist	Asset Mgt	Broker	Proprietary
Underwriting, M&A	$\surd$				
Market making	$\surd$	$\surd$			
Retail brokerage	$\surd$			$\surd$	
Institutional brokerage	$\surd$	$\surd$		$\surd$	
Asset Management	$\surd$		$\surd$	($\surd$)	
Proprietary trading	$\surd$	$\surd$	($\surd$)		$\surd$

Figures 1 & 2 show the changes in the mix of different groups on each exchange. All group types increase in number on DTB, but growth is particularly prominent among specialists and proprietary traders. In contrast, the number of traders of each type on LIFFE remains fairly stable over our sample period. There is a slight decline in investment bankers and proprietary traders, and a U-shaped pattern to the number of brokers. Except for investment bankers being the most numerous type on each exchange over the sample period, the exchanges exhibit very different mix of traders, and that mix changes significantly from early to late in our sample in the case of DTB. These descriptive statistics already are highly suggestive of the differential effect that interaction between different types of traders can have on liquidity in the market.

3.2 Exchange data

For both exchanges, we collected the following monthly data: (1) transaction and clearing fee per contract, (2) margins, (3) membership, and (4) trading volume in the Bund contract. Fees and margins were collected from exchange notices to members, membership was constructed on the basis of the information provided to us by both exchanges, and volume data come from Datastream. Furthermore, we collected data on the interest rates for other European treasury bonds (Germany, Spain, France, Italy, and the United Kingdom) over the January 1990 –

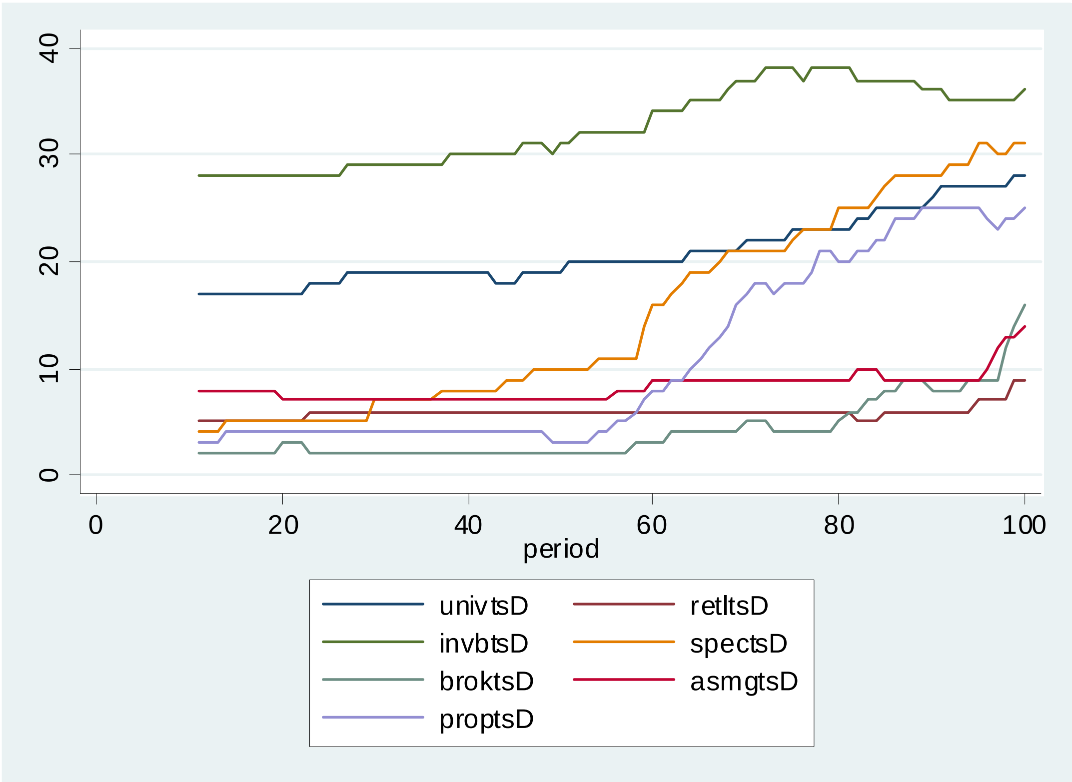

Figure 1: Number of groups of each type each month on DTB

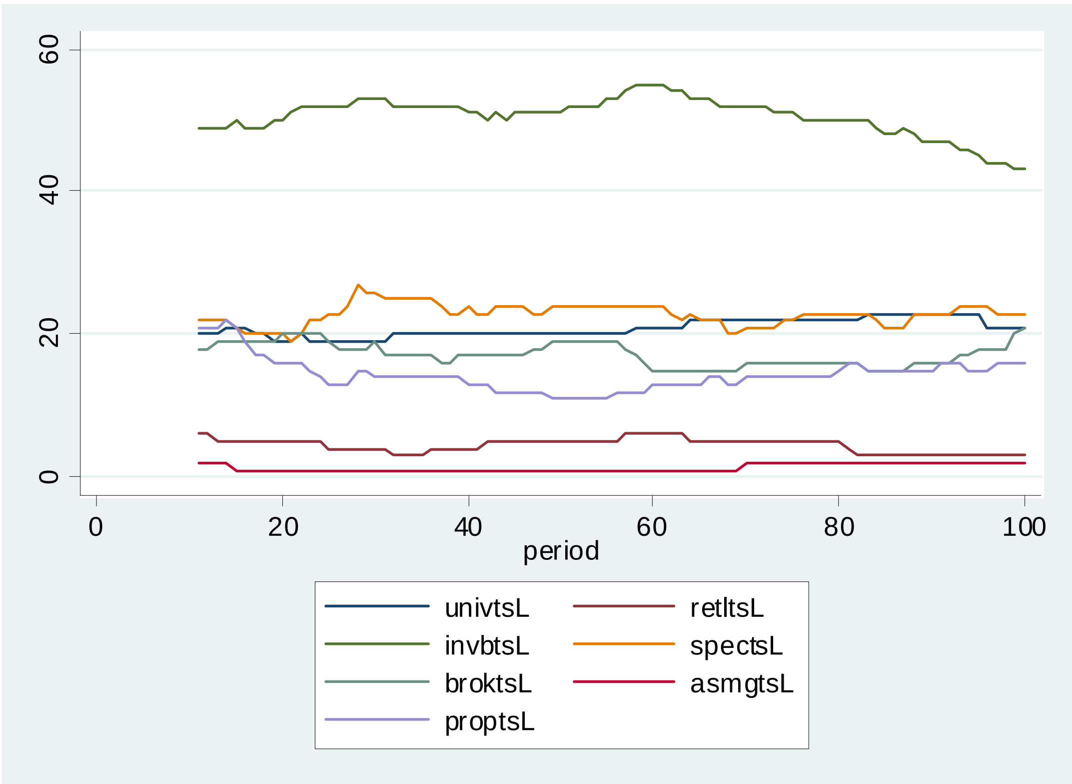

Figure 2: Number of groups of each type each month on LIFFE

December 1999 time period and calculated the normalized standard deviation between these rates each month as a measure of the convergence of interest rates over our sample period. As a measure of the attractiveness of the Bund future and in consideration of the importance of volatility to traders' liquidity contribution as highlighted in the finance literature, we collected data on the daily yield for the underlying Bund contract (the government bond on which the future is based) and constructed a monthly variable to capture its volatility. We define volatility of the underlying Bund contract as the monthly standard deviation of the yield.

We use the Deutsche Mark (DM) as the currency for all the data. Fees are converted into DM using the monthly average exchange rate for the Pound/DM. Maturities for the Bund are quarterly and generate three-month cycles in trading volumes. We will account for this cyclicality with expiry month fixed effects.

Table 2 provides descriptive statistics for our exchange variables for the period between November 1990 and April 1989. The number of month observations is 90.

Table 2: Descriptive statistics per month (all monetary values in DM)

	LIFFE[b]				DTB			
	Mean	Std.Dev.	Min	Max	Mean	Std.Dev.	Min	Max
V: volume	2.36E6	1.19E6	5.06E5	5.07E6	1.28E6	1.35E6	2.29E4	7.20E6
$\ln V$(volume)	14.52	0.59	13.13	15.44	13.58	1.09	10.04	15.79
groups	126.89	6.33	115	151	113.66	64.51	0	303
n_u: universal	20.88	1.30	19.00	23.00	20.91	3.20	17.00	28.00
n_r: retail	4.43	0.98	3.00	6.00	5.94	0.64	5.00	9.00
n_i: IB	50.53	2.67	43.00	55.00	32.59	3.62	28.00	38.00
n_s: specialist	22.88	1.55	19.00	27.00	15.11	9.18	4.00	31.00
n_b: broker	17.20	1.60	15.00	21.00	4.09	2.98	2.00	16.00
n_a: asset mgr	1.39	0.49	1.00	2.00	8.28	1.42	7.00	14.00
n_p: prop	14.37	2.31	11.00	22.00	10.92	8.49	3.00	25.00
fee	1.00	0.22	0.00	1.30	0.53	0.37	0.00	1.50
$margins^a$	2958.9	888.45	1500	6250	3567.33	964.1	2000	5000
$volatility$	0.08	0.03	0.02	0.18	0.08	0.03	0.02	0.18
$convergence$	0.20	0.06	0.07	0.31	0.20	0.06	0.07	0.31

[a] Margins refer to initial margins

[b] LIFFE membership restricted to those allowed to trade interest rate instruments.

4 Empirical model

To ensure greater comparability with the results of Cantillon & Yin (2008), we use the same unit of analysis: groups (instead of individual firm members) and monthly data by exchange. We assume that all traders of the same type are identical and that the parameters defining their trading behavior (α_k from Equations 2 & 3) are constant over time. As a baseline, we first consider a Cobb-Douglas functional form for f from Equation 1.

Consider the 7 business types of traders in a CD functional form for Equations 2 & 3.

Denote the number of each type of trader as n_u, n_r, n_i, n_s, n_b, n_a, and n_p, respectively for universal bank, retail bank, investment bank, specialist, broker, asset manager, and proprietary. Let K denote the set of indices for the business types. Using volume V_{et} on the exchange e per month t as our measure of liquidity, we then have

$$V_{et} = \left(\prod_K n_{ket}^{\alpha_k}\right) \exp(\boldsymbol{\alpha} Z_{et} + \varepsilon_{et}) \tag{6}$$

where ε_{et} is an error term and Z_{et} is a vector of regressors from Equation 1 that contains at minimum 1 to generate a constant term.

Taking logs, we get

$$\ln V_{et} = \sum_K \alpha_{ket} \ln n_{ket} + \boldsymbol{\alpha} Z_{et} + \varepsilon_{et} \tag{7}$$

We will estimate three different versions of Equation 7. The first version (Model 1) will only regress log volume on the log of the number of types; Z_{et} contains only 1. In the second version (Model 2), Z_{et} will include an additional variable: an estimate of the monthly effect of macro-level variables on total Bund futures volume generated from a first stage regression. The third version (Model 3) will add the exchange specific characteristics, fee_{et} and $margins_{et}$ to Z_{et}.

The estimate of the monthly effect of macro-level variables is the predicted value from a regression of total volume of Bund futures trading on drivers of volume that are exchange-independent. Specifically, the first stage in the estimation of Model 2 is as follows:

$$\begin{aligned} \ln(V_{LIFFEt} + V_{DTBt}) &= \beta_0 + \beta_{convergence} convergence_t + \beta_{volatility} volatility_t + \beta_{trend} trendd_t && (8) \\ &\quad + \beta_{trend2} trend_t^2 + \beta_{trend3} trend_t^3 + \beta_{december} december_t + \beta_{expiry} expiry_t + \varepsilon_{et} && (9) \end{aligned}$$

where $trend_t$ is linear time trend by month[4], $december_t$ is a dummy variable for every December expiry month, and $expiry_t$ is a dummy variable for every other expiry month excluding December.[5] The purpose of this first stage is twofold: (1) we estimate the effect on total volume, rather than volume on each exchange separately, of macro events and trends that drive Bund trading volume over our sample period, (2) we assign as much explanatory power as possible to these macro events and trends before estimating the marginal effects of the number of different types of bidders on volume of Bund trading on each exchange.

Note that in all models, identification of the coefficients on each of the types in these models comes strictly off of variation in the number of types across exchanges and over time related to the variation in volume over time.

5 Estimation

The regressions employ the Cobb-Douglas model of Equation 7 and first stage estimates of macro-drivers of liquidity from Equation 8 to estimate the average (over the sample period) contribution to volume conditional on other variables that would affect trading volume. Once we have estimated the α coefficients in Equation 7, we can then calculate the marginal effect of each time over the sample period.

Since we believe that the error terms for both of these exchanges would be correlated in each period, we use seemingly unrelated regression to simultaneously estimate the coefficients on types and other control variables for each exchange. Although we control as much as possible for drivers of volume trading associated with a time trend, expiry dates, and macro events, the finance literature suggests that trading in one period may be correlated with trading in the following period for reasons not captured by our regressors, so autocorrelation of our data is also a concern. We conduct various tests for serial correlation for

[4] Equation 8 is also estimated excluding the polynomial terms on $trend_t$. The coefficients on the other regressors do not change dramatically with the inclusion or exclusion of powers of the time trend, although the adjusted R-squared does increase by 0.10 when the quadratic term is added.

[5] Other fixed effects such as a dummy for whether a month was the first, second, or third month in the futures contract cycle were also employed, but these alternative controls were not significant.

each of our models. Only Model 1 exhibits a strong AR1 process, suggesting that the other controls in Models 2 & 3 do actually control for autocorrelation. Nevertheless, to correct for autocorrelation, we use feasible generalized least squares in combination with seemingly unrelated regression to correct for both serial and contemporaneous correlation in all cases. As a result, standard errors in Model 2 and Model 3 may be inflated.

Consistent with the empirical productivity literature, we may face an endogeneity problem where the number of traders on an exchange is likely the result of expectations on the part of traders about how much volume will be on the exchange. Alternatively, membership may be correlated with unobservable quality of the exchange that also drives trading volume. We deal with potential endogeneity in several ways, also consistent with what has been done in the literature. (cf. Griliches & Mairesse, 1995) First, we suggest that traders make membership decisions based on previous period volume, rather than current period volume, so that the number of traders each period can be considered effectively exogenous to trading volume in that period. Second, we employ flexible polynomial functions of time, fixed effects for cyclicality in trading, and measures of interest rate convergence in Europe and volatility of the Bund to control for any factors that might simultaneously drive trading volume and trader membership. We also estimate the coefficients for DTB and LIFFE separately, allowing quality to interact with the regressors and generate different marginal effects for trader types on each exchange. Finally, in a subsequent draft of this paper, we will investigate the use instrumental variables to correct for endogeneity as a robustness check.

5.1 First stage estimates

Table 3 presents the ordinary least squares estimates for the first stage presented in Equation 8. We choose to fit the natural log of total volume, $\ln(V_{LIFFEt} + V_{DTBt})$, rather than total volume directly since our second stage estimates will be using logged volume as dependent variables as well. The R-squared on this first stage indicates that already 94% of the variation in volume over our sample period can be explained by volatility in the underlying

Bund instrument, convergence of European interest rates, a flexible, polynomial time trend, and expiry date fixed effects. All coefficients except the non-December expiry dates are significant, and all coefficients are of the expected sign. The negative sign on *convergence* indicates that as interest rates converged (represented by a *decrease* in the convergence measure), trading in the Bund futures increased. As *volatility* increased, trading of the Bund futures increased in order to hedge the riskiness in the underlying instrument. A plot of the time *trend* effect maps out an increasing (exponential) effect on volume over our sample period (despite linearizing the volume pattern via logs). The *december* expiry effect picks up the negative spikes in trading that occur each December.

INSERT TABLE 3 HERE

The predicted value from this first stage is presented alongside the log of total volume in Figure 3. The per month average of macro event-predicted log of total volume is 14.89 (min = 13.16, max = 15.91, std deviation = 0.685), which is equal to the average log of total volume per month of 14.89 (min = 13.20, max = 16.16, std deviation = 0.704). We will employ this estimate as a regressor in our estimation of the second stage Equation 7, Model 2.

5.2 Second stage estimates

Table 4 presents the feasible generalized least squares (FGLS) combined with seemingly unrelated regression (SUR) estimates for Models 1, 2, and 3 as described in Section 4. The dependent variable in all cases is logged volume for DTB or LIFFE. Although reported, the use of SUR invalidates the typically calculated R-squared. Instead, graphical evidence of goodness of fit are presented. The estimates from Table 4 are transformed to generated predicted values for volume on DTB and LIFFE, and those are plotted alongside the observed volumes. In the interests of space, only the plots for LIFFE and DTB from Model 3 are presented; the fits are similarly close for Models 1 and 2 as well.

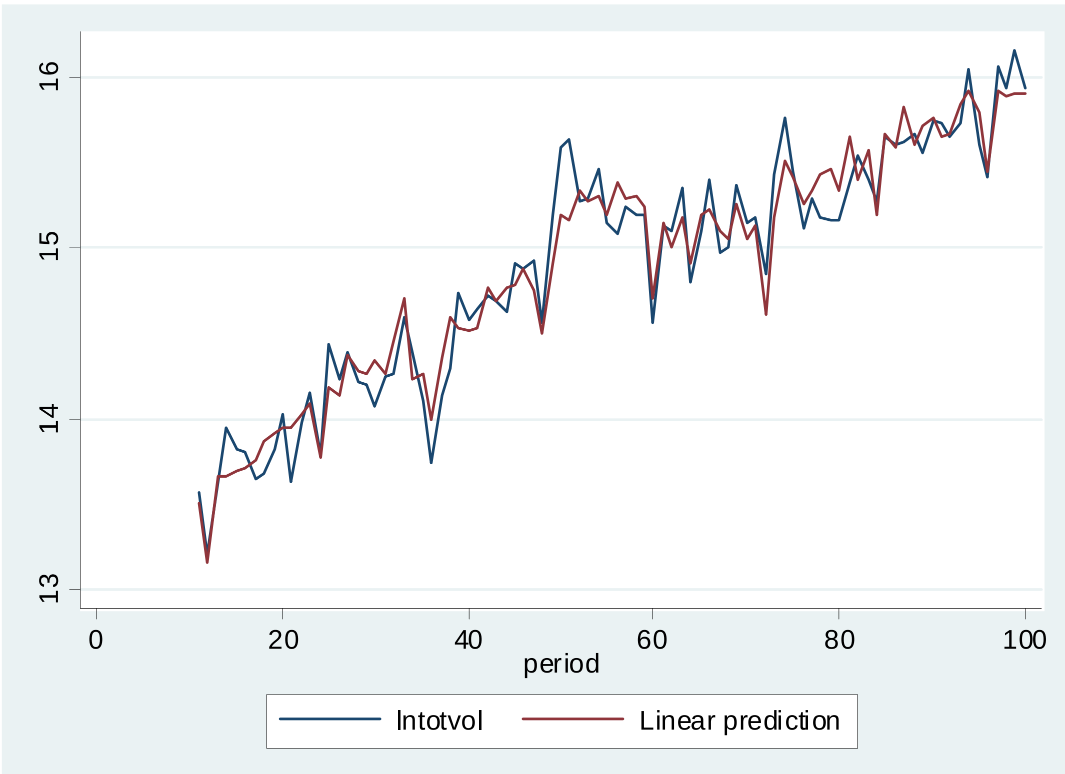

Figure 3: Comparison of dependent variable (log of total Bund futures volume) and predicted value from first stage regression on macro events. The predicted value will be employed as a regressor in the second stage estimation of exchange volumes on trader types.

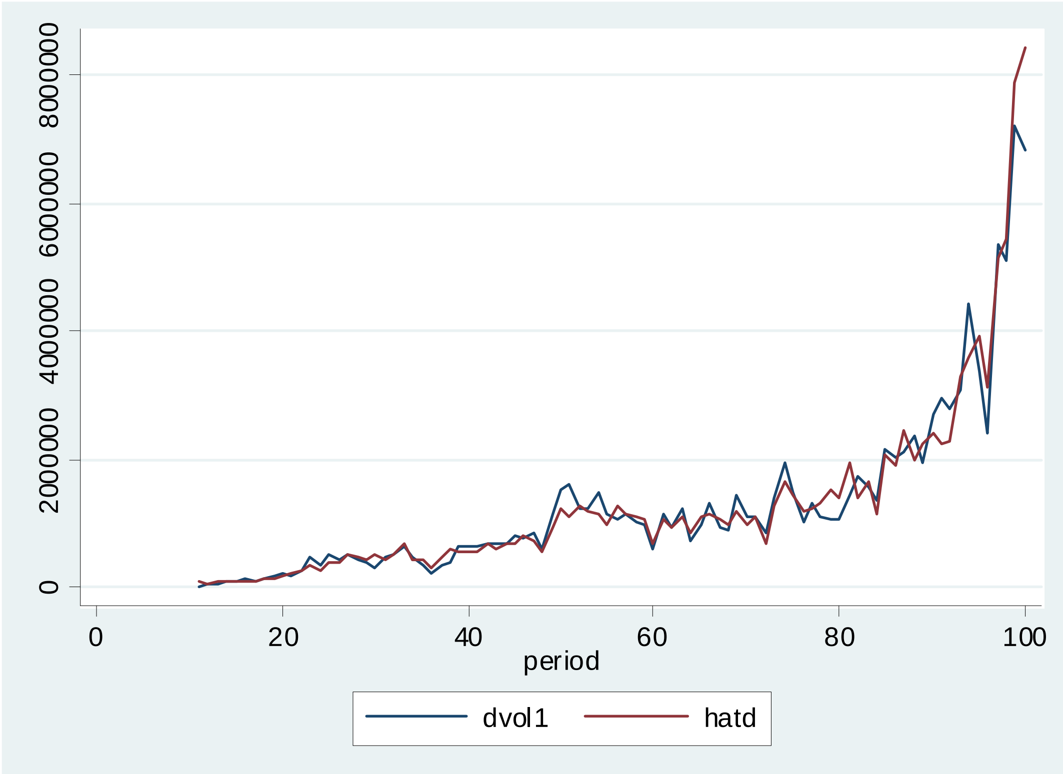

Figure 4: DTB volume and predicted DTB volume from Model 3

INSERT TABLE 4 HERE

The coefficients on most of the types in all three models are positive, indicating that adding a trader general increases liquidity. The one consistent exception is proprietary traders, who on both exchanges and in all three models has a negative effect on volume. The interpretation of a negative coefficient is that proprietary traders are substitutes for other traders: rather than contribute to liquidity, they actually detract from liquidity by substituting for other traders as a counterpart and trading less than those other traders would trade. The presence of an additional proprietary trader therefore decreases the total number of transactions. As can be seen from Equation 5, proprietary traders are substitutes for every other type that has a positive coefficient, since the interaction effect of the two types will be negative. The magnitudes of the coefficients indicate the percentage change in volume as a result of a percentage change in the number of a given type. Using the coefficient

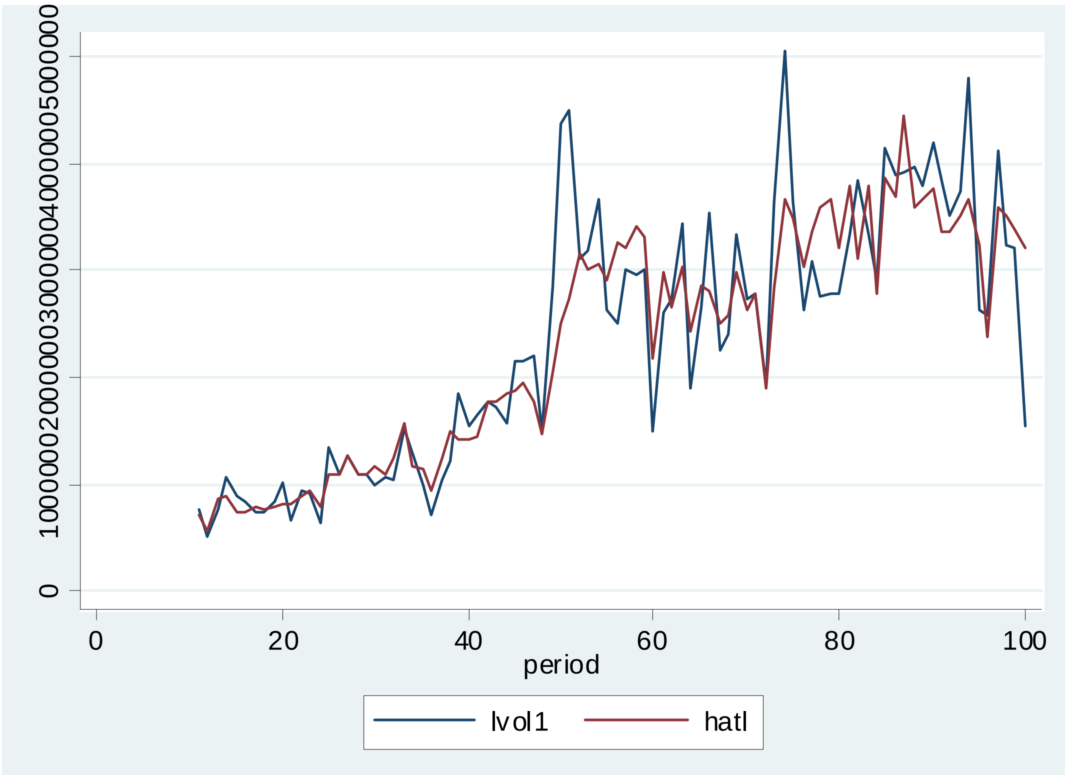

Figure 5: LIFFE volume and predicted LIFFE volume from Model 3

on universal types in Model 1, a 1% increase in the number of universal banks will translate into a 3.5% increase in trading volume.

It is hard to interpret the coefficients from Table 4, since the marginal effects depend on the values of all other variables at that point in time (cf. Equations 4 and 5). The easiest way to interpret the results of the Cobb-Douglas estimates is to calculate the marginal contribution to volume on each exchange in each month based on the observed values of all the regressors (number of business types and exchange and market characteristics) in that month (cf. Equation 4). We present the results from Model 3 only. As can be seen in Figures 6 and 7, there is quite a bit of variation in the contribution to volume of each type. On DTB, the largest contributors to liquidity are retail banks, followed by asset managers and then universal banks. Early in our sample period, however, specialists are on par with universal banks for contributions to liquidity. Brokerages and investment banks contribute very little to liquidity, while proprietary traders seem to act as substitutes to all other traders, with each extra trader reducing the amount of liquidity. The marginal trader contributions for Models 1 & 2 are similar except that asset managers are also substitutes rather than complements to other traders. On LIFFE, asset managers are the biggest contributors to liquidity, although their effect diminishes at the end of the sample period. The next largest contributors are investment banks, followed by retail and universal banks. Specialists, brokers, and proprietary traders all seem to be substitutes in this market.

As we move from Model 1 to Model 2 and add predicted volume from macro events, we see that the number of significantly estimated coefficients on trader types falls sharply. The signs and magnitudes of the type coefficients do not change dramatically, and given the lack of precision with which some coefficients are estimated, they are not significantly different from each other. The sign on macro events in Models 2 & 3 are significant and the right sign. The signs on fees and margins are also significant and the correct sign except in the case of fees for LIFFE: we would expect volume of trading to decrease with higher transaction fees and higher margins.

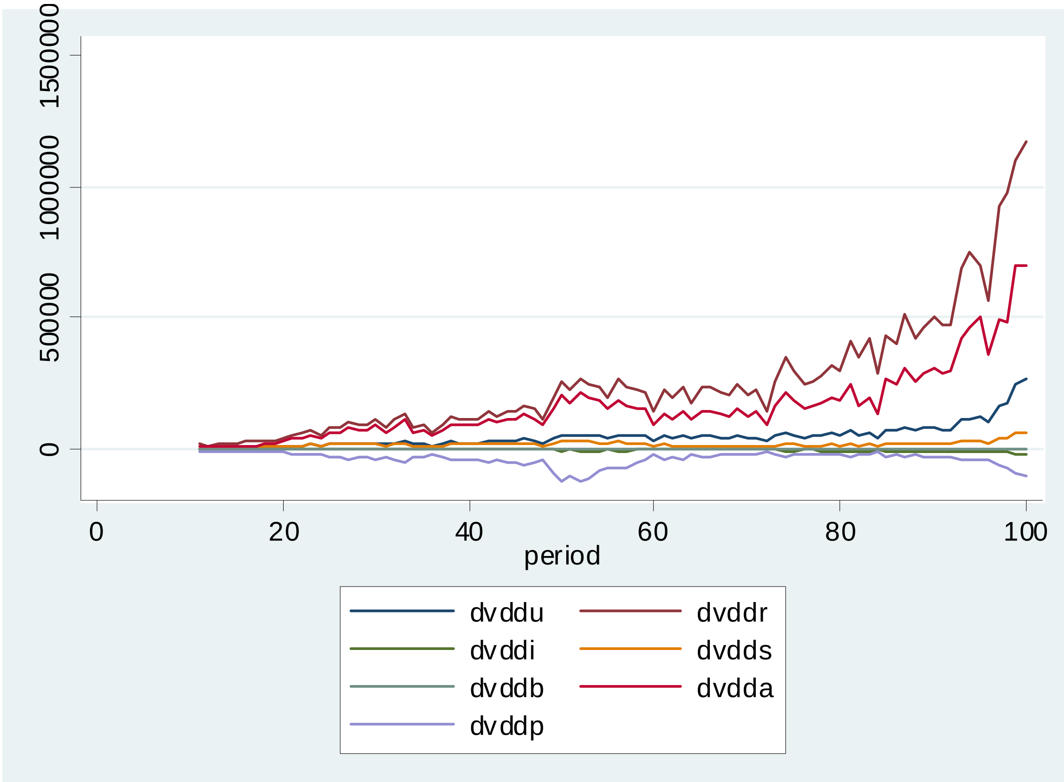

Figure 6: Calculations of the marginal contribution to liquidity of each business type to volume on DTB given observed values of each regressor in each month.

These results already suggest that different traders contribute to liquidity differently, and so exchanges should take into account the type of trader and mix of trader types when trying to assess which traders to target and subsidize (if any).

6 Value vs. contribution to liquidity

Figure 8 combines the results about trader preferences for liquidity from Cantillon & Yin (2008) with the calculations of marginal contributions to liquidity from the estimates in Model 3. A coefficient for each business types' preference for liquidity was estimated in Cantillon & Yin (2008). These preference are plotted along the y-axis. The value of the marginal contribution to liquidity in the first period of our sample for DTB are plotted along the x-axis. Figure 8 suggests that in a few cases, preferences for liquidity are correlated with

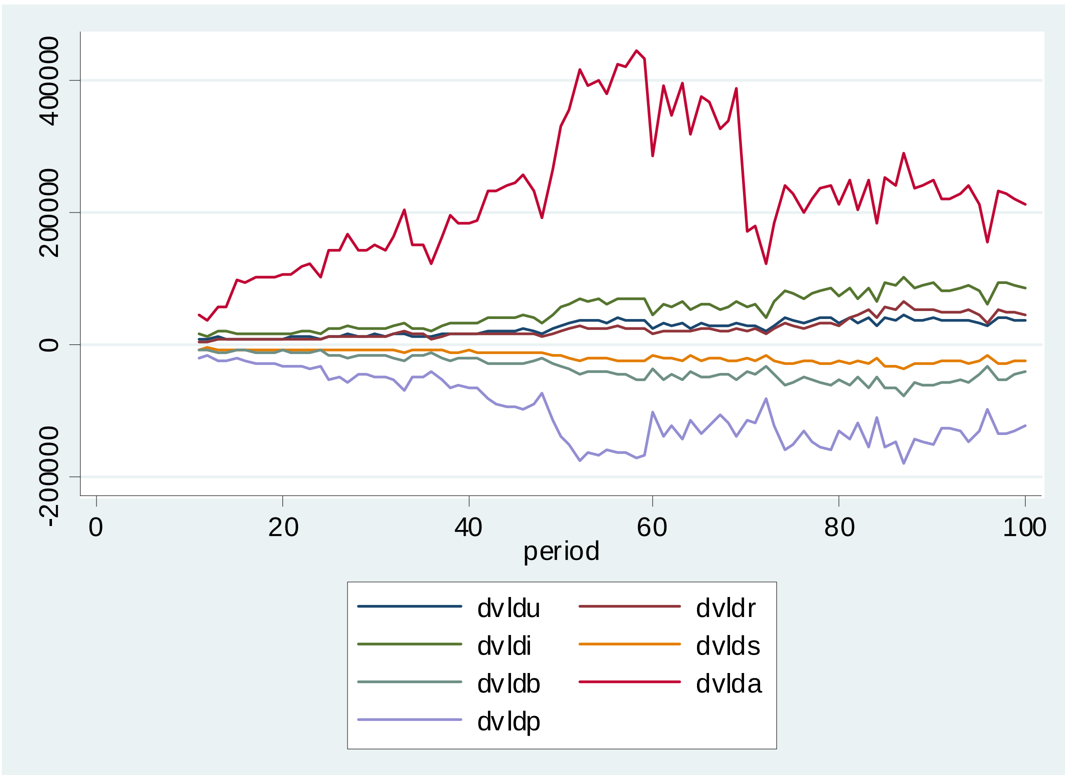

Figure 7: Calculations of the marginal contribution to liquidity of each business type to volume on LIFFE given observed values of each regressor in each month.

contributions to liquidity. This pattern is consistent with the logic that types who trade a lot are likely to seek a platform with greater liquidity to absorb their trades. Holding the mix of other traders constant, if DTB wanted to attract retail banks and asset managers for their liquidity contribution behavior, DTB would likely have to subsidize their memberships since they tend to care more about liquidity than other types, and thus may be reluctant to leave the incumbent exchange. Brokers care a great deal about liquidity but contribute relatively little. This suggest that they may represent more hedging than asset managers or retail banks, and therefore value liquidity but do not trade in large volumes. Relative to asset managers and retail banks, DTB does not need to expend as many resources targeting brokers or retail banks, since they likely require high subsidies to switch to a low liquidity platform but do not contribute much to liquidity. Proprietary, investment banks, and specialists are the types who may find DTB relatively more attractive. Given the mix of traders on DTB early in our sample, specialists and proprietary traders also are relatively larger contributors to liquidity than other types, so these traders who were particularly valuable to DTB early on also are easier to attract. When we compare these correlations with the initial members that opened DTB, the mix of traders adopting DTB may have been able to improve upon their initial liquidity growth. DTB opened in February 1990 with 13 investment banks, 10 universal banks, 7 asset managers, 4 retail banks, and 1 proprietary trader. DTB may have done better if they had invited more retail banks and specialists than investment banks. Investment banks seem less discouraged by lower liquidity than specialists; given that there were approximately 100 groups of both types existing in February 1990, it would have been better to court more of the specialists than the investment banks. Our results suggest potentially more effective targeting of initial membership composition for DTB at the time of its entry.

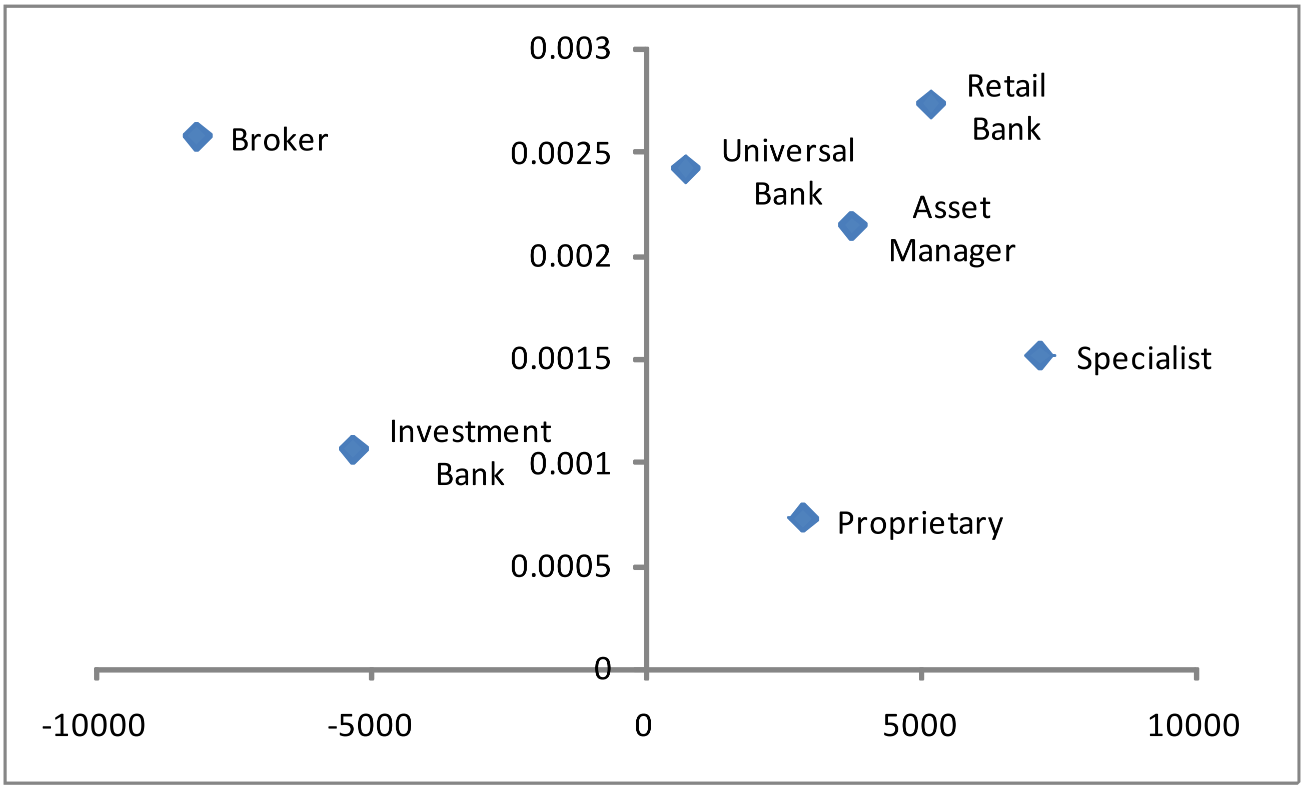

Figure 8: Preference for and contribution to liquidity by type. Contribution is plotted along the x-axis, and the corresponding preference for liquidity is plotted along the y-axis.

7 Conclusion

This paper estimates the coefficients on a Cobb Douglas production function that links the mix of trader types on an exchange to the volume on that exchange. Those estimates are used to calculate the marginal contribution to liquidity by each trader type conditional on the mix of other trader types present on the exchange. By combining these results with estimates of trader types' preferences for liquidity, we find evidence suggestive of better entry strategies with respect to subsidization and targeting of initial members by DTB during their competitive entry in the Bund futures trading market. By choosing a different set of initial members, DTB may have been able to generate liquidity faster than was accomplished with its observed choice of initial members.

In future versions of this paper, we would like to enrich the specification for unobservable member characteristics. The motivation for why different traders contribute to liquidity comes from our understanding of how trading behavior varies with trading motives (hedging, arbitrage, speculation, brokerage). In practice, our observable trader characteristics imperfectly proxy for this trading behavior. We will refine the empirical approach by adding a (logit) probability function of being one of these four types of traders (hedger, arbitrageur, speculator or broker) based on observable characteristics. The probability function will be jointly estimated with the production function (now based on these four types).

As a second attempt to infer information about trading motives from observable information, we will integrate information on the level of open interest. Different trading motives have different implications for how trading volumes related to open interest, and the level of open interest reveals something about the mix of traders.

The Cobb-Douglas function already allows for complementary and substitutability among trader types. We will nevertheless consider its extension, the translog function, that allows for richer patterns of interactions.

With the empirical results at hand, we will be able to identify which aspects of the Jullien (2001, 2006) are most in need of extension to derive normative interpretations of our results and suggest interesting counterfactuals.

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Table 3: OLS results for first stage regression of log of total Bund volume per month on macro variables

	$\ln(V_{LIFFE} + V_{DTB})$
convergence	-2.231* *0.544*
volatility	2.976* *0.556*
trend	0.085* *0.011*
trend^2	-0.001* *0.000*
trend^3	0.000* *0.000*
december	-0.431* *0.064*
expiry	-2.231* *0.544*
constant	2.976* *0.556*
Adjusted R^2	0.942
No. of obs.	90

Standard errors are presented below coefficient estimates in italics. *significant @ 5%

Table 4: FGLS+SUR results for Cobb Douglas model of business type contributions to logged volume/month on DTB & LIFFE

	Model 1		Model 2		Model 3	
Trader types	DTB	LIFFE	DTB	LIFFE	DTB	LIFFE
lnUniversal	3.462* *0.872*	5.681* *0.928*	1.359† *0.717*	1.579† *0.890*	0.884 *0.597*	0.236 *0.917*
lnRetail	2.440* *0.424*	0.263 *0.172*	2.202* *0.339*	0.278* *0.136*	1.250* *0.319*	0.043 *0.157*
lnInvestmentBank	0.523 *1.288*	-1.486 *1.003*	-0.322 *1.021*	1.248 *0.839*	-0.098 *0.850*	1.141 *0.821*
lnSpecialist	0.909* *0.266*	0.998* *0.484*	0.141 *0.226*	0.018 *0.393*	0.248 *0.189*	-0.173 *0.400*
lnBroker	0.136 *0.206*	-0.105 *0.505*	0.139 *0.165*	0.080 *0.409*	-0.003 *0.138*	-0.258 *0.390*
lnAssetManager	-1.041* *0.422*	0.465* *0.151*	-0.327 *0.341*	0.173 *0.122*	1.152* *0.363*	0.130 *0.120*
lnProprietary	-0.462* *0.190*	-1.991* *0.255*	-0.124 *0.162*	-0.331 *0.288*	-0.289* *0.135*	-0.602* *0.305*
Macro events						
predicted lnTotalVolume	-------	-------	0.973* *0.110*	0.717* *0.076*	1.021* *0.096*	0.736* *0.073*
Exchange specific controls						
Fees	-------	-------	-------	-------	-0.394* *0.080*	0.075 *0.093*
Margins	-------	-------	-------	-------	-9.56E-5* *0.000*	-9.56E-5* *0.000*
constant	-2.333 *4.941*	5.043 *6.738*	-7.368† *3.908*	-5.706 *5.548*	-8.049* *3.252*	0.786 *5.672*
Reported R^2	0.999	0.999	0.999	0.999	0.999	0.999
No. of obs.	89		89		89	

Standard errors are presented below coefficient estimates in italics. *significant @ 5%, †significant at 10%