Cologne Economic History Paper

Universität zu Köln

Seminar für **Wirtschafts- und** Unternehmensgeschichte

No. 2 (2012)

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Liquidity measures, liquidity drivers and expected returns on an early call auction market

Carsten Burhop and **Sergey Gelman**[*]

Abstract
This paper analyzes the determinants of illiquidity as well as its impact on asset pricing for purely call-auction traded stocks on the Berlin Stock Exchange using 22 years of daily data (1892-1913).We use the Lesmond et al. (1999) measure of transaction costs to proxy illiquidity. Our results show that transaction costs were low and comparable to today's costs. Liquidity was negatively correlated with information asymmetry, particularly being low for small and distressed stocks and in crises times. Furthermore, liquidity concerns were a major driver of asset pricing: we find significant illiquidity level and illiquidity risk premia as well as an explicit premium for the absence of liquidity providers.

JEL-Classification
G 12, G 14, N 23

Keywords
Transaction Costs; Liquidity Premium; Liquidity Provision

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I. Introduction

In this paper, we empirically investigate theoretical predictions for the interplay of transaction costs, liquidity provision and asset pricing using daily stock prices from the Berlin Stock Exchange from the period 1892-1913. The data are especially insightful for studying the link between insider behaviour and liquidity because the design of the market closely resembles the assumptions of sequential auction games (as in Kyle, 1985; Madhavan, 1992; etc.). More specifically, the Berlin Stock Exchange, which was then the major German stock exchange, was a call auction market with an official broker arranging one price fixing a day. The broker was prohibited to take positions in the market. A large stakeholder (such as a custodian bank), however, could play a role of a liquidity provider, and there exists anecdotal evidence that he often did. However, unlike a typical market maker, such a liquidity provider could possess some insider information about the fundamental value of the stock and could decide to exploit it and demand liquidity instead of providing it. A close alignment of the actual market design and theoretical assumptions allows us to distinguish these two types of behaviour from stock price dynamics: a high negative serial correlation of stock returns indicates liquidity supply by a large stakeholder, whereas a positive correlation of returns could indicate speculation based on private information of this large stakeholder (Llorente et al. 2002).

One of the implications of theoretical market microstructure models is that a high information-to-noise ratio leads to low liquidity (e.g. Madhavan 1992, Rochet and Vila, 1994: 145). We test this hypothesis indirectly, analyzing the impact of states with likely high information asymmetry on transaction costs. We apply the Lesmond, Ogden and Trzcinka (1999, further LOT) indirect measure of transaction costs as a liquidity measure and use small and distressed companies as high information-to-noise states. We also provide further evidence on liquidity deterioration in crises times, comparable with findings for modern US stock market (Pastor and Stambaugh 2003). Moreover, we investigate, whether liquidity supply behavior of a large stakeholder had an impact on transaction costs.

Beyond measuring transaction costs and identifying the link between information asymmetry and liquidity, we address three theoretical propositions with respect to the liquidity premia. First, investors dislike illiquid stocks and require a premium for holding them (Acharya and Pedersen, 2005; Amihud and Mendelson, 1986). By and large, the empirical literature supports this view (Asparouhova et al., 2009; Eleswarapu, 1997; Chalmers and Kadlec, 1998). Second, investors dislike stocks which are illiquid in bad times, as they can not be used to offset income flow shocks (e.g. Acharya and Pedersen, 2005; Pastor and Stambaugh 2003). Third, liquidity provision by large stakeholders benefits liquidity traders, while liquidity demand from large stakeholders destroys the wealth of uninformed traders and deters their participation in such stock. Whereas the first and the second hypotheses have been tested on the modern continuous trading data, the third one, to our knowledge, is novel to the literature. We assess these three hypotheses in an asset pricing framework, where LOT transaction costs proxy for illiquidity, a regression coefficient of individual transaction costs shocks on market returns proxies for the co-movement of illiquidity and market downturns, and (negative) first order autocorrelation of daily returns proxies for liquidity provision by large stakeholders.

We show that transaction costs at the Berlin Stock Exchange a century ago were pretty low and of about the same size as they are in modern financial markets. The LOT measure indicates that the cost for a roundtrip transaction were about 0.97 percent of the share price. This compares to an estimate of 1.23 percent for the largest decile of firms listed at the New York Stock Exchange for the period 1963-1990 (Lesmond et al., 1999). We find support for the negative impact of the information-to-noise ratio on liquidity: transaction costs are higher for small stocks and after a year of negative returns. Moreover, illiquidity increases in crises times. Liquidity provision seems to moderate illiquidity, but this result is not robust to alternative specifications.

The estimation of multifactor asset pricing models provides strong support of a liquidity premium: for one percentage point higher transaction costs, investors require an about 3.6 percentage points higher expected annual return. We find a significant positive premium for liquidity risk: investors impose a significant discount on the price of securities, which transaction costs rise stronger in the case of market downturns. Moreover, we find support for the liquidity provision discount: securities, in which large stakeholders rather demand liquidity than provide it, yield higher expected returns. The magnitude of this impact is economically strongly significant, being up to 4% per annum. Thereby usual asset pricing benchmarks – market risk and size – turn out to have no impact on the cross-section of stock prices.

Our finding of comparatively low transaction costs supports the theoretical superiority of call auction markets over the nowadays prevalent continuous trading or dealership markets (Pagano and Roell, 1996). Empirical results using data from modern markets are not as clear cut. For example, data from the Tel Aviv stock exchange show that prices and liquidity increase when stocks move from a call auction market to continuous trading (Amihud et al, 1997; Kalay et al., 2002). However, data from the Singapore and London stock exchange illustrate that the introduction of opening and closing call auctions decreases the extent of price manipulation and increases the extent of price discovery (Chang et al., 2008; Chelley-Steeley, 2008). Moreover, Pagano and Schwartz (2003) show that introduction of the closing auction on the Paris Bourse in 1996 led to the reduction of execution costs. In addition, experimental studies point out that call auction markets reduce asymmetric information between different groups of traders and lead to lower transaction costs, but reduce the speed of information processing (Schmitzlein, 1996; Theissen, 2000).

The liquidity dynamics of a call auction market seems to be very similar to that of modern continuous trading markets. In particular, liquidity dry-outs found during the Balkan war crisis 1913 and after the bankruptcy of Leipziger bank 1901 are consistent with findings of liquidity drops during the Mideast oil crisis 1973 and after the LTCM collapse and Russian default in 1998 reported by Pastor and Stambaugh (2003). As the bankruptcy of the Leipziger bank 1901 was accompanied by an aggregate market decline this finding is in line with deteriorating liquidity in times of major market downturns reported by Chordia et al. (2001).

Our evidence on the liquidity premium suggests a stable relationship between liquidity and asset pricing through time and across market types. Despite relatively low transaction costs, the liquidity premium observed in our data corresponds in magnitude to the one reported for modern day markets with continuous trading: 3.6% annually for 1% transaction cost in our historical auction market compared to 3.5% for US markets in 1964-1999, reported by Acharya and Pedersen (2005).

We find the liquidity risk premium much stronger pronounced than in the recent literature. Its statistical significance is higher than for the modern US market provided by Acharya and Pedersen (2005) and is in line with significant results reported by Lee (2011) for modern global markets. The economic significance, however, exceeds both modern US and global market findings: our data yields an about fivefold larger premium compared to modern day US (Acharya and Pedersen 2005) and about a fourfold larger premium with respect to modern global markets (Lee 2011).

Our main contribution is the evidence of required return discount for liquidity provision. Our results show that on top of usual liquidity level measures, investors care about the liquidity supply behavior from large stakeholders. Given the same level of transaction costs, stocks where large stakeholders exploit there private information instead of providing liquidity are worth substantially less, as they yield up to 4% p.a. higher expected return. Such relevance of liquidity providers for asset pricing can be related to liquidity risk, as these agents could still trade in situations of sharp market downturns, whereas other investors would not, thus guaranteeing some minimal liquidity in critical periods.

We also provide a minor contribution to the methodology, introducing confidence intervals for LOT estimates of transaction costs, what allows making inference about different liquidity levels across stock and time.

Beyond contributing to the financial economics literature, our paper also supports recent findings from economic history showing that Germany's historical stock market was quite efficient. Starting with the work of Weigt (2005), it has been shown that stock price differentials among German stock exchanges (Weigt, 2005: 199) and between the Berlin Stock Exchange and other major European stock exchanges were small (Baltzer, 2006), that stock prices reflected the risk and return characteristics of the shares quite well (Weigt, 2005: 224), and that the Berlin Stock Exchange was weakly information efficient (Gelman and Burhop, 2008). Furthermore, Gehrig and Fohlin (2006) estimate in a paper closely related to our work that the effective spreads of samples of Berlin traded shares during the benchmark years 1880, 1890, 1900, and 1910 were low and decreasing in firm size.

The remaining parts of the paper are organised as follows. In Section II we give a short description of price fixing at the Berlin Stock Exchange at the turn of the 20th century and describe our data sources. The LOT measure of the round-trip transaction costs is illustrated in Section III, along with a brief description of implemented econometric techniques. The results are presented in Section IV, followed by robustness checks in Section V and conclusion in Section VI.

II. Market Structure and Data Description

Shares were traded at the Berlin Stock Exchange six days peer week using a call auction mechanism. Prices were fixed once a day by official, government appointed brokers. The brokers' association allocated two official brokers to each stock listed at the exchange. They jointly fixed the official price of the share and they both had the duty to act as brokers for the stock, i.e. they could not decline to take orders. They started taking orders at noon and stopped taking orders not earlier than 1.30 p.m. and not later than 2 p.m. Orders were made orally by representatives of banks and other participants on the trading floor. The official broker orally repeated the order and his substitute recorded the order into the order book. The order book was arranged in four columns, one for unlimited buying orders, one for limited buying orders, one for unlimited selling orders, and one for limited selling orders. The official price had to reflect the true commerce at the stock exchange. At the official price, it had to be possible that all unlimited buy and sell orders as well as buy orders with a higher price limit and sell orders with a lower price limit were carried out. Whenever the official broker expected a major price change (i.e., a price change of more than one percent), he had to make a written announcement to the trading floor. Moreover, in this case, a state commissioner joined the two official brokers to monitor the price fixing. The first tentative price was prepared in public and all interested parties could attend this event. Moreover, it was still possible to place further orders or to cancel formerly made orders. Afterwards, the two official brokers went to the back office, where the official quotation was registered, signed by the state commissioner, and published in the official price list (Obst, 1921: 380, 386-392).

Turning to transaction costs, we can distinguish three types of observable costs: taxes, broker fees, and bank fees. Transactions at German stock exchanges were taxed from 1881 onwards. More specifically for the period under consideration here, the stock market turnover tax was 0.01 percent of the underlying transaction value between 1892 and April 1894. From May 1894 onwards, the tax was doubled to 0.02 percent; another increase to 0.03 percent followed in October 1900. In addition to turnover taxes, the fees for brokers influence transaction costs. The fee for official brokers was 0.05 percent of the underlying transaction value (Gelman and Burhop, 2008). Furthermore, fees for the banks or other intermediaries varied between 0.1 and 0.33 percent (Weigt, 2005: 192). In sum, broker fees, fees for intermediaries, and turnover taxes added up to a total cost for a roundtrip transaction (i.e., buying and selling of a share) in the range of 0.252 to 0.82 percent.[1]

To investigate the size of actual transaction costs and to evaluate whether they changed over time, we use daily stock prices for the period 31 December 1891 to 31 December 1913 collected from the *Berliner Börsenzeitung* – Germany's leading financial daily of the pre-1913 period – for a sample of 27 continuously traded corporations from the Berlin stock exchange. The data were obtained from Gelman and Burhop (2008) who construct a daily stock market index for the period 1892-1913.[2] The sample contains 6,692 daily returns. Descriptive statistics of individual stocks are shown in Table 1. The average daily return of an individual stock was slightly above one basis point and the average standard deviation with 94 basis points was about a half of the modern stock return volatility, but corresponds to the values reported by Gehrig and Fohlin (2006: 10,

[1] Tick size, which could have relevance for price impact, was 0.05 percent of face value (of typically 1,000 Mark).

[2] Starting point for the index construction was the collection of daily share prices from the *Berliner Börsenzeitung* for a sample of 39 continuously listed non-insurance corporations from the Berlin stock exchange. Insurance companies were excluded from the index since trading in them was heavily restricted. They only issued *vinkulierte Namensaktien*, registered shares with restricted transferability. Then securities with the portion of zero daily returns in the period under study of one third or higher were deleted from the index. 27 corporations remained.

12) for 1890, 1900 and 1910. Most of the stock returns are negatively skewed; all of them are leptokurtic, somewhat stronger than the modern day stock returns.

To make some statements in how far our sample is representative for the whole universe of stocks traded on Berlin stock exchange, we compare the size of selected companies to the full cross-section in 1900 (the only data available to us for all listed stocks). From 826 listed companies there is market capitalization data only for 764 companies.[3] The aggregate market capitalization of our sample accounts for 16 percent of the total market capitalization. The average capitalization of all listed stocks with reported data was with 1.1 million mark about five times smaller than the average capitalization of the selected 27 companies, which amounted to 5.2 million in 1900. Both a simple t-test of the mean as well as a non-parametric Mann-Whitney test indicate that our sample is biased towards larger stock. In fact, the average size rank (ordered descending) of our sample stocks is 170.1 compared to the expected 382.5; 5 out of the 10 largest companies listed on the exchange belong to the sample.

[3] Details are available on demand.

Table 1. Distributional properties of stock returns of the Gelman-Burhop-index constituent companies

	Name	Mean (ann.)	Median (ann.)	Max.	Min.	Std. Dev.	Skew-ness	Kur-tosis	Proportion of zero returns	ρ(1)	Average Market Cap. (1,000 M)
1	AG für Anilinfabrikation	0.0678	0.0000	0.1257	-0.2270	0.0082	-3.85	126.25	0.1638	0.0008	2727
2	Allgemeine Elektricitätsgesellschaft	0.0336	0.0000	0.0526	-0.0611	0.0065	-0.18	11.94	0.0807	0.0820*	14997
3	Berlin-Anhaltinische Maschinenbau	0.0134	0.0000	0.1037	-0.0878	0.0078	-0.65	25.62	0.1540	-0.0474*	1179
4	Bochumer Bergwerk (Lit C)	0.2457	0.0000	4.6522	-0.3611	0.0603	68.59	5285.9	0.2192	0.0060	351
5	Deutsche Bank	0.0294	0.0000	0.0333	-0.0544	0.0042	-1.64	24.72	0.1001	-0.0119	32778
6	Dresdner Bank	0.0129	0.0000	0.0446	-0.0554	0.0048	-0.85	17.74	0.1062	0.0230	19931
7	Darmstädter Bank (BHI)	0.0006	0.0000	0.0642	-0.0846	0.0044	-1.21	40.81	0.1903	-0.0231	16689
8	Deutsche Jute Spinnerei und Weberei	0.0465	0.0000	0.0674	-0.1040	0.0079	-0.53	16.89	0.2061	0.0024	430
9	Deutsche Spiegelglas	0.0687	0.0000	0.0921	-0.0838	0.0080	-0.30	18.32	0.1877	0.0716*	643
10	Erdmannsdorfer Spinnerei	0.0001	0.0000	0.1143	-0.0774	0.0106	0.62	13.70	0.2497	-0.0425*	286
11	Gelsenkirchener Bergwerksgesellschaft	0.0254	0.0000	0.0484	-0.0858	0.0071	-0.82	13.87	0.0555	0.0240	15580
12	Gerresheimer Glashütten	0.0480	0.0000	0.0739	-0.1208	0.0079	-1.61	33.11	0.2452	-0.0551*	1112
13	Hallesche Maschinenfabriken	0.0266	0.0000	0.1000	-0.2788	0.0093	-6.04	169.13	0.1666	-0.0287*	667
14	Harpener Bergbau AG	0.0212	0.0000	0.0668	-0.0682	0.0075	-0.28	11.77	0.0517	0.0282*	10400
15	Kattowitzer AG für Bergbau und Eisen	0.0348	0.0000	0.0609	-0.0603	0.0068	-0.26	13.77	0.1313	0.0402*	4652
16	Maschinenfabrik Kappel	0.0711	0.0000	0.2014	-0.2138	0.0113	-0.61	48.92	0.1725	0.0721*	340
17	Norddeutsche Wollkämmerei	0.0192	0.0000	0.0738	-0.0838	0.0080	0.01	15.22	0.2025	0.0272*	1926
18	Schaffhausen'scher Bankverein	0.0000	0.0000	0.0454	-0.0409	0.0037	0.07	22.24	0.2688	0.1121*	14043
19	Oberschlesische Portland-Cement AG	0.0390	0.0000	0.1267	-0.0943	0.0098	0.72	23.25	0.1515	-0.0238	440
20	Rheinische Stahlwerke	0.0151	0.0000	0.1095	-0.1427	0.0085	-0.77	39.52	0.1230	-0.0337*	3745
21	Rositzer Zuckerfabrik	0.0435	0.0000	0.0833	-0.0826	0.0092	0.05	11.73	0.1413	0.0237	717
22	Chemische Fabrik vormals Schering	0.0162	0.0000	0.0652	-0.0657	0.0083	0.17	10.17	0.1630	0.0610*	1298
23	Schlesische Zinkhütten	0.0336	0.0000	0.1079	-0.0853	0.0066	-0.52	33.99	0.2360	-0.0582*	7947

	Name	Mean (ann.)	Median (ann.)	Max.	Min.	Std. Dev.	Skew-ness	Kur-tosis	Proportion of zero returns	ρ(1)	Average Market Cap. (1,000 M)
24	Schlesische Leinen-Industrie	-0.0043	0.0000	0.0703	-0.0679	0.0063	-0.56	21.28	0.3194	-0.1558*	1015
25	Schultheiss Brauerei	0.0097	0.0000	0.0897	-0.0853	0.0057	-1.23	65.22	0.1714	-0.2016*	2522
26	Siemens Glas-Industrie	0.0287	0.0000	0.0438	-0.0576	0.0058	-1.12	19.17	0.1966	-0.0273*	2290
27	Stettiner Chamottewaren	-0.0096	0.0000	0.0804	-0.2538	0.0088	-3.85	126.25	0.1452	0.0281*	2640
	Average	0.0347	0.0000	n/a	n/a	0.0094	1.61	231.87	0.1703	-0.0040	5976
	Gelman-Burhop index	0.0687	0.0909	0.0296	-0.0562	0.0032	-1.68	30.78	n/a	0.165*	161344
	Equally-weighted price index	0.0327	0.0600	0.1780	-0.0325	0.0036	17.80	913.90	n/a	0.167*	161344

Notes: Mean and median returns are presented on the annual basis (location measure x300) for illustrative purposes.
* denotes significance of the autocorrelation coefficient on the 5 percent level.

Although our sample is skewed towards larger companies it spans a wide range of stocks in terms of size, from the largest (Deutsche Bank) to those ranked 590th and 495th from the top (Bochumer Bergwerk and Erdmannsdorfer Spinnerei correspondingly). The difference in distribution of logged market capitalization (which is supposed to stay in linear relationship with liquidity, see Gehring and Fohlin (2006) and Section IV) is by far not that striking, with averages of 19.9 and 21.4 for 764 stocks and our sample respectively. The scope of zero returns seems also to be adequate: it ranges from 5 percent of trading days for Harpener Bergbau to 32 percent of trading days for Schlesische Leinen, with an average of 17 percent or approximately 51 days per year. This is slightly less than 22 percent reported by Gehrig and Fohlin (2006) for their sample of 114 stocks from the Berlin stock exchange in 1900. Hence, our sample can be regarded as representative of stocks traded on the Berlin Stock Exchange at the turn of the 20th century except for a small bias towards larger and more liquid stocks.

The dynamic properties indicate possible informed insider trading: for most of the stocks (15 out of 27) we report positive daily return autocorrelation. The latter makes indirect effective spread measures, based on the bid-ask bounce, inapplicable.

Beyond the reported properties of stock prices we have also obtained dividend data taken from the *Berliner Börsenzeitung*. Comparison of the average return on Gelman-Burhop performance index with that of the price index indicates average dividend yield of approximately 3.5 percent annually.

Data on aggregate annual trade volume of all securities in Imperial Germany can serve as a proxy of the overall trading activity (obtained from Wetzel 1996). The aggregate trade volume time series behaves stationary with the approximately same value of securities traded in 1913 as in 1892 (see Appendix 8).

III. LOT measure an econometric technique

In an information-efficient stock market, prices of stocks should incorporate new information instantaneously. On the real-world stock exchanges, however, the presence of transaction costs induces some deviations from such behaviour. Uncovering these deviations and analyzing them allows tracking back full transaction costs.

This idea is exploited in a measure of transaction costs, proposed by Lesmond et al. (1999). The LOT measure reflects the total costs of a roundtrip transaction, which includes not only the difference between bid and ask prices, but also all further expenses carried by the trader, including the price change induced by the trade itself (so called price impact, see Lesmond 2005). The LOT measure is based on the idea that transactions will only occur if the deviation of the market price from the true value of a stock is larger than the costs of a transaction. Thus, there are upper and lower thresholds – τ_i^l and τ_i^h – such that the measured return r is non-zero only if the true return exceeds the threshold:

$$\text{(4a)}\quad r_{i,t} = R_{it}^* - \tau_i^l \text{ if } r_{i,t}^* < \tau_i^l$$
$$\text{(4b)}\quad r_{i,t} = 0 \text{ if } \tau_i^l < r_{i,t}^* < \tau_i^h$$
$$\text{(4c)}\quad r_{i,t} = R_{it}^* - \tau_i^h \text{ if } r_{i,t}^* > \tau_i^h.$$

The true return depends on the market return $r_{m,t}$ in a linear way: $r^*_{i,t} = \beta_i r_{m,t} + e_{i,t}$.
The estimated difference between the upper and the lower threshold – i.e. τ_i^h less τ_i^l – is a measure of the roundtrip transaction costs.
We use the following maximum likelihood estimator, developed by Lesmond et al. (1999), to estimate the LOT measure:

$$L\left(\tau_i^l, \tau_i^h, \beta_i, \sigma_i \middle| r_{it}, r_{mt}\right) = \prod_1 \frac{1}{\sigma_i}\phi\left[\frac{r_{it} + \tau_i^l - \beta_i r_{mt}}{\sigma_i}\right] \times \prod_0 \left[\Phi\left(\frac{\tau_i^h - \beta_i r_{mt}}{\sigma_i}\right) - \Phi\left(\frac{\tau_i^l - \beta_i r_{mt}}{\sigma_i}\right)\right]$$

$$\text{(5)} \times \prod_2 \frac{1}{\sigma_i}\phi\left[\frac{r_{it} + \tau_i^h - \beta_i r_{mt}}{\sigma_i}\right]$$

$$\text{S.T. } \tau_i^l \le 0, \tau_i^h \ge 0, \beta_i \ge 0, \sigma_i \ge 0,$$

Where $\Phi()$ is the standard normal cumulative distribution function. Region 1 (indicated by the subscript “1” of Π) corresponds to the negative expected latent variable when the observed is nonzero ($\hat{r}_{it}^* < 0$, or equivalently r_{mt}<0 and $r_{it} \neq 0$), region 2 to the positive expected latent variable if the observed is nonzero (r_{mt}>0 and $r_{it} \neq 0$), and region 0 corresponds to the observation with zero observed returns ($r_{it} = 0$). σ_i denotes the root out of the residual variance, measured over the non-zero returns region.
The LOT measure thus includes the bid-ask spread, fees, transaction taxes, costs of information acquirement and processing, as well as price impact. Its size should be therefore larger than the regulated costs, i.e., the sum of broker fees, provisions, and transaction taxes. We calculate this measure for each company and each year, and then provide also aggregated estimates across companies and years.
In this paper we also calculate standard errors and confidence intervals for the transaction cost estimates, which is novel to the literature. It allows assessing the credibility of the estimates and inferring the significance of cross-section and time-series

differences. We obtain standard errors for each stock i and year t from the standard expression:

$$(6)\ \sigma\left(S_{it}\right)=\sqrt{\operatorname{var}\left(\tau_{it}^{h}-\tau_{it}^{l}\right)}=\sqrt{\left(\operatorname{var}\left(\tau_{it}^{h}\right)-2\operatorname{cov}\left(\tau_{it}^{h},\tau_{it}^{l}\right)+\operatorname{var}\left(\tau_{it}^{l}\right)\right)},$$

where $\operatorname{var}\left(\tau_{it}^{h}\right)$, $\operatorname{var}\left(\tau_{it}^{l}\right)$ and $\operatorname{cov}\left(\tau_{it}^{h},\tau_{it}^{l}\right)$ are the elements of the coefficient variance-covariance matrix, yielded by maximum likelihood estimation in (5). To obtain standard errors of annual averages we take into account possible cross-correlations of stock returns:

$$(7)\ \sigma\left(\bar{S}_{t}\right)=\sqrt{\frac{\Sigma'\cdot\Omega\cdot\Sigma}{27^{2}}},$$

where $\Sigma'=\left(\sigma\left(S_{1t}\right)\ \cdots\ \sigma\left(S_{27t}\right)\right)$ is a row vector with standard errors for each stock obtained for the year from (6) and Ω is a 27x27 correlation matrix of residuals from the limited dependent variable regressions, estimated by (5). For the standard errors of company transaction costs averages (7) can be simplified, as we can assume independence of estimates across time:

$$(8)\ \sigma\left(\bar{S}_{i}\right)=\sqrt{\frac{\Sigma_{i}'\cdot\Sigma_{i}}{22^{2}}},$$

where $\Sigma_{i}'=\left(\sigma\left(S_{i1892}\right)\ \cdots\ \sigma\left(S_{i1913}\right)\right)$ is a row vector with standard errors for the stock i obtained for years 1892-1913. Confidence intervals are then estimated in a standard way under the assumption of normality of estimates.

The precision of LOT transaction costs estimates relies on the explanatory power of the market model for stock returns. Thus, if further information sources or factors, such as returns on Fama-French (1993) small minus big (SMB) and high minus low (HML) factor portfolios have significant influence on individual stock returns, effective transaction costs may be substantially under- or overestimated.[4] Yet, since the LOT-measure proved to be a good proxy for transaction costs in modern financial markets (see Goyenko et al. 2009; Lesmond 2005), we see it as justified to use it for the historical data in our study.

As we find considerable differences in transaction costs across companies, similar to Gehrig and Fohlin (2006), we run cross-section regressions of estimated average transaction costs on a set of explanatory variables:

$$(9)\ \bar{S}_{i}=\alpha+\beta'X_{i}+\varepsilon_{i},$$

[4] We are grateful to Christian Julliard for this comment.

where X denotes a vector of explanatory variables and β a vector of corresponding coefficients. However, as we observe remarkable time variation of transaction cost estimates we also run a panel regression:

$$(10)\ S_{it} = \alpha + \beta' X_{it} + \mu_i + \lambda_t + v_{it},$$

where μ_i denotes cross-sectional individual effects, λ_t denotes year effects and v_{it} is an idiosyncratic error term.

We rely on the standard technique in the asset pricing literature, the Fama-MacBeth (1973) regression, when analyzing the impact of transaction costs on the cross-sectional variation of returns. It is based on the assumption that expected returns of stocks are fully described by the linear combination of risk premia and factor loadings for all relevant factors:

$$E\left[Z_i\right] = \boldsymbol{\lambda}' B_i,$$

whereby $Z_{it} = r_{it} - r_{ft}$ denotes excess return, $\boldsymbol{\lambda}'$ is a transposed vector of risk-premia, and B_i is a vector of factor loadings or risk characteristics of company i. Given the values of factor loadings for each stock in each period the risk premia are estimated running T cross-section regressions (one for each period) and averaging the estimates:

$$Z_{it} = \lambda_t' B_{it}$$

$$\bar{\boldsymbol{\lambda}} = \frac{1}{T}\sum_{t=1}^{T}\hat{\boldsymbol{\lambda}}_t \,.$$

The corresponding standard errors for each k-th element of the risk-premia vector are calculated from the corrected time variance of the estimated premia:

$$\operatorname{var}\left[\lambda_{kt}\right] = \frac{1}{T}\sum_{t=1}^{T}\left(\hat{\lambda}_{kt} - \bar{\lambda}_k\right)^2$$

$$\operatorname{stderr}\left[\bar{\lambda}_k\right] = \sqrt{\operatorname{var}\left[\lambda_{kt}\right]\cdot\left(1 + \frac{\bar{z}_{mt}^{\,2}}{\operatorname{var}\left[z_{mt}\right]}\right)\Big/ T},$$

where z_{mt} denotes the excess return of the market index. For the risk factor k to be priced the corresponding risk premium should be significantly different from zero.

To obtain the illiquidity risk factor loadings β_i^{IL} we calculate the sensitivity of unpredicted transaction costs to market movements using the following linear regression:

$$\tilde{s}_{it} = \omega + \beta_i^{IL}\cdot r_{mt} + u_{it}\,.$$

Unpredicted illiquidity is defined as the residual from a second order panel vector-autoregression of transaction costs and annual stock returns (without dividends):

$$X_{it} = A_0 + A_1 X_{it-1} + A_2 X_{it-2} + C z_{it-1} + U_{it},$$

where $X_{it} = \begin{pmatrix} r_{it} \\ s_{it} \end{pmatrix}$ is the vector of dependent variables and $U_{it} = \begin{pmatrix} \varepsilon_{it}^{r} \\ \tilde{s}_{it} \end{pmatrix}$ the residual vector; z_{it} denotes the fraction of the market capitalisation of the company in the aggregate market capitalisation. A_0 and C are vectors and A_1 and A_2 matrices of coefficients which are kept invariable across companies.

IV. Results

1. Estimated transaction costs

Table 2 presents the averages across all shares of the annual LOT measure of round trip transaction costs as well as the average for the full sample period 1892-1913. The transaction costs at the Berlin Stock Exchange varied between 0.66 percent (in 1906) and 1.68 percent (in 1901). The transaction costs were positive for any randomly chosen yearly period and they were always higher than the lower bound of the regulated fees. The average transaction costs amounted to 0.97 percent. Therefore, we broadly confirm the result presented by Gehrig and Fohlin (2006), who estimated an average LOT measure of 0.71 percent for the four benchmark years 1880, 1890, 1900, and 1910. Moreover, we find our transaction cost measures rather precisely estimated, with 95% confidence bounds being about ±10 basis points for most of the years. Significant transaction cost increases are revealed in 1901, 1910, 1912 and 1913 relative to the respective previous years. Significant transaction cost decreases appear in 1894, 1902 and in 1911 as compared to the respective previous years.[5]

It may come as a surprise that transaction costs were rather stable at the German stock exchange over the last century. We find that the 27 companies under study at the turn of the twentieth century had, on average, lower transaction costs than the 2nd tier German blue chips at the turn of the twenty-first century: Applying the same technique to 47 MDAX companies for 1995-2009 yields an average LOT measure of 2.6 percent.[6] Evidence for other modern stock markets supports the impression that transaction costs were quite low at the Berlin Stock Exchange a century ago. Goyenko et al. (2009) document LOT measures for the Dow Jones Industrial Average index of 0.6 percent for the mid 1970s and 1980s which is comparable to our results for the Berlin Stock Exchange index in mid 1900s. Very advantageous is the comparison to the modern emerging markets: Stocks in the Gelman-Burhop (2008) index have lower transaction

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[5] The explosive increase in the standard deviation of the transaction cost estimates in 1902 is caused by the untypical behavior of Bochumer Bergwerk stock returns.

[6] The results are available upon request from the authors.

costs according to the LOT measure than any of the 31 emerging markets in the 1990s, covered in the study of Lesmond (2005). Their average transaction costs range from 2.3 percent for Taiwan to 18 percent for Russia.

TABLE 2: ANNUAL AVERAGE OF TRANSACTION COSTS

Year	LOT	Std. error	95% confidence interval	
			lower bound	upper bound
1892	1.454	0.062	1.333	1.575
1893	1.584	0.067	1.452	1.716
1894	1.072	0.050	0.975	1.169
1895	0.925	0.046	0.835	1.015
1896	0.805	0.039	0.729	0.881
1897	0.814	0.041	0.735	0.893
1898	0.908	0.044	0.821	0.995
1899	0.878	0.045	0.789	0.967
1900	1.029	0.057	0.917	1.141
1901	1.678	0.073	1.534	1.822
1902	0.977	0.224	0.537	1.417
1903	0.848	0.040	0.769	0.927
1904	0.825	0.041	0.744	0.906
1905	0.696	0.036	0.625	0.767
1906	0.658	0.034	0.591	0.725
1907	0.775	0.042	0.693	0.857
1908	0.846	0.045	0.757	0.935
1909	0.731	0.040	0.653	0.809
1910	1.039	0.046	0.949	1.129
1911	0.713	0.036	0.642	0.784
1912	0.883	0.044	0.797	0.969
1913	1.124	0.049	1.028	1.220
Average	0.966	0.012	0.942	0.990

Own calculations based on daily returns for 27 stocks for the period 1892-1913. Expressed in percent of share price, equally weighted averages. Four outliers were dropped. Standard errors are calculated taking into account cross-correlations between stocks, see (6)-(7) . Confidence interval is given by $\bar{S}_{LOT,t} \pm 1.96 s.e.\left(\bar{S}_{LOT,t}\right)$

2. Explaining transaction costs

Transaction costs varied across companies (see Appendix 1). Whereas textile companies, such as Deutsche Jute Spinnerei und Weberei and Erdmannsdorfer Spinnerei report LOT measures of 1.1 percent and 1.7 percent – which could be found also for median modern Chinese stock (Lesmond, 2005) – the transaction costs of banking sector stocks like Deutsche Bank (0.38 percent) and Dresdner Bank (0.45 percent) is on the same level with Dow Jones companies in the 1980s and 1990s (Goyenko et al., 2009). These deviations, however, cannot be attributed fully to industrial differences: companies included into the index stemming from the banking sector have a much higher market capitalization, e.g., the value of Deutsche Bank was on average 114 times the value of Erdmannsdorfer Spinnerei.

The explanation may rather have informational origins, as market capitalization of companies usually proxies the information asymmetry (Llorente et al. 2002). The intuition here is twofold: assuming the same share of trading relative to market capitalization across companies, the volume of trade for large companies was higher, allowing for faster incorporation of new information. Furthermore, large companies had probably better newspaper and analyst coverage, providing more thorough information to investors, thus decreasing information asymmetry. Therefore, it seems that lower information asymmetry lessened the proportion of informed trading and thus provided for lower transaction costs.

We also hypothesize that liquidity provision by large stakeholders, such as custodian banks of the issuing company, could have lowered transaction costs. We introduce two proxies for liquidity provision. Our main proxy is the first-order autocorrelation of daily stock returns. If some agents act as liquidity providers one should obtain negative autocorrelation of returns as evidence of some implicit bid-ask bounce. If, on the contrary, some speculators exploit their private information and liquidity provided by noise traders, it should lead to a price under-reaction to information, which is then raised in later periods, as information becomes public, thus inducing positive autocorrelation (see Llorente et al. 2002). An alternative proxy for the liquidity provision is a dummy for the location of the company headquarters in Berlin. The rationale behind it is the following: we assume that the location of the headquarters of large stakeholders was the same as company headquarters, and they should have been in Berlin in order to be physically able to act as liquidity providers. The second assumption made here is that if it was physically possible large stakeholders would provide liquidity on Berlin Stock Exchange. Admittedly, the imposed assumptions are quite strong (for instance, a custodian bank of a non-Berlin resident company might have operated through an affiliate at the company's location), so we use this proxy only to reinforce findings obtained with our primary proxy.

Some evidence for the information asymmetry and liquidity provision hypotheses can be obtained from a simple cross section regression of average transaction costs on the log of the market capitalization and one of our proxies. One should nevertheless be cautious as

Amihud and Mendelson (1986) reveals the possibility of a reversed causal relationship: transaction costs can raise expected returns and thus reduce the market capitalization of a company. To avoid the endogeneity problem and to ensure the pre-determinacy we use the market capitalization of 1892 (which is measured at the beginning of the year) to explain company transaction costs averaged over the twenty-two year sample. With regard to autocorrelation we cannot ensure pre-determinacy, as the coefficient is measured over the same period as transaction costs.

Another issue possibly relevant for transaction costs is tick size, which was 0.05 percent of the nominal (face) value of a stock. Thus, our transaction costs measure expressed in percent of the price could be higher for stocks with lower value.

Testing both hypotheses and controlling for tick size we obtain for the twenty-six companies (standard errors of estimates are in parenthesis):[7]

$$\begin{aligned} \overline{S_i^{LOT}} &= \underset{(0.81)}{5.39} - \underset{(0.03)}{0.19} \cdot \ln\left(MC_i^{1892}\right) - \underset{(0.61)}{0.82}\,\rho_i - \underset{(0.11)}{0.10} \ln\left(P_i^{1892}\right) + \hat{e}_i, \\ R^2 &= 0.67, \qquad \hat{e}_i \approx \left(0, 0.20^2\right) \end{aligned} \quad (11)$$

The coefficient for log market capitalization is highly significant and supports the hypothesis that size reduces transaction costs: raising the market capitalization by 2.3 million Mark (what corresponds to a one unit change of log market capitalization at the mean of the variable) leads to 0.19 percentage point lower transaction costs.[8] In addition, market capitalization explains almost two thirds of the inter-company transaction cost variation in our sample.[9]

We do not, however, find support for a positive influence of market making: the coefficient of the return autocorrelation is insignificant and of the wrong sign. The reason could be that negative autocorrelation arises not only from liquidity provision but also from zero return days, as the stock reverses its return to its long-run mean on the first day of trading afterwards (see Campbell et al. 1997). Since the LOT measure is correlated with the proportion of zero return days and is measured over the same period, the opposite relationship emerges. Therefore, using the other proxy of liquidity provision would be more adequate:

[7] We exclude Bochumer Bergwerk henceforth from the analysis, as it has unusually high transaction costs due to several months long periods of non-trading.

[8] Our estimation coincides with the one reported by Gehrig and Fohlin (2006) for the year 1900 for the log of the book value and is considerably close to their results for 1890 and 1910.

[9] Using equation (11) we could address the size bias, in the previous sub-section: Since the average (log) market cap in our sample is about 1.5 units higher than the population average in 1900, the population average transaction costs can be expected to be about 29 basis points higher than reported in Table 2. Still they turn out to be lower than they are in modern emerging markets and for constituents of 2nd tier developed market indices.

$$\overline{S_i^{LOT}} = \underset{(0.79)}{4.76} - \underset{(0.03)}{0.18} \cdot \ln\left(MC_i^{1892}\right) - \underset{(0.09)}{0.16} d_i^{Berlin} - \underset{(0.11)}{0.00} \ln\left(P_i^{1892}\right) + \hat{e}_i, \qquad (12)$$
$$R^2 = 0.69, \qquad \hat{e}_i \approx \left(0, 0.19^2\right)$$

In fact, we obtain the predicted relationship – the possible liquidity provision lowers transaction costs by 16 basis points – which is significant on the 10% level.

Including the (log) price level at the beginning of the sample does not significantly help to explain the cross-section of transaction costs, neither in specification (11) nor in specification (12).

However, given that the liquidity, market capitalization, and price level substantially varies over the 22 years' period, using the first year and average values could be insufficient to uncover the hypothesized relationship. Therefore, we run regressions of type (11)-(12) in a balanced panel set-up with individual effects, after some straightforward modifications. We assume that trade volume is proportional to market capitalization not only across companies, but also across time. If higher trading volume of larger firms is associated with lower transaction costs, then we should find the same relationship in the panel regression as in the cross section regressions (11) and (12). As market capitalization is clearly non-stationary over the 22 year sample, we use the fraction of the overall market capitalization contributed by each company. Furthermore, we include the aggregate annual trade volume of all securities in Imperial Germany per year, which, under our assumption of proportionality, should capture changes in the overall market capitalization. In order to treat the non-stationarity of log price levels we take first differences and obtain returns (neglecting dividends). To address the previously outlined reverse causality problem we use lagged log price changes. Since market capitalization is reported for the beginning of each year, we do not face possible reverse causality with regard to this variable. We use also daily return autocorrelations, measured over the previous year, to ensure that they are predetermined with respect to transaction costs.

Since the Hausman test result allows using random effects, we apply this more efficient specification alternative. As transaction costs are believed to be rather persistent (Bekaert et al. 2007, Amihud 2002), we use White period standard errors, which account for clustering by stocks. Furthermore, we directly address the issue of persistence including the lagged dependent variable as a regressor in several specifications. To avoid the problem of co-linearity of the lagged dependent variable and the error term we transform all variables using forward orthogonal deviations, following Arellano and

Bover (1995) and then apply general method of moments estimation for dynamic panel data (further DPD-GMM).[10]

Table 3: Panel regression to explain the size of transaction costs

	(1) RE	(2)RE	(3)RE	(4) RE	(5) GMM	(6)GMM	(7) GMM
Constant	1.85***	1.85***	1.88***	1.74***			
	(0.20)	(0.21)	(0.21)	(0.20)			
S_{it-1}					0.43***	0.44***	0.44***
					(0.06)	(0.06)	(0.06)
$MC_{it}/\sum MC_{it}$	-4.29***	-4.32***	-4.05***	-4.27***	-1.77**	-1.89**	-1.97*
	(0.73)	(0.72)	(0.74)	(0.76)	(0.87)	(0.91)	(1.03)
ΔlnP_{it-1}	-0.44***	-0.44***	-0.44***	-0.26*	-0.28**	-0.30**	-0.13
	(0.16)	(0.16)	(0.16)	(0.15)	(0.12)	(0.12)	(0.11)
$lnTV_t$	-0.20***	-0.20***	-0.20***	-0.18***	-0.15***	-0.15***	-0.18***
	(0.05)	(0.20)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
ρ^1_{t-1}		-0.05				0.26**	
		(0.13)				(0.12)	
HQ in Berlin			-0.12*				
			(0.07)				
t_{1901}				0.22***			0.19***
				(0.08)			(0.07)
t_{1913}				0.25***			0.26***
				(0.07)			(0.06)
Time effects	N		N	N	N	N	N
Firm effects	N		N	N	Y	Y	Y
R^2	0.27	0.28	0.28	0.29	0.55	0.55	0.57

Estimates of LS individual effects models as well as DPD-GMM for the transaction costs (LOT measures) for the sample period from 1892 to 1913 for the panel of 26 companies of the type: $S_{it} = \alpha + \beta' X_{it} + \mu_i (+\lambda_t) + v_{it}$. White period standard errors are reported in parenthesis. Values marked with ***, ** and * are significant at 1%, 5% and 10% level respectively. R^2 is calculated as one minus the fraction of the residual variance to the variance of the dependent variable.

[10] The lagged LOT measure is instrumented by its second lag, all other explanatory variables are instrumented by themselves.

All columns in Table 3 support the hypothesis: relative market capitalization has a significant negative impact. According to column 1, if the share of market capitalization in the index increases by one standard deviation (5 percentage points), transaction costs decrease by 0.21 percentage points. The statistical significance of the size variable depends on the specification: it is the highest in the random effects specification (columns 1-4), but decreases to the ten percent level in the GMM specifications with crises dummies (column 7). The reason for it is rather straightforward: market capitalization is less variable over time than in cross section. In fact, the between variance of the market capitalization variable constitutes about 96 percent of its overall variance.[11]

Previous year log price changes have a negative impact on transaction costs, which is significant in all specifications but GMM with crises dummies (columns 1-6 of Table 3). This result supports the findings of Griffin et al. (2004) and Bekaert et al. (2007), who find that returns help predicting liquidity on modern financial markets.

Furthermore, the increase in transaction costs by about 20 basis points in crises years 1901 and 1913 is highly significant and helps explaining 2 percent of the illiquidity variance (see columns 4 and 7). In 1901 the bankruptcy of Leipziger Bank, one of Germany's largest banks, caused a stock exchange turmoil and possibly high degree of uncertainty about fair prices of shares which forced speculative traders to act more conservative, thus reducing liquidity. In 1913, the fear of a Balkan war led to similar effects on the financial market. These two years are known to have caused worsening information efficiency (Gelman and Burhop, 2008). Our findings are in line with results on modern markets, such as Pastor and Stambaugh (2003) revealing liquidity troughs on the US stock market in years corresponding to the LTCM crisis in 1998 and to the 1973 oil embargo.

The log of the German securities trading volume as an indicator of the overall trading activity picks up only about 1 percent of the variance of transaction costs, but is highly significant in all specifications. The lower R^2 of the random effects vs. the GMM specification suggests that about 26 percent of the variance is jointly explained by cross-sectional individual firm effects and previous year liquidity shocks.

Our primary liquidity provision proxy – previous year daily returns first-order autocorrelation – is insignificant in the random effects specification (column 2) and is of the wrong sign, as in the cross-section. However, in the GMM specification it is positive

[11] The result of a negative correlation of transaction costs with size proves to be rather stable over time: A panel regression of transaction costs of 47 MDAX stocks over 1999-2009 on the fraction of overall market capitalization yields a coefficient of -5.34, which is also significant on the 10% level and explains about 6% of the variation of transaction costs. Results are available on demand.

and significant at the 5 percent level. This discrepancy has the following intuitive explanation: whereas when estimating the model with random effects we can not control for the zero return channel of negative autocorrelation, in the GMM specification the lagged LOT measure, which is strongly dependent on the proportion of zero returns, can capture them rather well. The explanatory power of the liquidity provision seems, however, to be rather low, below one percentage point.

The impact of our alternative proxy for liquidity provision – the location of headquarters of a stock issuing company in Berlin – can be estimated only in random effects set-up (column 3), as it is time invariant. The coefficient is of the correct sign and is weakly significant. The presence of a liquidity provider on spot decreases transaction costs by 12 basis points.

Standard random effects regression residuals exhibit a strong and highly significant autocorrelation.[12] In fact, the DPD-GMM model estimates in columns 5-7 reveal highly significant autoregressive coefficients for illiquidity, supporting earlier empirical evidence of the persistence of transaction costs (Bekaert et al. 2007, Amihud 2002).

Hence, we find some support for increasing illiquidity with rising information asymmetry or a larger information-to-noise ratio. In particular, a decline in company size leads to higher illiquidity. The evidence is weaker for the relevance of corporate distress periods for illiquidity. Contemporaneous backdrops in trading activity and crises deteriorate liquidity significantly. Moreover, liquidity supply by large stakeholders seems to keep transaction costs somewhat lower.

3. Transaction costs, liquidity, and asset prices

The large dispersion of transaction costs should be reflected in asset pricing. Here we test three hypotheses of the liquidity impact.

First, as Amihud and Mendelson (1986) noted, given the set of investment opportunities, investors should avoid assets which have lower liquidity yielding same returns. This should, in the long run, decrease the price of such securities and raise their return. Therefore, in the long run one should find a positive relation between transaction costs and expected returns in the cross-section should exist.

Second, we hypothesize that noise traders (ordinary, non-informed investors) should prefer stocks with de-facto market makers, as it presumes matching of their orders on both sides of the market. Correspondingly, in the long run noise traders should avoid stocks with pronounced informed trading (proxied by positive autocorrelation), since in these stocks noise traders' orders are more likely to get matched if the information is

[12] Details are available on demand

unfavorable. Thus, there should be a discount for liquidity provision or, equivalently, a premium for informed trading on top of the transaction costs. Beyond autocorrelation of returns, we again use the Berlin location dummy as an alternative proxy for liquidity supply.

Third, in line with the Liquidity-adjusted CAPM of Acharya and Pedersen (2005), we expect a premium for liquidity risk. Acharya and Pedersen (2005) suggest three liquidity risk channels: the covariance of individual stock liquidity with market liquidity, the covariance of individual stock returns with market liquidity, and the covariance of individual stock liquidity with market returns. As the authors report strong correlation between these measures and with the level of illiquidity, we decide to use only the channel with the strongest economic effect, namely the sensitivity of individual stock illiquidity to market return (Acharya and Pedersen 2005: 398).[13]

To perform the tests we analyze excess returns, calculated as total returns (price changes plus dividends) less the risk free rate. Including dividends is important as the companies may compensate investors with higher dividends for lower prices. In line with the asset pricing literature, we use monthly return data. We run Fama-MacBeth (1973) regressions with Shanken (1992) corrections for the traditional CAPM and several multifactor extensions, including transaction costs, serial daily return autocorrelation, liquidity risk beta, and we control for size.[14]

The liquidity risk beta is calculated as a regression slope of unpredicted individual illiquidity shocks on market return shocks. Unpredicted illiquidity shocks are residuals of a panel VAR(2) of annual returns and illiquidity measures (analog to Bekaert et al., 2007). As the risk free rate proxy we use the money market rate obtained from the NBER (series: 13018). Size is the log of market capitalization and varies on an annual basis. Transaction costs are our LOT estimates, which also vary yearly. Market betas and the first-order autocorrelation coefficient of daily price percentage changes are constant for each company throughout the sample. We also include a constant as we do not demean the explanatory variables.

[13] Pastor and Stambaugh (2003) and Gernandt et al. (2011) choose another risk channel – sensitivity of individual stock returns to market liquidity shocks. Whereas Pastor and Stambaugh (2003), using, however, a substantially different liquidity specification, find liquidity risk relevant for pricing of assets on modern US markets, Gernandt et al. (2011) find no significant impact of liquidity risk on asset pricing on the Swedish stock market between 1901 and 1919.

[14] We are aware of possible within firm and within month error clustering, as outlined in Petersen (2009). Having a considerably greater time dimension than cross-section dimension makes the within month clustering the primary problem. However, as Petersen (2009) shows, Fama-MacBeth (1973) technique is able to address it adequately. Turning to within firm clustering, it could be a problem in our data at a first glance, as our right hand side variables are very persistent, since transaction costs change only yearly and betas and autocorrelation coefficient stay constant throughout the sample. But our dependent variable – return – is not persistent at all, thus yielding slightly negatively correlated residuals and thus nullifying the problem of underestimation of standard errors.

Table 4. Results of cross-sectional asset pricing regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	.0018	-.0024	.0024	.0034	.0032	-.0034
	(.0014)	(.0021)	(.0107)	(.0108)	(.0107)	(.0023)
Market beta	-.0003	.0016	.0013	-.0001	.0013	.0024
$\bar{\lambda}_{\beta}$	(.0019)	(.0020)	(.0021)	(.0022)	(.0021)	(.0022)
Transaction		.3266**	.3068*	.3055*	.3244*	.2490*
cost lagged $\bar{\lambda}'_{TC}$		(.1324)	(.1773)	(.1771)	(.1854)	(.1413)
Size $\bar{\lambda}_S$			-.0002	-.0002	-.0003	
			(.0004)	(.0004)	(.0005)	
Autocorrelation				.0105*		
$\bar{\lambda}_{\rho}$				(.0058)		
Location					.0007	
premium					(.0009)	
Illiquidity risk						-.0020***
premium $\bar{\lambda}_I$						(.0007)
Average R^2	0.07	0.12	0.16	0.20	0.20	0.17
# of stocks	26	26	26	26	26	26
# of cross-sections T	264	252	252	252	252	252

Estimates of the Fama-MacBeth (1973) regressions for the sample period from 1892 to 1913 for 26 companies. Reported coefficient values $\bar{\lambda}_k$ are averages of 264 (252 for columns (2)-(5)) regression estimates of the type: $Z_{it} = \alpha_t + \lambda_t' B_{it} + u_i$, where λ_t' denotes the transposed vector of risk premia and B_{it} denotes the vector of risk factor loadings, which serve as explanatory variables in each cross section. Standard errors are calculated as $\sqrt{\operatorname{var}\left[\lambda_{kt}\right] \cdot \left(1 + \frac{\bar{z}_{mt}^{\;2}}{\operatorname{var}\left[z_{mt}\right]}\right) \Big/ T}$, according to the Fama-MacBeth (1973) procedure with the Shanken (1992) correction, and are reported in parentheses. Values marked with ***, ** and * are significant at the 1%, 5% and 10% level respectively. Average R^2 is an arithmetic mean of R^2 for each cross-section.

As expected, the premium for transaction costs is significant and positive in all specifications (see Table 4). A one percentage point higher transaction cost (which is equivalent to moving from the most liquid stocks to the bottom of our sample, see Appendix 1) raises expected monthly return by 25 to 33 basis points or 3 percent to almost 4 percent annually, depending on the specification. This range covers the 3.5

percent annual premium obtained by Acharya and Pedersen (2005) for the US value-weighted portfolios in 1964-1999. The illiquidity premium estimates also suggest an average holding period of three to four months, which is required for returns net of transaction costs to become equal across different stocks.

Furthermore, our results based on the primary proxy yield a discount for liquidity provision, which is significant on the 10% level (see Table 4, column 4): stocks with a negative autocorrelation of daily price percentage changes have on average lower expected returns. This implies that informed trading (performed instead of liquidity provision) deteriorates the value of a company. The effect of investing in stock with the highest autocorrelation coefficient of 0.11 instead of in stock with the lowest one of -0.20 would lead to an increase in expected monthly returns by 33 basis points or about 4% annually. Use of an alternative proxy (Table 4, column 5) leads to insignificant results.

The illiquidity risk premium is, as predicted by theory, negative. The sign is due to undesired negative sensitivity of illiquidity to market movements: negative market shocks increase illiquidity and vice versa. Thus, the expected return is higher for those stocks, which liquidity deteriorates during market downturns. Our result for the premium on the individual illiquidity sensitivity to market returns is statistically highly significant, in line with results obtained by Lee (2011) for a large battery of stocks from 54 countries and the 1988-2007 sample period (Lee 2011, Tables 3-4), whereas Acharya and Pedersen (2005) for modern US data fail to find a statistically significant premium for this liquidity risk channel alone. The economic extent of the liquidity risk effect in our data is rather strong: if sensitivity to liquidity risk moves from 0 to -0.7 (about one standard deviation) the expected return increases by 14 basis points per month. The difference between maximum and minimum liquidity risk sensitivity is about four times as large and would lead to a 55 basis points increase (see Appendix 7). Annualizing the full range move in liquidity sensitivity would yield a 6.6 percent return increase, which by far exceeds the overall liquidity risk effects of 1.1 percent, reported by Acharya and Pedersen (2005: 398) for the US and 1.5 percent reported by Lee (2011) for the global market, but is comparable to the economic effect of 5.6 percent for modern emerging markets (Lee 2011: 146).

Moreover, our results reveal that the CAPM does not hold since the market risk premium is insignificant in all four specifications, which is consistent with empirical results of Gernandt et al. (2011) for the contemporary (1901-1919) Swedish stock market and with results of Acharya and Pedersen (2005) and Lee (2011) for modern US and global data. In addition, there is no significant size effect, which supports the result of Lee (2011) for modern stocks except emerging markets. Seemingly, size to a large extent proxies liquidity risk, which is much better captured here by transaction costs. However, the inclusion of the size variable increases, due to correlation with transaction costs, the standard error of the latter coefficient, which leads to some loss in significance of illiquidity.

The results of this subsection suggest that liquidity solely drives asset pricing and causes expected return variation of the magnitude of 7 percent (liquidity level plus informed trading differences) to 9.6 percent (liquidity level plus liquidity risk differences) per year. It shows that investors value liquidity even more in a more efficient call auction market design than what has been reported for continuous trading (or combined) mechanisms for modern US or global markets (Acharya and Pedersen 2005, Lee 2011).

De-facto liquidity provision seems to raise the company value by considerable amount (about 4 percent p.a.).

V. Robustness checks

The results of the previous section rely upon the assumption that the standard LOT measure is a good proxy of illiquidity. To address concerns that this is not the case, we also repeat the tests for alternative indirect measures of transaction costs, which include a multifactor extension of the LOT measure and the proportion of zero returns.

The standard estimate of LOT may be distorted by a falsely specified function of latent returns (market model). A straightforward extension is to include excess returns to the SMB portfolio as a risk factor.

To construct the SMB portfolio we form “small” and “big” portfolios, which are equally weighted portfolios of the smallest five and largest five companies respectively. Portfolios are rebalanced at the beginning of each year based on 1 January market capitalization. The SMB factor return is calculated as a return of a portfolio with a unit long position in the “small” portfolio and a unit short position in the “big” portfolio. The list of the constituent companies is in Appendix 5. In fact, the augmented market model explains non-zero returns sufficiently better than a simple market model: the average R-squared increases from 16 percent to 25 percent. The fit increases tremendously for small stocks (see Appendix 2 and 6). The transaction cost estimation is then performed maximizing

$$L\left(\tau_i^l,\tau_i^h,\beta_{M,i},\beta_{SMB,i}\sigma_i\left|r_{it},r_{mt},r_{SMB,t}\right.\right)=\prod_1\frac{1}{\sigma_i}\phi\left[\frac{r_{it}+\tau_i^l-\beta_{M,i}r_{mt}-\beta_{SMB,i}r_{SMB,t}}{\sigma_i}\right]$$
$$\times\prod_0\left[\Phi\left(\frac{\tau_i^h-\beta_{M,i}r_{mt}-\beta_{SMB,i}r_{SMB,t}}{\sigma_i}\right)-\Phi\left(\frac{\tau_i^l-\beta_{M,i}r_{mt}-\beta_{SMB,i}r_{SMB,t}}{\sigma_i}\right)\right]$$
$$\times\prod_2\frac{1}{\sigma_i}\phi\left[\frac{r_{it}+\tau_i^h-\beta_{M,i}r_{mt}-\beta_{SMB,i}r_{SMB,t}}{\sigma_i}\right]$$
$$\text{S.T. }\tau_i^l\le 0,\tau_i^h\ge 0,\beta_{M,i}\ge 0,\sigma_i\ge 0.$$

Here region 1 (indicated by subscript "1" of Π) corresponds to the negative expected latent variable when the observed one is nonzero ($\hat{r}_{it}^*<0$, or equivalently $\beta_{M,i}r_{mt}+\beta_{SMB,i}r_{SMB,t}<0$ and $r_{it}\neq 0$), region 2 – to the positive expected latent variable if the observed one is nonzero ($\beta_{M,i}r_{mt}+\beta_{SMB,i}r_{SMB,t}>0$ and $r_{it}\neq 0$), and region 0 corresponds to the observation with zero observed returns ($r_{it}=0$). Note that since we cannot impose any restrictions on sensitivity to SMB risk, we have to pre-estimate the latent variable to define the regions and to solve the likelihood iteratively.

Obtained transaction costs are generally rather similar: the correlation with the LOT measure in a panel set-up is about 97 percent, the average for the period is very close to the LOT average with 0.94 percentage points (see Appendix 3 and 4). However, the Augmented LOT measure has a higher variance in the cross-section: transaction costs for low-liquidity stocks tend to be higher and for the high-liquidity ones tend to be lower.

Qualitative findings on liquidity and transaction costs drivers remain in general the same: liquidity is lower for small and distressed stocks and declines in crises periods (Table 7). However, the effect of the liquidity provision proxy becomes statistically insignificant (even though being of the correct sign in the GMM specification).

Table 7: Panel regression to explain the size of transaction costs

	(1) RE	(2)RE	(3) RE	(4) RE	(5) GMM	(6) GMM	(7) GMM
Constant	1.90***	1.90***	1.92***	1.78***			
	(0.29)	(0.29)	(0.29)	(0.29)			
S_{it-1}					0.39***	0.40***	0.37***
					(0.04)	(0.04)	(0.04)
$MC_{it}/\Sigma MC_{it}$	-4.67***	-4.70***	-4.49***	-4.66***	-1.98**	-2.06**	-1.83*
	(0.78)	(0.71)	(0.82)	(0.78)	(0.81)	(0.84)	(0.95)
ΔlnP_{it-1}	-0.36***	-0.35**	-0.36**	-0.18	-0.23*	-0.25*	-0.10
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)
$lnTV_t$	-0.22***	-0.22***	-0.22***	-0.19***	-0.18***	-0.18***	-0.18***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
ρ^1_{t-1}		-0.18				0.16	
		(0.15)				(0.13)	
HQ in Berlin			-0.09				
			(0.10)				
t_{1901}				0.23***			0.22***
				(0.08)			(0.08)
t_{1913}				0.24***			0.28***
				(0.08)			(0.06)
Time effects	N	N	N	N	N		
Firm effects	N	N	N	N	Y		
R^2	0.27		0.28		0.76		

Estimates of LS individual effects models as well as GMM for the augmented LOT measure per year for the sample period from 1892 to 1913 for the panel of 26 companies of the type: $S_{it} = \alpha + \beta' X_{it} + \mu_i \left(+\lambda_t\right) + v_{it}$. White period standard errors are reported in parenthesis. Values marked with ***, ** and * are significant at the 1%, 5%, and 10% level respectively. R^2 is calculated as one minus the fraction of the residual variance to the variance of the dependent variable.

Asset pricing analysis with Augmented LOT supports our previous findings (see Table 8): there is a substantial liquidity premium of about the same magnitude, which is statistically significant at least on the 10 percent level if we do not include the size characteristics. The primary liquidity provision proxy tends to lead to lower expected returns, and the liquidity risk premium is of a similarly high economic and statistic significance. Thus, the choice of a possibly incomplete model for the latent returns seems not to distort our finding on the drivers of illiquidity as well as on the impact of illiquidity and market makers on the prices of assets.

Table 8: Results of asset pricing regressions

	(1)	(2)	(3)	(4)	(5)
Constant	.0018	-.0013	.0053	.0059	-.0038
	(.0014)	(.0020)	(.0106)	(.0107)	(.0024)
Market beta	-.0003	.0010	.0011	-.0002	.0034
$\bar{\lambda}_\beta$	(.0019)	(.0021)	(.0021)	(.0023)	(.0024)
Augm. LOT lagged $\bar{\lambda}'_{TC}$		0.2927** (0.1277)	0.2498 (0.1747)	0.2567 (0.1737)	.2587* (.1350)
Size $\bar{\lambda}_S$			-.0003	-.0003	
			(.0005)	(.0005)	
Autocorrelation				.0099*	
$\bar{\lambda}_\rho$				(.0060)	
Illiquidity risk					-.0018***
premium $\bar{\lambda}_I$					(.0007)
Average R^2	0.07	0.12	0.16	0.19	0.17
# of stocks	26	26	26	26	26
# of cross-sections T	264	252	252	252	252

Estimates of the Fama-MacBeth (1973) regressions for the sample period from 1892 to 1913 for 26 companies. Reported coefficient values $\bar{\lambda}_k$ are averages of 264 (252 for columns (2)-(4)) regression estimates of the type: $Z_{it} = \alpha_t + \boldsymbol{\lambda}_t' B_{it} + u_i$, where λ_t' denotes the transposed vector of risk premia and B_{it} denotes the vector of risk factor loadings, which serve as explanatory variables in each cross section. Standard errors are calculated as $\sqrt{\operatorname{var}\left[\lambda_{kt}\right]\cdot\left(1+\frac{\bar{z}_{mt}^{2}}{\operatorname{var}\left[z_{mt}\right]}\right)\Big/T}$, according to the Fama-MacBeth (1973) procedure with Shanken (1992) correction, and are reported in parenthesis. Values marked with ***, ** and * are significant at 1%, 5% and 10% level respectively. Average R^2 is an arithmetic mean of R^2 for each cross-section.

To address deeper concerns with the LOT measure, such as LOT being distorted by idiosyncratic variance we also use an illiquidity measure which does not involve statistical estimation – namely the proportion of zero returns. We calculated the proportion of days with zero returns for each security for each month, as well as annually aggregated. The proportion of zero returns is substantially correlated with our

LOT transaction costs estimates (ρ=0.68), so that zero returns alone explain a bit less than one half of the variance of transaction costs estimates (R^2=0.47).

Table 9: Panel regression to explain the proportion of zero returns

	(1) RE	(2)RE	(3) RE	(4) RE	(5) GMM	(6) GMM	(7) GMM
Constant	.27***	.26***	.27***	.26***			
	(.05)	(.05)	(.05)	(.05)			
S_{it-1}					.48***	.47***	.47***
					(.05)	(.05)	(.05)
$MC_{it}/\sum MC_{it}$	-.58***	-.54***	-.54***	-.58***	-.22	-.21	-.26*
	(.19)	(.17)	(.20)	(.19)	(.16)	(.16)	(.13)
ΔlnP_{it-1}	-.10***	-.10***	-.10***	-.08***	-.06***	-.06***	-.05***
	(.03)	(.03)	(.03)	(.03)	(.02)	(.02)	(.02)
$lnTV_t$	-.02	-.02	-.02	-.02	-.03***	-.03***	-.03***
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
ρ^1_{t-1}		-.07**				-.02	
		(.03)				(.03)	
HQ in Berlin			-.02				
			(.03)				
t_{1901}				.01			.02*
				(.02)			(.01)
t_{1913}				.04***			.03***
				(.01)			(.01)
Time effects	N	N	N	N	N	N	N
Firm effects	N	N	N	N	Y	Y	Y
R^2	0.09	0.12	0.10	0.10	0.52	0.52	0.52

Estimates of LS individual effects models as well as GMM for the transaction costs (proportion of zero returns) for the sample period from 1892 to 1913 for the panel of 26 companies of the type: $S_{it} = \alpha + \beta' X_{it} + \mu_i \left(+\lambda_t\right) + v_{it}$. White period standard errors are reported in parentheses. Values marked with ***, ** and * are significant at the 1%, 5%, and 10% level respectively. R^2 is calculated as one minus the fraction of the residual variance to the variance of the dependent variable.

Despite the less than perfect correlation of LOT with the proportion of zero returns, all main qualitative findings remain the same (see Table 9). The alternative illiquidity measure is negatively related to company size, the relationship is significant on the at least 10 percent level in five out of seven specifications. The number of days with zero returns is also significantly larger after lower price percentage changes. The negative impact of turnover on this measure of illiquidity is, however, significant only in GMM specifications.

Our main proxy for liquidity provision is insignificant in the GMM specification.

Table 10. Results of cross-sectional asset pricing regressions

	(1)	(2)	(3)	(4)	(5)
Constant	.0018	-.0021	.0098	.0101	-.0025
	(.0014)	(.0025)	(.0082)	(.0084)	(.0025)
Market beta $\bar{\lambda}_\beta$	-.0003	.0020	.0023	.0013	.0025
	(.0019)	(.0022)	(.0022)	(.0024)	(.0022)
% of zero returns p. a.		.0145** (.0065)	.0103 (.0066)	.0114* (.0069)	.0126* (.0067)
Size $\bar{\lambda}_S$			-.0006	-.0005	
			(.0004)	(.0004)	
Autocorrelation $\bar{\lambda}_\rho$				.0088 (.0062)	
Illiquidity risk premium $\bar{\lambda}_I$					-.0066* (.0039)
Average R^2	0.07	0.11	0.15	0.19	0.15
# of stocks	26	26	26	26	26
# of cross-sections T	264	252	252	252	252

Estimates of the Fama-MacBeth (1973) regressions for the sample period from 1892 to 1913 for 26 companies. Reported coefficient values $\bar{\lambda}_k$ are averages of 264 (252 for columns (2)-(5)) regression estimates of the type: $Z_{it} = \alpha_t + \lambda_t' B_{it} + u_i$, where λ_t' denotes the transposed vector of risk premia and B_{it} denotes the vector of risk factor loadings, which serve as explanatory variables in each cross section. Standard errors are calculated as $\sqrt{\mathrm{var}\left[\lambda_{kt}\right] \cdot \left(1 + \frac{\bar{z}_{mt}^2}{\mathrm{var}\left[z_{mt}\right]}\right) \Big/ T}$, according to the Fama-MacBeth (1973) procedure with the Shanken (1992) correction, and are reported in parentheses. Values marked with ***, ** and * are significant at the 1%, 5%, and 10% level respectively. Average R^2 is an arithmetic mean of R^2 for each cross-section.

As for the asset pricing, the results are also qualitatively about the same: the illiquidity premium is significant, whereas size and market risk are not (see Table 10). The premium for daily autocorrelation is positive, but slightly short of significance on the 10 percent level. The illiquidity risk premium is of the correct sign and significant at the 10% level.

VI. Conclusion

We find an early call auction market at the Berlin Stock Exchange about as liquid as modern stock exchanges with transaction costs averaging about one percent between 1892 and 1913 according to the measure proposed by Lesmond et al. (1999). Thus, transaction costs a century ago were quite similar to today's cost, possibly due to the efficient trading design. We find some robust evidence that the ratio of informed to uninformed investors drives liquidity: we find significantly higher transaction costs for cases, where this ratio is believed to be higher: for small and distressed stocks. Moreover, in line with liquidity risk literature, liquidity deteriorates in the periods of rapid and stark market downturns.

Liquidity seems to matter even more for investors on our early call auction market than nowadays, as it emerges as the main driver of asset pricing. We find economically and statistically significant liquidity level and liquidity risk premia, whereas market risk has no impact. The economic scale of liquidity risk premium exceeds by far the ones reported for modern day data. Therefore, we provide evidence of a stronger role of liquidity than the literature on the modern markets with continuous trading. Subsequent research could clarify whether this rather high relevance of liquidity is due to the market design or different liquidity preferences at the turn of the 20th century.

We find also evidence of a discount for the presence of implicit market makers, thus the presence of liquidity providers per se seems to create substantial value on top of the general liquidity level. The scale of this effect suggests that it deserves a further study.

A possible line of further research could explore whether implicit liquidity providers moderate liquidity risk and decrease expected return through this channel. In particular, one could analyze the actions of potential liquidity providers during unexpected market downturns, and their impact on asset pricing. In this context future research could make use of a larger number of measures for liquidity provision from the data available for modern stock markets.

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Appendix 1: Average transaction costs of corporations

Number	Name	Average LOT measure	Standard error	95% confidence interval	
				Lower	upper
1	AG für Anilinfabrikation	0.943	0.026	0.892	0.994
2	Allgemeine Elektricitätsgesellschaft	0.520	0.020	0.482	0.558
3	Berlin-Anhaltinische Maschinenbau	0.902	0.025	0.854	0.950
4	Bochumer Bergwerk (Lit C)	3.164	0.269	2.637	3.691
5	Bank für Handel und Industrie	0.543	0.014	0.516	0.570
6	Deutsche Bank	0.384	0.016	0.353	0.415
7	Dresdner Bank	0.446	0.015	0.417	0.475
8	Deutsche Jute Spinnerei und Weberei	1.109	0.025	1.060	1.158
9	Deutsche Spiegelglas	1.097	0.027	1.045	1.149
10	Erdmannsdorfer Spinnerei	1.689	0.035	1.621	1.757
11	Gelsenkirchener Bergwerksgesellschaft	0.427	0.021	0.387	0.467
12	Gerresheimer Glashütten	1.284	0.029	1.228	1.340
13	Hallesche Maschinenfabriken	1.112	0.029	1.054	1.170
14	Harpener Bergbau AG	0.425	0.022	0.383	0.467
15	Kattowitzer AG für Bergbau und Eisen	0.667	0.020	0.627	0.707
16	Maschinenfabrik Kappel	1.239	0.033	1.174	1.304
17	Norddeutsche Wollkämmerei	1.135	0.028	1.081	1.189
18	Oberschlesische Portland-Cement AG	1.094	0.013	1.069	1.119
19	Rheinische Stahlwerke	0.781	0.030	0.723	0.839
20	Rositzer Zuckerfabrik	1.053	0.025	1.005	1.101
21	Schaaffhausen'scher Bankverein	0.572	0.028	0.518	0.626
22	Chemische Fabrik vormals Schering	1.001	0.025	0.952	1.050
23	Schlesische Zinkhütten	0.959	0.022	0.916	1.002
24	Schlesische Leinen-Industrie	1.183	0.022	1.139	1.227
25	Schultheiss Brauerei	0.684	0.018	0.650	0.718
26	Siemens Glas-Industrie	0.776	0.018	0.740	0.812
27	Stettiner Chamottewaren	0.905	0.027	0.852	0.958

Source: Gelman and Burhop (2008), own calculations. Standard errors are calculated assuming independence of transaction cost estimates across time.

Appendix 2: Explanatory power of the market model for non-zero returns

Number	Name	Average R-squared
1	AG für Anilinfabrikation	0.092322
2	Allgemeine Elektricitätsgesellschaft	0.329350
3	Berlin-Anhaltinische Maschinenbau	0.116825
4	Bochumer Bergwerk (Lit C)	0.065104
5	Bank für Handel und Industrie	0.351353
6	Deutsche Bank	0.397444
7	Dresdner Bank	0.488626
8	Deutsche Jute Spinnerei und Weberei	0.073646
9	Deutsche Spiegelglas	0.051038
10	Erdmannsdorfer Spinnerei	0.030019
11	Gelsenkirchener Bergwerksgesellschaft	0.508946
12	Gerresheimer Glashütten	0.054653
13	Hallesche Maschinenfabriken	0.043489
14	Harpener Bergbau AG	0.462738
15	Kattowitzer AG für Bergbau und Eisen	0.192785
16	Maschinenfabrik Kappel	0.043751
17	Norddeutsche Wollkämmerei	0.057130
18	Oberschlesische Portland-Cement AG	0.096344
19	Rheinische Stahlwerke	0.264628
20	Rositzer Zuckerfabrik	0.065095
21	Schaaffhausen'scher Bankverein	0.269807
22	Chemische Fabrik vormals Schering	0.072648
23	Schlesische Zinkhütten	0.089340
24	Schlesische Leinen-Industrie	0.010887
25	Schultheiss Brauerei	0.043544
26	Siemens Glas-Industrie	0.054630
27	Stettiner Chamottewaren	0.105594
	Average	**0.164138**

Numbers in the third column represent for each stock averages of 22 R-squared values obtained from yearly market model regressions for non-zero return observations.

Appendix 3: Average alternative transaction costs

Year	ALOT	Std. error	95% confidence interval lower bound	95% confidence interval upper bound
1892	1.475	0.060	1.358	1.592
1893	1.601	0.062	1.480	1.722
1894	1.029	0.038	0.954	1.105
1895	0.903	0.031	0.842	0.964
1896	0.763	0.028	0.709	0.818
1897	0.797	0.029	0.740	0.853
1898	0.877	0.032	0.815	0.940
1899	0.834	0.035	0.765	0.903
1900	0.975	0.038	0.901	1.049
1901	1.785	0.102	1.585	1.985
1902	0.952	0.114	0.729	1.175
1903	0.841	0.028	0.787	0.896
1904	0.793	0.029	0.737	0.850
1905	0.657	0.025	0.608	0.705
1906	0.617	0.026	0.565	0.669
1907	0.702	0.029	0.645	0.760
1908	0.816	0.031	0.755	0.878
1909	0.666	0.027	0.612	0.719
1910	1.030	0.034	0.964	1.096
1911	0.689	0.026	0.638	0.741
1912	0.816	0.028	0.762	0.870
1913	1.062	0.041	0.981	1.143
Average	0.940	0.010	0.921	0.960

Own calculations based on daily returns for 27 stocks for the period 1892-1913. Expressed in percent of share price, equally weighted averages. Four outliers were dropped. Standard errors are calculated taking into account cross-correlations between stocks. Confidence interval is given by $\bar{S}_{ALOT,t} \pm 1.96 s.e.\left(\bar{S}_{ALOT,t}\right)$

Appendix 4: Average alternative transaction costs of corporations, included in the investigation

Number	Name	Average alternative transaction cost measure	Standard error	95% confidence interval	
				Lower	upper
1	AG für Anilinfabrikation	0.966	0.023	0.921	1.011
2	Allgemeine Elektricitätsgesellschaft	0.451	0.015	0.421	0.480
3	Berlin-Anhaltinische Maschinenbau	0.893	0.022	0.851	0.935
4	Bochumer Bergwerk (Lit C)	3.334	0.171	2.998	3.669
5	Bank für Handel und Industrie	0.454	0.011	0.433	0.474
6	Deutsche Bank	0.342	0.008	0.325	0.358
7	Dresdner Bank	0.361	0.009	0.343	0.378
8	Deutsche Jute Spinnerei und Weberei	1.011	0.023	0.966	1.055
9	Deutsche Spiegelglas	1.024	0.025	0.974	1.073
10	Erdmannsdorfer Spinnerei	1.524	0.033	1.460	1.588
11	Gelsenkirchener Bergwerksgesellschaft	0.315	0.013	0.290	0.341
12	Gerresheimer Glashütten	1.382	0.032	1.319	1.446
13	Hallesche Maschinenfabriken	1.126	0.024	1.078	1.174
14	Harpener Bergbau AG	0.324	0.014	0.297	0.351
15	Kattowitzer AG für Bergbau und Eisen	0.623	0.016	0.591	0.655
16	Maschinenfabrik Kappel	1.129	0.028	1.074	1.183
17	Norddeutsche Wollkämmerei	1.205	0.040	1.127	1.284
18	Oberschlesische Portland-Cement AG	0.994	0.025	0.945	1.043
19	Rheinische Stahlwerke	0.706	0.020	0.668	0.744
20	Rositzer Zuckerfabrik	1.008	0.026	0.958	1.058
21	Schaaffhausen'scher Bankverein	0.530	0.011	0.509	0.552
22	Chemische Fabrik vormals Schering	1.022	0.024	0.974	1.070
23	Schlesische Zinkhütten	0.998	0.023	0.952	1.044
24	Schlesische Leinen-Industrie	1.249	0.026	1.198	1.300
25	Schultheiss Brauerei	0.709	0.015	0.679	0.739
26	Siemens Glas-Industrie	0.783	0.017	0.749	0.817
27	Stettiner Chamottewaren	0.946	0.024	0.900	0.993

Source: Gelman and Burhop (2008), own calculations. Standard errors are calculated assuming independence of transaction cost estimates across time.

Appendix 5: Constituents of the "small" and "big" portfolios

"Small" portfolio constituents

Period	1892	1893-1894	1895-1903	1904-1907	1908-1910	1911	1912	1913
	Maschinenfabrik Kappel	Maschinenfabrik Kappel	Maschinenfabrik Kappel	Maschinenfabrik Kappel	Erdmannsdorfer Spinnerei	Erdmannsdorfer Spinnerei	Erdmannsdorfer Spinnerei	Erdmannsdorfer Spinnerei
	Rositzer Zuckerfabrik	Oberschlesische Portland-Cement AG	Oberschlesische Portland-Cement AG	Oberschlesische Portland-Cement AG	Maschinenfabrik Kappel	Maschinenfabrik Kappel	Maschinenfabrik Kappel	Maschinenfabrik Kappel
	Oberschlesische Portland-Cement AG	Deutsche Spiegelglas	Deutsche Spiegelglas	Deutsche Jute Spinnerei und Weberei	Deutsche Jute Spinnerei und Weberei	Deutsche Jute Spinnerei und Weberei	Deutsche Jute Spinnerei und Weberei	Rositzer Zuckerfabrik
	Deutsche Spiegelglas	Deutsche Jute Spinnerei und Weberei	Deutsche Jute Spinnerei und Weberei	Erdmannsdorfer Spinnerei	Oberschlesische Portland-Cement AG	Oberschlesische Portland-Cement AG	Oberschlesische Portland-Cement AG	Oberschlesische Portland-Cement AG
	Berlin-Anhaltinische Maschinenbau	Berlin-Anhaltinische Maschinenbau	Erdmannsdorfer Spinnerei	Hallesche Maschinenfabriken	Rositzer Zuckerfabrik	Hallesche Maschinenfabriken	Rositzer Zuckerfabrik	Hallesche Maschinenfabriken

"Big" portfolio constituents

Period	1892-1895	1896	1897-1905	1906-1908	1909-1910	1911-1913
	Gelsenkirchener Bergwerksgesellschaft	Harpener Bergbau AG	Allgemeine Elektricitätsgesellschaft	Gelsenkirchener Bergwerksgesellschaft	Schaaffhausen'scher Bankverein	Bank für Handel und Industrie
	Schaaffhausen'scher Bankverein	Schaaffhausen'scher Bankverein	Schaaffhausen'scher Bankverein	Schaaffhausen'scher Bankverein	Deutsche Bank	Deutsche Bank
	Bank für Handel und Industrie	Bank für Handel und Industrie	Bank für Handel und Industrie	Bank für Handel und Industrie	Dresdner Bank	Dresdner Bank
	Deutsche Bank	Deutsche Bank	Deutsche Bank	Deutsche Bank	Allgemeine Elektricitätsgesellschaft	Allgemeine Elektricitätsgesellschaft
	Dresdner Bank	Dresdner Bank	Dresdner Bank	Dresdner Bank	Gelsenkirchener Bergwerksgesellschaft	Gelsenkirchener Bergwerksgesellschaft

Appendix 6: Explanatory power of the augmented market model for non-zero returns

Number	Name	Average R-squared
1	AG für Anilinfabrikation	0.107059
2	Allgemeine Elektricitätsgesellschaft	0.348324
3	Berlin-Anhaltinische Maschinenbau	0.141805
4	Bochumer Bergwerk (Lit C)	0.074821
5	Bank für Handel und Industrie	0.369678
6	Deutsche Bank	0.411315
7	Dresdner Bank	0.508748
8	Deutsche Jute Spinnerei und Weberei	0.229672
9	Deutsche Spiegelglas	0.158531
10	Erdmannsdorfer Spinnerei	0.250039
11	Gelsenkirchener Bergwerksgesellschaft	0.520432
12	Gerresheimer Glashütten	0.065981
13	Hallesche Maschinenfabriken	0.097760
14	Harpener Bergbau AG	0.469876
15	Kattowitzer AG für Bergbau und Eisen	0.199731
16	Maschinenfabrik Kappel	0.304432
17	Norddeutsche Wollkämmerei	0.069061
18	Oberschlesische Portland-Cement AG	0.294411
19	Rheinische Stahlwerke	0.272544
20	Rositzer Zuckerfabrik	0.126384
21	Schaaffhausen'scher Bankverein	0.289018
22	Chemische Fabrik vormals Schering	0.082454
23	Schlesische Zinkhütten	0.105702
24	Schlesische Leinen-Industrie	0.016795
25	Schultheiss Brauerei	0.047726
26	Siemens Glas-Industrie	0.078423
27	Stettiner Chamottewaren	0.130465
	Average	**0.245094**

Numbers in the third column represent for each stock averages of 22 R-squared values obtained from yearly augmented market model regressions for non-zero return observations.

Appendix 7. Market and liquidity risk betas

Number	Name	Market beta	Liquidity risk beta
1	AG für Anilinfabrikation	0.91	-1.03
2	Allgemeine Elektricitätsgesellschaft	1.07	0.03
3	Berlin-Anhaltinische Maschinenbau	0.84	-0.11
5	Bank für Handel und Industrie	0.89	-0.21
6	Deutsche Bank	0.77	-0.33
7	Dresdner Bank	1.07	-0.45
8	Deutsche Jute Spinnerei und Weberei	0.73	-1.62
9	Deutsche Spiegelglas	0.67	-1.10
10	Erdmannsdorfer Spinnerei	0.67	-0.49
11	Gelsenkirchener Bergwerksgesellschaft	1.31	0.02
12	Gerresheimer Glashütten	0.43	-1.28
13	Hallesche Maschinenfabriken	0.78	-1.29
14	Harpener Bergbau AG	1.36	-0.17
15	Kattowitzer AG für Bergbau und Eisen	0.88	-0.87
16	Maschinenfabrik Kappel	0.82	-1.92
17	Norddeutsche Wollkämmerei	0.89	0.12
18	Oberschlesische Portland-Cement AG	0.95	-0.72
19	Rheinische Stahlwerke	1.35	-0.79
20	Rositzer Zuckerfabrik	0.81	-1.07
21	Schaaffhausen'scher Bankverein	0.77	-0.14
22	Chemische Fabrik vormals Schering	0.74	0.79
23	Schlesische Zinkhütten	0.63	-1.60
24	Schlesische Leinen-Industrie	0.46	-0.32
25	Schultheiss Brauerei	0.39	-1.67
26	Siemens Glas-Industrie	0.59	-0.91
27	Stettiner Chamottewaren	0.86	0.83
	Average	**0.92**	**-0.60**

Market beta is the slope of regression of monthly stock excess returns on excess market returns. Liquidity risk beta is the slope of regression of yearly individual stock illiquidity shocks on excess market returns.

Appendix 8. Trade volume of stocks in Imperial Germany, 1892-1913

Year	Trade volume in bill. mark
1892	72.07
1893	45.78
1894	73.60
1895	79.17
1896	51.40
1897	63.62
1898	59.20
1899	71.89
1900	59.77
1901	47.84
1902	50.72
1903	53.78
1904	56.34
1905	80.28
1906	63.79
1907	38.84
1908	37.80
1909	73.80
1910	84.72
1911	87.36
1912	91.61
1913	60.64
Average	**63.82**

Source: Wetzel (1996)

Appendix 9

Year	Proportion of zero returns
1892	0.253
1893	0.277
1894	0.179
1895	0.140
1896	0.143
1897	0.170
1898	0.160
1899	0.157
1900	0.164
1901	0.204
1902	0.180
1903	0.156
1904	0.136
1905	0.122
1906	0.128
1907	0.145
1908	0.167
1909	0.133
1910	0.178
1911	0.167
1912	0.182
1913	0.211
Average	0.171