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Abstract

We revisit and extend the study by Chordia et al. (2014) which documents that, in recent years, increased liquidity has significantly decreased exploitable returns of capital market anomalies in the US. Using a novel international dataset of arbitrage portfolio returns for four well-known anomalies (size, value, momentum and beta) in 21 developed stock markets and more advanced statistical methodology (quantile regressions, Markov regime-switching models, panel estimation procedures), we arrive at two important findings. First, the US evidence in the above study is not fully robust. Second, while markets worldwide are characterized by positive trends in liquidity, there is no persuasive time-series and cross-sectional evidence for a negative link between anomalies in market returns and liquidity. Thus, this proxy of arbitrage activity does not appear to be a key factor in explaining the dynamics of anomalous returns.

JEL-Codes: G140, G150.

Keywords: capital market anomalies, attenuation, liquidity, quantile regression, Markov regime-switching, panel analysis.

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1 Introduction

Recent years have been characterised by unprecedented changes in trading technology and transaction costs. While Hendershott et al. (2011) document significant advances in algorithmic trading and increased utilisation of online brokerage accounts, Chakravarty et al. (2005) and French (2008) observe drastic declines in, for example, standardised aggregate costs of trading for NYSE, NASDAQ and AMEX stocks of on average 97% from 146 basis points in 1980 to 11 basis points in 2006. Consequently, Jones (2002), Chordia et al. (2001) and Chordia et al. (2011) show that standard measures of liquidity have increased substantially because this new market environment of reduced trading frictions stimulates trading activity. For example, they present evidence that (i) the average monthly share turnover on the NYSE rose from about 5% in 1993 to about 26% in 2008 (and the average daily number of transactions increased about ninetyfold in the same period), whereas it was almost unchanged in the decades before, (ii) mainly institutional trading volume accounts for this increase and (iii) increased volume is associated with higher market quality (i.e., closer conformity to random walk behaviour).

Motivated by these observations, several studies have analysed whether increased liquidity has triggered greater anomaly-based arbitrage and thus attenuated capital market anomalies (see Mashruwala et al., 2006; Roll et al., 2007; Boehmer and Kelley, 2009; Chordia et al., 2008; Green et al., 2011; Brogaard et al., 2014; Chordia et al., 2014; Akbas et al., 2015; Cotter and McGeever, 2016).[1] Analysing this question of greater market efficiency, Chordia et al. (2014) explore how Fama and MacBeth (1973) and Brennan et al. (1998) cross-sectional coefficients (the reward for exposure to anomaly-based characteristics) and decile-based (long-short) hedge portfolio returns have changed over time. In trend regressions, they find that both attenuate towards zero. To identify the origins of this tendency, they model different proxies for arbitrage activity. Among other results, they find that the returns of a comprehensive portfolio exploiting 12 anomalies in the US market have (i) dropped by more than half after the shift to decimal pricing[2] and (ii) declined as aggregate trading activity increased.[3] Thus, in line with Fama (1965, 1970) and Schwert (2003), increased arbitrage activity appears to limit anomaly persistence. Concentrating on the firm-level

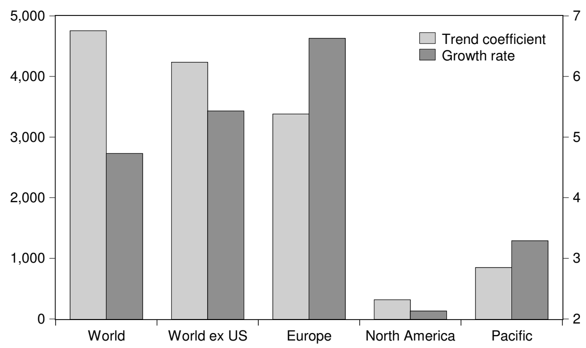
[1]Another strand of the literature attributes anomaly disappearance to data mining because anomaly discovery rates rise spuriously as researchers repeatedly investigate the same datasets (see Harvey et al., 2016).

[2]For studies analysing other effects of decimalisation, see Frazzini et al. (2012) and Israel and Moskowitz (2013).

[3]Furthermore, they can link declines to an increase in hedge funds' assets under management and short interest. In contrast to McLean and Pontiff (2016), they find mixed results on a post-publication weakening of anomalies.

regressions of the Chordia et al. (2014) study, Cotter and McGeever (2016) provide additional evidence for this argument for nine anomalies in the UK stock market.

In their conclusion, Chordia et al. (2014, p. 57) argue that "return predictability would diminish to a greater extent in countries that have experienced greater enhancements in trading technologies and larger increases in trading activity and liquidity" and that this "hypothesis awaits rigorous testing in an international context". This is where we step into the picture. We extend the hedge portfolio evidence of Chordia et al. (2014) to an international setting.[4] Figure 1, reporting trends and growth rates for the number of traded shares in different regions of the world, shows positive tendencies worldwide and that there are indeed differences in the timely development of trading activity. For example, trading activity appears to have increased more significantly in European markets than in the US.[5] Thus, we would not only expect to find evidence on vanishing anomaly returns in other markets as well but also that the magnitudes of the changes in anomaly returns are quite different across individual markets.



From July 1990 to January 2017 and similar to Chen et al. (2001), we estimate the slope coefficients of the monthly linear trend model $VO_t = \theta + \lambda t + \epsilon_t$, $t = 1, ..., T$, where "turnover by volume" (VO) is the Datastream data type (for Datastream aggregate stock market indices) measuring the total number of constituent shares traded on the relevant exchanges. That is, λ (left axis) quantifies the average rise in absolute trading numbers (in millions) when stepping forward one month in time. Furthermore, we report the average monthly percentage growth (right axis) of the trading volume.

Figure 1: Worldwide growth in trading activity

Using a novel dataset containing arbitrage portfolio returns for the four well-known anomalies of size (small firm stocks show higher returns than large firm stocks; see Banz, 1981; Keim, 1983), value (stocks with high book-to-market ratios have higher returns than stocks with low book-to-market ratios; see Basu, 1977; Fama and French, 1998; Zhang, 2005), momentum (past winners and losers tend to continue their trends in the intermediate future; see Jegadeesh and Titman, 1993;

[4] We cannot extend the Fama-MacBeth results because we do not have access to the relevant firm-level data.

[5] For an interesting comparison of other characteristics (like financial co-movement) of international stock markets, see Evans and McMillan (2009).

Dunham, 2011; Daniel and Moskowitz, 2016) and beta (low-risk stocks outperform high-risk stocks; see Frazzini and Pedersen, 2014; Auer and Schuhmacher, 2015) for a wide range of developed stock markets,[6] we start our analysis by testing whether these anomalies still exist and whether the corresponding arbitrage portfolio returns exhibit trending behaviour. We also investigate trends in market liquidity in a more detailed fashion than in our previous illustration.

After this preliminary analysis, we answer the question of whether, in our set of markets, higher liquidity tends to induce lower anomaly returns over time. In other words, we take the perspective of an investor who is interested in whether his arbitrage activity pays off continuously or whether he should expect reduced profits over time because of his own trades and the arbitrage activity of other market participants. For the US market, Chordia et al. (2014) investigate this question by performing two tests. First, they model two periods − characterised by low and high market liquidity − and perform dummy regressions to analyse whether or not there are significant differences in arbitrage portfolio returns between those periods. Specifically, they interpret the decrease in tick size (and the bid-ask spread) due to decimalisation as a proxy for a reduction in trading costs that might have led to increased arbitrage activity and test for differences in returns before and after January 2001.[7] Second, besides this indirect approach, they use share turnover as a direct measure of liquidity and arbitrage activity (see Datar et al., 1998). If higher turnover indeed favours an effective exploitation and corresponding weakening of anomalies, then regression analysis should uncover a negative link between anomalous returns and market liquidity (see Focault et al., 2013). Because the indirect approach is tailored to the US and thus not applicable to our full set of countries,[8] we follow the direct method.

Besides a country extension, we contribute to the literature by methodological innovation, which not only ensures the robustness of our new international results but also sheds light on the stability of Chordia et al. (2014)'s US results. First, because financial returns and especially anomaly returns exhibit quite large extremes (see Bali et al., 2011; Annaert et al., 2013; Daniel and Moskowitz, 2016), which can distort classic ordinary least squares (OLS) regressions (see Belsley

[6] While size and value have the longest research history, momentum and beta are typically considered to be among the most robust and persistent anomalies (see Fama and French, 2008; Baker et al., 2011). However, some studies challenge this persistence (see Bhattacharya et al., 2017).

[7] In its more than 200-year history, the NYSE has reduced tick size only a few times: from 8th to 16th in June 1997 and from 16th to penny in January 2001. Comparing 1993 to 2000 with 2001 to 2008, Chordia et al. (2011) document a 75% decrease in the average effective daily spread for large trades. Furthermore, French (2008) shows that, despite increased transaction volumes, the total amount investors pay to trade declined by more than 35%, from 50.7 billion dollars in 2000 to 32.1 billion in 2006.

[8] There is, however, some evidence that, for developed stock markets other than the US, especially bid-ask spreads tend to be lower after the millennium (see Corwin and Schultz, 2012; Cunzhi and Hongwei, 2012) and approach levels comparable to the US (see Credit Suisse, 2011).

et al., 1980), we supplement our simple regression analysis with several quantile regression (QR) settings. They are more robust to outliers, avoid assumptions about the parametric distribution of the error process and provide a richer characterisation of the data, allowing us to consider the impact of liquidity on the entire distribution of anomaly returns, not merely its conditional mean (see Koenker and Hallock, 2001). Second, empirical research has shown that many financial time series have a Markov regime-switching (MRS) property (see Cecchetti et al., 1990; Smith, 2002; Dueker and Neely, 2007; Zou and Chen, 2013). In other words, there is often a finite number of unobservable regimes (or states) that govern the stochastic properties of the series at any given time. Specifically, the marginal distribution of the series at time t is solely determined by the regime operating at time t, while the dynamics of the regime-switching is determined by a Markov process. Thus, a MRS setting is a particularly interesting alternative way to analyse the relation between anomaly returns and liquidity. In our application, we (i) estimate simple two-state models to identify potential low- and high-return regimes and (ii) regress estimated regime probabilities on liquidity. Thus, to support Chordia et al. (2014) based on this framework, high (low) probabilities for the low-return regime should correspond to high (low) liquidity values. Finally, while these techniques exclusively focus on the time-series dimension, i.e., investigate each market separately, we also perform panel regressions additionally considering cross-sectional information (see Flaig and Rottmann, 2013; Assefa et al., 2017). That is, we estimate various random- and fixed-effects models of the interaction of returns and liquidity.

The remainder of our article is organised as follows. Section 2 describes the return and liquidity dataset and presents our preliminary analysis on anomaly significance and trends in arbitrage portfolio returns and liquidity. Section 3 presents our main results, i.e., simple, quantile, Markov regime-switching and panel regressions analysing the link between anomaly returns and liquidity. It also summarises the outcomes of some additional robustness checks with respect to our dataset and model specifications. Section 4 concludes and outlines directions for future research.

2 Data and preliminary results

2.1 AQR dataset

Our empirical analysis is based on AQR's arbitrage portfolio dataset originally constructed by Frazzini and Pedersen (2014) and now regularly updated by AQR.[9] From July 1990 to January

[9]The dataset and a detailed description of the portfolio construction are available under www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly.

2017 it covers the monthly returns of long-short arbitrage portfolios exploiting four capital market anomalies (size, value, momentum, beta) in 21 stock markets (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States).[10] The portfolio construction follows Fama and French (1992, 1993, 1996), Asness and Frazzini (2013), Asness et al. (2014) and Frazzini and Pedersen (2014). That is, for size and value, six market capitalisation-weighted portfolios are formed based on one size and two book-to-market breakpoints.[11] The size (value) arbitrage portfolio return is then obtained as the average of the three small-sized portfolios (two high book-to-market portfolios with small and big size) minus the average of the three big-sized portfolios (two low book-to-market portfolios with small and big size). The momentum portfolio is formed similar to the value portfolio with the difference that momentum replaces the value characteristic. Finally, the beta portfolio is long in low-beta stocks and short in high-beta stocks according to a median breakpoint and with a risk-oriented stock weighting. All portfolios are based on common stocks covered by the union of the CRSP tape and the Compustat/XpressFeed Global database (supplemented by Moody's data). Portfolio returns are in US dollars and do not include any currency hedging. One set of four anomaly portfolios is formed for each country, and five aggregates (world, world excluding the US, Europe, North America, Pacific; see Table A1 of the appendix) are computed by weighting each country's portfolio by the country's total lagged market capitalisation. Thus, for each anomaly, we have 26 different arbitrage portfolios.

Tables 1 and 2 report some descriptive statistics (minimum, maximum, mean, standard deviation, skewness and kurtosis) of the percentage portfolio returns. Furthermore, they present the results of two statistical tests. First, we report the portfolios' approximate risk-adjusted performance, i.e., the ratio of the mean to the standard deviation of returns, and use the Bailey and López de Prado (2012) test, which a non-normal generalisation of the Lo (2002) procedure, to evaluate its statistical significance. In other words, we test whether the anomalies documented in the previous literature still exist. Under the null hypothesis of a risk-adjusted performance of zero,

[10]The dataset also includes returns for Greece, Israel and Portugal. However, because of insufficient return data, we have to exclude these countries from our analysis.

[11]In the case of size, we have a median breakpoint for US data and a 80th percentile breakpoint for international securities. For value, the 70th and 30th percentiles are used regardless of the market. For details on this choice, see Schmidt et al. (2017).

the test statistic

$$Z = \frac{\hat{\rho}}{\sqrt{\frac{1-\hat{\upsilon}\hat{\rho}+\frac{\hat{\kappa}-1}{4}\hat{\rho}^2}{T-1}}}, \tag{1}$$

where T is the sample size and $\hat{\rho}$, $\hat{\upsilon}$ and $\hat{\kappa}$ are the estimated reward-to-risk ratio, return skewness and kurtosis, respectively, is normally distributed even if the returns are not. If we rejected this hypothesis, we could conclude that a statistically large anomaly exists.

Second, we test the null hypothesis that anomaly returns have not attenuated against the alternative of attenuation. To this end, we follow Chordia et al. (2014) by fitting the exponential decay model

$$R_t = \chi exp(\eta t + \epsilon_t), \tag{2}$$

where $R_t = 1 + r_t$ is one plus the return of an arbitrage portfolio in a given month and t is a time index. We scale the time index to be between -1 and $+1$ such that the mean of the time variable is zero.[12] The model is estimated by OLS in log-linear form. Sign and significance of its slope parameter η can be used to evaluate trending behaviour in anomaly returns.[13]

Starting with a look at the descriptive measures and performance tests for the size effect, we find that monthly mean returns are low and range from -0.47% (Germany) to 0.30% (Austria). The reward-to-risk ratio is positive in 11 cases (0 being statistically significant) and negative in 21 cases (1 being statistically significant). Thus, in line with earlier evidence that the size effect is not robust, waning or already dead (see McDonald and Miller, 1989; van Dijk, 2011), we find no support for an international size effect. In comparison, the value effect is more pronounced with means between -0.15% (Denmark) and 0.98% (Austria). The reward-to-risk ratio, which is positive for 25 (15 significant) portfolios and negative for only 1 (0 significant) portfolio, confirms the larger effect strength for almost all markets. Turning to the momentum and beta effects, which have received significant attention in the recent literature (see Menkhoff et al., 2012; Asness et al., 2013; Fuertes et al., 2015), we document the strongest portfolio performance. For example, at the global scale, the mean of the momentum (beta) portfolio is 0.66% (0.82%) accompanied by a risk-adjusted performance of 0.17 (0.29), whereas the size (value) portfolio only shows 0.06% (0.36%) and 0.03 (0.17). As far as the momentum effect is concerned, we observe that it is characterised by the largest monthly losses of up to -56.77%, which are related to a momentum crash (reversal)

[12]The scaled time index t_s can be obtained from the original index $t_o = 1, ..., T$ via $t_s = (b-a)[t_o - \min t_o]/[\max t_o - \min t_o] + a$, where $a = -1$ and $b = +1$.

[13]Note that using a linear model (as in Olson, 2004) leads to largely similar results.

in year 2009 of the financial crisis (see Daniel and Moskowitz, 2016) and cause larger deviations from normality (i.e., higher skewness and kurtosis) than we obtain for the other effects. For both momentum and beta effect, all 26 reward-to-risk ratios are positive with 21 and 24 instances of significance, respectively. For Canada (Japan), we find the highest (lowest) average momentum and beta returns of 1.65% and 1.94% (0.11% and 0.22%), respectively.

We now turn to our results on potential anomaly attenuation. As far as US returns are concerned, we document a positive trend coefficient for size and negative ones for value, momentum and beta. These trend directions may be related to a recovery of the size effect from ceasing investor attention (which was strongest after its publication; see Dimson et al., 2002) and an increase of arbitrage activity for the other effects because of a more intensive coverage in recent investment research publications. However, all estimated coefficients turn out to be statistically insignificant at conventional levels of 1% and 5%.[14] Thus, our findings are in contrast to Chordia et al. (2014) who document significant attenuation for size, value and momentum in the US market.[15] Looking at our entire set of international portfolios, we count 21 (5), 8 (18), 16 (10) and 18 (8) accentuations (attenuations) for size, value, momentum and beta portfolios, respectively. With only a few significantly negative cases, we cannot declare a general attenuation tendency.

2.2 Liquidity data

The problem with measuring liquidity is that there is no single unambiguous, theoretically correct or universally accepted definition of liquidity (see Kyle, 1985; Baker, 1996). Sarr and Lybek (2002) argue that a liquid market has five characteristics: tightness (low transaction costs), immediacy (high speed of order execution), depth (existence of abundant orders), breadth (orders large in volume with minimal impact on price) and resiliency (new orders flow quickly to correct order imbalances). While all these terms reflect important dimensions of the extent to which an asset quickly and without significant costs can be transformed into legal tender, not all of them are easy to measure. As a result, most empirical studies concentrate on the issues of tightness (mostly

[14] There are two ways to explain such persistence of the beta anomaly. First, institutional investors who are largely responsible for the effect (because of their mandate to beat fixed benchmarks; see Baker et al., 2011) have become more numerous in recent years. French (2008) shows that, in the US market, the percentage of private investors declined from 48% to 22% from 1980 to 2007, while the share of open investment funds increased from 5% to 32%. Second, bonuses for investment bankers also lead to increased demand for high risk stocks and thus additionally fuel the anomaly (see Baker and Haugen, 2012).

[15] Unfortunately, we cannot directly compare our UK results to the study of Cotter and McGeever (2016) because they do not perform trend regressions. However, their descriptive subsample comparison of quintile hedge portfolio returns shows declines for size, value and momentum. A switch to decile portfolios changes their size results to an increase, whereas low-risk anomalies have not been analysed. Our Tables 1 and 2 support these findings.

	Size								Value							
	Min	Max	Mean	StdDev	Skew	Kurt	Exists?	Trend?	Min	Max	Mean	StdDev	Skew	Kurt	Exists?	Trend?
Australia	−12.95	9.64	−0.23	3.40	−0.04	0.66	−0.07	−0.22	−9.61	9.02	0.90	2.96	−0.04	0.59	0.30^a	−0.09
Austria	−13.26	16.18	0.30	4.06	0.09	0.99	0.07^c	0.83^b	−13.91	16.13	0.98	4.47	0.26	1.22	0.22^a	−0.10
Belgium	−19.29	10.59	−0.11	3.31	−0.54	3.63	−0.03	0.25	−12.18	19.44	0.53	4.07	0.29	1.50	0.13^a	−0.47
Canada	−9.39	12.36	−0.03	2.73	0.03	2.00	−0.01	0.01	−18.49	21.94	0.55	3.96	0.01	5.06	0.14^a	0.26
Denmark	−12.34	13.82	−0.23	3.44	0.02	1.33	−0.07	0.21	−13.26	14.91	−0.15	4.30	−0.13	0.39	−0.03	−0.15
Finland	−13.55	13.98	0.00	4.50	−0.19	0.87	0.00	0.33	−19.26	31.65	0.59	6.70	0.65	3.11	0.09^c	−0.02
France	−10.24	9.46	0.07	2.98	0.23	0.66	0.02	0.25	−24.11	14.46	0.35	3.48	−0.73	8.72	0.10^b	0.00
Germany	−12.92	8.73	−0.47	3.31	−0.35	1.37	-0.14^a	0.46^c	−15.66	23.44	0.63	3.60	0.96	8.64	0.18^a	−0.15
Hong Kong	−15.79	17.38	0.13	4.80	0.48	2.07	0.03	0.22	−18.59	14.82	0.48	4.15	0.03	2.23	0.12^b	0.34
Ireland	−47.17	22.30	0.01	6.57	−1.08	8.03	0.00	−0.68	−29.18	48.25	0.32	7.53	0.65	5.94	0.04	-1.11^c
Italy	−9.19	13.73	−0.07	3.37	0.39	1.46	−0.02	0.17	−11.34	12.57	0.26	3.87	0.00	0.58	0.07	0.06
Japan	−9.91	15.65	0.05	2.90	0.30	2.99	0.02	0.37^c	−9.33	8.07	0.51	2.57	0.01	1.13	0.20^a	−0.11
Netherlands	−8.11	9.90	−0.07	3.06	0.05	0.29	−0.02	0.32	−16.42	13.94	0.52	4.28	−0.08	1.09	0.12^b	0.20
New Zealand	−14.43	16.96	0.09	3.93	0.51	3.63	0.02	−0.21	−19.09	28.26	0.08	5.16	0.43	4.40	0.01	0.03
Norway	−11.32	13.66	−0.01	3.68	0.00	0.86	0.00	−0.09	−18.37	17.24	0.24	5.18	0.00	1.08	0.05	0.06
Singapore	−15.98	27.55	−0.31	4.14	1.33	8.51	−0.08	−0.20	−15.20	25.00	0.62	3.85	0.75	7.31	0.16^a	0.18
Spain	−11.18	10.05	−0.20	3.33	−0.12	0.28	−0.06	0.00	−12.92	15.07	0.23	3.98	0.05	1.13	0.06	-0.84^b
Sweden	−15.99	10.90	−0.09	3.50	−0.26	1.87	−0.03	0.09	−23.63	23.39	0.37	5.47	0.16	3.33	0.07	−0.23
Switzerland	−11.68	15.01	0.08	3.00	0.09	2.49	0.03	0.78^a	−8.18	15.49	0.26	3.50	0.68	1.43	0.07^c	-0.52^c
United Kingdom	−13.75	14.66	0.06	3.48	0.21	1.83	0.02	0.15	−12.54	16.52	0.45	3.11	0.33	3.82	0.14^a	−0.18
United States	−7.73	12.42	0.17	2.76	0.72	2.13	0.06	0.07	−8.68	12.85	0.20	2.71	0.34	2.25	0.07^c	−0.22
World	−4.55	6.81	0.06	1.93	0.47	1.14	0.03	0.14	−8.30	12.00	0.36	2.12	0.59	4.82	0.17^a	−0.19
World ex US	−5.33	6.71	−0.03	1.96	0.13	0.71	−0.02	0.22	−8.14	11.03	0.50	1.99	0.54	5.85	0.25^a	−0.15
Europe	−5.80	7.67	−0.04	2.09	0.14	0.60	−0.02	0.23	−11.13	14.12	0.40	2.33	0.82	7.23	0.17^a	−0.18
North America	−7.72	12.29	0.15	2.69	0.72	2.24	0.06	0.06	−8.87	13.23	0.23	2.69	0.33	2.51	0.08^c	−0.19
Pacific	−8.80	11.29	−0.01	2.54	0.23	2.16	0.00	0.23	−9.10	7.12	0.56	2.20	−0.22	1.51	0.26^a	−0.05
pos. (sign.)							11 (0)	21 (2)							25 (15)	8 (0)
neg. (sign.)							15 (1)	5 (0)							1 (0)	18 (1)

For the period from July 1990 to January 2017, this table presents the minimum, maximum, mean, standard deviation, skewness and kurtosis of the monthly percentage returns of AQR's arbitrage portfolios exploiting size and value effects in 21 international stock markets (and five value-weighted aggregates). Furthermore, we perform two tests. First, we report the portfolios' approximate risk-adjusted performance via the ratio of the mean to the standard deviation of returns and test its statistical significance based on test (1). This way we can judge whether or not a market anomaly actually exists. Second, we estimate the log-version of the decay model (2), report its slope coefficient (multiplied by 100; similar to the visualisation adjustment of Campbell et al., 2001) and test its significance based on a classic t-test. This allows us to detect trends in returns. a, b and c imply significance at the 1%, 5% and 10% level, respectively. Finally, for a better overview, we count the number of positive and negative performance and trend measures across all portfolios (countries and aggregates) and the number of significant outcomes (at the 5% level).

Table 1: Descriptive statistics – Size and value

	Momentum								Beta							
	Min	Max	Mean	StdDev	Skew	Kurt	Exists?	Trend?	Min	Max	Mean	StdDev	Skew	Kurt	Exists?	Trend?
Australia	−17.10	14.46	1.55	4.25	−0.44	2.00	0.37^a	0.07	−9.95	23.13	1.86	4.80	1.21	3.44	0.39^a	-1.14^a
Austria	−39.32	21.08	0.53	5.39	−1.68	11.52	0.10^c	0.13	−19.60	26.23	0.72	6.85	0.62	1.74	0.11^b	1.28^b
Belgium	−30.90	19.17	0.87	4.97	−1.09	7.04	0.17^a	0.02	−18.72	23.16	0.70	4.72	0.20	2.27	0.15^a	−0.24
Canada	−27.04	22.48	1.65	5.71	−0.78	3.38	0.29^a	−0.44	−13.72	18.50	1.94	4.67	0.20	1.73	0.42^a	1.28^a
Denmark	−22.03	13.10	1.19	4.54	−0.95	3.22	0.26^a	0.41	−20.65	29.01	0.77	5.19	0.47	3.79	0.15^a	0.15
Finland	−34.09	26.17	1.12	6.47	−0.35	3.62	0.17^a	−0.18	−20.45	31.39	1.07	6.59	0.30	2.54	0.16^a	0.08
France	−26.61	20.69	0.80	4.80	−0.62	5.97	0.17^a	0.02	−16.81	24.37	1.24	4.90	0.28	1.79	0.25^a	0.63^c
Germany	−23.23	26.95	1.25	5.44	−0.39	6.52	0.23^a	0.61	−21.49	17.19	0.91	5.16	−0.15	1.65	0.18^a	0.71^c
Hong Kong	−27.91	21.79	0.62	5.62	−1.23	4.99	0.11^b	−0.01	−31.01	31.39	1.89	6.87	0.60	5.11	0.27^a	0.83
Ireland	−56.77	34.02	1.11	9.34	−0.94	7.04	0.12^b	−0.24	−43.83	49.03	0.85	10.58	0.06	2.59	0.08^c	1.25
Italy	−21.16	20.08	0.74	5.14	−0.28	2.16	0.14^a	0.06	−14.31	21.97	0.61	4.06	0.55	3.06	0.15^a	−0.20
Japan	−24.84	13.60	0.11	4.65	−0.74	3.67	0.02	0.20	−11.62	15.07	0.22	4.23	0.15	0.71	0.05	0.89^b
Netherlands	−29.52	19.04	0.49	5.35	−0.74	4.29	0.09^c	−0.50	−22.04	21.92	1.00	4.69	−0.25	3.04	0.21^a	0.36
New Zealand	−14.45	13.96	1.10	4.03	−0.18	1.26	0.27^a	−0.10	−17.60	25.82	1.42	5.94	0.86	2.43	0.24^a	0.03
Norway	−22.26	19.75	1.18	6.12	−0.22	0.98	0.19^a	0.93^c	−18.70	22.47	1.25	6.08	0.27	1.30	0.21^a	1.19^b
Singapore	−46.72	12.97	0.36	5.59	−3.11	19.84	0.06	0.66	−13.43	29.95	1.20	4.12	1.25	9.66	0.29^a	0.26
Spain	−28.14	13.91	0.63	5.12	−0.83	3.61	0.12^b	0.57	−20.76	21.47	0.59	4.85	0.08	2.63	0.12^b	−0.45
Sweden	−27.09	20.71	0.71	6.22	−0.53	3.40	0.11^b	0.98^c	−20.70	23.39	1.28	5.66	−0.26	2.90	0.23^a	0.05
Switzerland	−25.02	22.63	0.88	4.75	−0.61	5.63	0.19^a	0.05	−15.99	36.32	0.71	5.08	1.55	9.32	0.14^a	−0.46
United Kingdom	−34.21	13.49	1.12	4.72	−1.76	10.45	0.24^a	−0.10	−19.97	16.44	0.54	4.71	−0.54	2.63	0.11^b	−0.29
United States	−34.58	17.03	0.59	4.79	−1.79	12.02	0.12^b	-0.76^c	−15.13	13.06	0.80	3.79	−0.55	2.71	0.21^a	−0.29
World	−28.28	14.17	0.66	3.96	−1.64	10.44	0.17^a	−0.17	−10.10	10.71	0.82	2.86	−0.34	1.90	0.29^a	0.22
Global ex US	−23.25	11.12	0.74	3.65	−1.18	6.68	0.20^a	0.32	−8.00	11.59	0.85	2.79	0.13	0.98	0.30^a	0.63^a
Europe	−26.76	14.94	0.98	4.05	−1.30	8.51	0.24^a	0.11	−11.72	14.33	0.85	3.40	−0.08	1.81	0.25^a	0.11
North America	−33.94	16.66	0.66	4.74	−1.75	11.71	0.14^b	-0.71^c	−14.35	12.74	0.89	3.69	−0.55	2.73	0.24^a	−0.18
Pacific	−18.72	11.73	0.35	4.05	−1.02	3.73	0.09^c	0.43	−9.17	14.82	0.65	3.32	0.15	1.37	0.19^a	1.10^a
pos. (sign.)							26 (21)	16 (0)							26 (24)	18 (6)
neg. (sign.)							0 (0)	10 (0)							0 (0)	8 (1)

For the period from July 1990 to January 2017, this table presents the minimum, maximum, mean, standard deviation, skewness and kurtosis of the monthly percentage returns of AQR's arbitrage portfolios exploiting momentum and beta effects in 21 international stock markets (and five value-weighted aggregates). Furthermore, we perform two tests. First, we report the portfolios' approximate risk-adjusted performance via the ratio of the mean to the standard deviation of returns and test its statistical significance based on test (1). This way we can judge whether or not a market anomaly actually exists. Second, we estimate the log-version of the decay model (2), report its slope coefficient (multiplied by 100; similar to the visualisation adjustment of Campbell et al., 2001) and test its significance based on a classic t-test. This allows us to detect trends in returns. a, b and c imply significance at the 1%, 5% and 10% level, respectively. Finally, for a better overview, we count the number of positive and negative performance and trend measures across all portfolios (countries and aggregates) and the number of significant outcomes (at the 5% level).

Table 2: Descriptive statistics – Momentum and beta

measured by the bid-ask spread) and depth/breadth (i.e., trading activity; mainly captured by aggregate trading volume) (see Gabrielsen et al., 2011).[16]

	Mean	StdDev	Trend?
Australia	4.00	0.38	0.48^a
Austria	3.53	0.42	-0.21^a
Belgium	3.14	0.55	0.72^a
Canada	3.83	0.40	0.40^a
Denmark	3.46	1.09	1.11^a
Finland	3.70	1.33	1.59^a
France	3.94	0.64	0.50^a
Germany	5.14	0.36	0.14^a
Hong Kong	3.57	0.30	0.06^b
Ireland	3.74	0.42	-0.12^a
Italy	4.19	1.02	1.30^a
Japan	3.97	0.67	0.99^a
Netherlands	4.37	0.39	0.19^a
New Zealand	3.38	0.38	0.39^a
Norway	4.08	0.48	0.21^a
Singapore	3.38	0.52	0.45^a
Spain	4.18	0.50	0.54^a
Sweden	4.17	0.56	0.48^a
Switzerland	3.97	0.35	0.20^a
United Kingdom	4.15	0.44	0.12^a
United States	4.76	0.48	0.67^a
World	4.38	0.40	0.49^a
World ex US	4.01	0.34	0.26^a
Europe	4.14	0.29	-0.06^b
North America	4.72	0.46	0.64^a
Pacific	3.92	0.60	0.70^a
pos. (sign.)			23 (23)
neg. (sign.)			3 (3)

For the period from July 1990 to January 2017 and our 21 international stock markets and five aggregates, this table reports the means and standard deviations of the monthly logarithmic share turnover of Datastream total market indices. Share turnover is measured as the ratio of the Datastream data type "turnover by value" (VA) (for Germany "alt. exch. value" (VY)) and "market value" (MV). Furthermore, similar to Tables 1 and 2, we estimate a decay model (which now has to be linear because of the definition of the liquidity variable) and count the number of (significantly) positive and negative trends. a, b and c imply significance at the 1%, 5% and 10% level, respectively.

Table 3: Descriptive statistics – Market liquidity

Our analysis follows Subrahmanyam (2005) and Daouk et al. (2006) by measuring liquidity via share turnover, i.e., the ratio of trading volume to market capitalisation (both denoted in local currencies).[17] We obtain monthly data on the volume of trade and market capitalisation from Datastream via the data types "turnover by value" (VA) and "market value" (MV) for Datastream total market indices, where the former gives the number of shares traded (separately reported by "turnover by volume" (VO)) multiplied by the closing price for each stock.[18] In line

[16]More complex volume-based measures are, for example, the ones proposed by Martin (1975), Hui and Huebel (1984) and Amihud (2002). More sophisticated transaction cost metrics are developed in Roll (1984), Stoll (1989) and Huang and Stoll (1997). Lam and Tam (2011) implement some widely used liquidity proxies.

[17]Concentrating on this volume-based measure instead of the bid-ask spread is typically justified by the fact that low transaction costs increase the number of active participants and trades in a market and thus higher volumes also capture a regime of lower transaction costs (see Sarr and Lybek, 2002).

[18]In the case of Germany, the alternative data types "alt. exch. value" (VY) and "alt. exch. volume" (VZ) have to be considered because of changes in measurement introduced by Datastream in 2000.

with the literature standard, we use the natural logarithm of share turnover in our regressions. This is because, in addition to our robust econometric procedures, it helps to weaken the distorting effects of outliers (occurring because of small denominators in some markets).

Table 3 presents the means and standard deviations of the logarithmic share turnover for each of our markets and aggregates. Furthermore, it is supplemented by the slope coefficients of trend regressions performed similar to Section 2.1. Germany and the US are the most liquid stock markets on average, whereas New Zealand and Belgium are rather illiquid in comparison. Volatility in liquidity is quite different across markets with Finland and Denmark (Switzerland and Hong Kong) showing the most (least) significant fluctuations.

Turning to the estimated trend coefficients, we observe that 23 (3) are positive (negative) and all are highly significant. That is, most markets exhibit significant growth in liquidity. On an aggregate level, we find the most impressive upward trend in the Asia Pacific region.[19] Based on the international hypothesis of Chordia et al. (2014) this observation should be accompanied by strong anomaly attenuation. However, our results of Section 2.1 suggest otherwise.

3 Empirical analysis

While our preliminary calculations have looked at returns and liquidity separately, we now seek to establish a direct link between the variables. In short, we go beyond a simple trend analysis and investigate whether the returns of our arbitrage portfolios are significantly lower (higher) when liquidity is high (low).

3.1 Time-series regressions

3.1.1 OLS and QR regressions

To answer this question, we follow Chordia et al. (2014) by assuming that liquidity is the only variable influencing anomaly returns. Specifically, we use the parameters of the regression model

$$r_t = \delta + \gamma l_t + \epsilon_t, \tag{3}$$

where r_t is the period t return of an arbitrage portfolio, l_t is our (logarithmic) measure of liquidity and ϵ_t is a classic error term. If higher liquidity leads to a reduction of arbitrage profits, our

[19] Note that differences between Figure 1 and Table 3 are related to different measures of liquidity (number of trades vs. scaled value of trades).

estimation results will show a significantly negative γ.[20] Note that, for all models of our study, we estimate settings with and without detrended liquidity (main text vs. Tables A3 to A6 of the appendix) and find that the choice of setting does not influence our global conclusions.[21]

Standard OLS regression summarises the average relationship between r and l based on the conditional mean function $E(r|l)$. This allows only a partial analysis of the link between the variables, as we might be interested in describing it at different points in the conditional distribution of r. Quantile regression, associated with Koenker and Bassett (1978), provides that capacity.

Analogous to the conditional mean function of OLS regression, we may consider the relationship between r and l using the conditional quantile function $Q_q(r|l)$, which expresses the $q \in (0,1)$ quantile of the conditional anomaly return distribution as a function of liquidity. $q = 0.5$ is the median. Quantile regression minimizes a sum that, for $q \neq 0.5$, gives asymmetric penalties $(1-q)|e_i|$ for overprediction and $q|e_i|$ for underprediction, where the prediction error is given by $e_i = r_t - \hat{\delta} - \hat{\gamma} l_t$. Specifically, it minimizes the objective function $\Sigma_{t:e_i \geq 0}^{T} q|e_i| + \Sigma_{t:e_i<0}^{T}(1-q)|e_i|$. This nondifferentiable function is minimized via the simplex method, which is guaranteed to yield a solution in a finite number of iterations. Although the estimator is proven to be asymptotically normal with an analytical covariance matrix, the estimation of the latter requires some subjective decisions. Therefore, bootstrap standard errors are often used in place of analytic standard errors (see Buchinsky, 1998).

Tables 4 and 5 present the OLS and QR estimates (with $q \in \{0.25, 0.50, 0, 75\}$) of the slope parameter γ and the corresponding standard errors. The latter are obtained following Newey and West (1987) for OLS and Gould (1992) for QR. Starting with a discussion of our US results, we find a positive OLS slope for size and negative ones for the other anomalies. However, these links between returns and liquidity are significant only for momentum and beta. In comparison, Chordia et al. (2014) report a significantly negative relationship for size, value and momentum.[22] However, when we switch to the robust QR, the results are quite different. For example, for $q = 0.50$, the slope coefficient for the momentum portfolio decreases drastically (in absolute terms) and thus

[20] Such an outcome would also be in line with Chen et al. (2001) showing, in an analysis of nine international stock market indices, that trading volume can have significant impact on stock returns.

[21] Using trending variables in regressions can cause spurious results (see Noriega and Ventosa-Santaulària, 2007). Finding similar results for detrended liquidity variables, whose stationarity can be verified (for each country) by the augmented test of Dickey and Fuller (1979), shows that spurious regression problems are negligible in our application.

[22] While we detect significance for the portfolio related to the low-risk anomaly, Chordia et al. (2014) report insignificance. This may be traced back to the facts that we use a different risk measure (beta vs. idiosyncratic volatility) and a more up-to-date sample.

turns insignificant. In other words, outliers have a crucial influence on the standard OLS results for the momentum returns.

A look across the OLS results for all individual markets and aggregates reveals that, for size, value, momentum and beta, we only have 1, 10, 11 and 8 negative slopes with 0, 0, 5 and 3 instances of significance, respectively. Thus, the evidence on anomaly attenuation because of increased liquidity is rather weak. Even though we have more cases of significant attenuation for QR, we still cannot argue that anomaly attenuation is a global phenomenon. We observe 11, 13, 17 and 12 (2, 0, 6 and 4 significant) negative slopes for $q = 0.25$, 7, 12, 14 and 7 (1, 1, 1 and 2 significant) for $q = 0.50$ and 7, 10, 4 and 6 (0, 3, 0 and 3) for $q = 0.75$. Combined with the finding of similar numbers for positive slopes there appears to be no significant relationship between returns and liquidity in the vast majority of markets.

3.1.2 Markov switching regressions

To identify low- and high-return regimes for our arbitrage portfolios and to check whether we can explain the probabilities of such regimes by variation in liquidity, we resort to a MRS setting. We follow Brooks and Persand (2001) and Bergman and Hansson (2005) by using a simple two-state MRS model with regime-dependent means. Specifically, we have

$$r_t = \phi + \varphi s_t + \epsilon_t, \tag{4}$$

where s_t is an unobservable state variable taking the values 0 or 1, and the error term fulfills $\epsilon_t \sim N(0, \sigma^2)$.[23] This is a process with mean $\mu_0 = \phi$ when $s_t = 0$, and it switches to another process with mean $\mu_1 = \phi + \varphi$ when s_t changes from 0 to 1. If we observed $s_t = 0$ for $t = 1, ..., \tau$ and $s_t = 1$ for $t = \tau + 1, ..., T$, we would have a classic dummy variable model with a single exogeneous structural change in which the mean return experiences only one abrupt change after $t = \tau$. Allowing for random Bernoulli switching permits multiple changes (see Quandt, 1972), yet the state variable is still exogeneous to the dynamic structures of the model. In addition, the state variables are independent over time which can cause problems with time series data.

[23] Motivated by evidence on volatility differences in bull and bear markets (see Maheu and McCurdy, 2000), we have also estimated models with state-dependent variances (as in Engel, 1994). However, in this alternative specification, our main conclusions remained unchanged.

	Size								Value							
	OLS		QR 25		QR 50		QR 75		OLS		QR 25		QR 50		QR 75	
	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE
Australia	−0.57	0.51	-1.52^b	0.66	−0.54	0.71	0.32	0.71	−0.07	0.41	−0.02	0.58	−0.45	0.47	−0.32	0.61
Austria	0.03	0.55	−0.98	1.04	1.43^b	0.68	0.87^c	0.58	0.17	0.59	−0.21	0.82	−0.33	0.67	0.02	0.73
Belgium	0.07	0.50	0.18	0.54	0.12	0.32	-0.89^c	0.69	-0.77^c	0.47	−0.37	0.49	-0.82^c	0.62	-1.27^b	0.70
Canada	0.11	0.42	−0.34	0.47	0.54^c	0.40	1.19^a	0.34	0.83^b	0.43	−0.04	0.51	0.93^b	0.41	1.16^b	0.60
Denmark	0.37^a	0.14	0.14	0.35	0.09	0.21	0.35^b	0.16	0.04	0.19	−0.16	0.36	0.03	0.26	0.13	0.27
Finland	0.03	0.21	0.30	0.36	−0.07	0.18	-0.46^c	0.34	-0.42^c	0.28	0.08	0.40	-0.40^c	0.26	-0.47^b	0.27
France	0.10	0.26	−0.02	0.40	0.02	0.34	−0.04	0.37	0.26	0.30	0.01	0.58	0.03	0.36	0.06	0.30
Germany	0.65	0.54	0.07	0.68	0.94^c	0.73	1.14^c	0.87	0.46	0.49	0.22	0.62	0.10	0.39	1.06	0.87
Hong Kong	0.01	1.10	-1.79^c	1.30	0.16	1.17	1.96^c	1.29	−0.48	0.74	−0.21	0.84	−1.30	1.08	0.25	0.95
Ireland	0.41	1.26	−0.82	1.46	−0.54	1.74	0.86	1.05	-1.76^c	1.30	−0.26	2.08	-2.51^a	1.04	−0.73	1.67
Italy	0.25	0.22	0.38	0.30	0.37^b	0.19	−0.04	0.35	0.30	0.25	0.89^b	0.47	−0.12	0.32	−0.25	0.26
Japan	0.36^c	0.25	0.65^b	0.30	0.68^a	0.29	0.31	0.29	0.12	0.19	0.22	0.19	0.02	0.23	0.01	0.30
Netherlands	0.61^c	0.39	0.57	0.51	0.12	0.43	1.23^b	0.56	0.17	0.70	−0.31	0.85	0.63	0.57	1.09	0.99
New Zealand	0.32	0.61	1.59^a	0.45	0.20	0.83	−0.34	0.50	−0.39	0.85	1.35^c	0.90	−0.14	0.93	-2.02^b	0.92
Norway	0.54	0.44	0.49	0.44	0.33	0.43	0.56	0.78	1.22^a	0.51	1.11^c	0.84	0.85^c	0.61	1.62^b	0.82
Singapore	0.06	0.46	-1.20^a	0.30	-0.67^b	0.40	0.14	0.50	1.34^a	0.36	0.73^b	0.40	0.97^a	0.31	1.47^a	0.41
Spain	0.24	0.40	0.40	0.63	0.19	0.52	0.00	0.54	−0.52	0.45	-0.79^c	0.58	−0.44	0.49	-0.77^c	0.60
Sweden	0.01	0.32	−0.11	0.33	−0.04	0.25	−0.10	0.60	0.03	0.62	0.13	0.66	−0.56	0.57	−0.61	0.73
Switzerland	0.89^c	0.57	1.11^c	0.80	1.09^b	0.65	1.66^a	0.48	0.05	0.65	-1.39^c	0.86	0.51	0.82	−0.32	0.82
United Kingdom	0.09	0.42	−0.37	0.56	0.14	0.47	1.08^c	0.81	0.84^a	0.33	0.96^b	0.42	0.90^a	0.35	0.46	0.39
United States	0.18	0.31	−0.04	0.54	−0.03	0.27	0.18	0.46	−0.22	0.30	−0.23	0.28	−0.11	0.40	0.20	0.53
World	0.38^c	0.29	0.31	0.33	0.09	0.33	0.51^c	0.39	−0.04	0.27	−0.16	0.36	0.10	0.26	−0.02	0.46
World ex US	0.13	0.43	−0.41	0.54	0.14	0.49	0.69^c	0.51	0.20	0.48	0.34	0.39	0.36	0.30	0.12	0.63
Europe	0.25	0.38	0.47	0.49	0.46^c	0.35	0.21	0.61	0.21	0.30	0.43	0.36	0.19	0.30	0.36	0.30
North America	0.17	0.32	0.06	0.47	−0.06	0.29	0.11	0.39	−0.17	0.30	−0.30	0.29	−0.08	0.40	0.33	0.51
Pacific	0.13	0.34	0.74^a	0.23	0.44	0.40	−0.03	0.44	0.13	0.19	0.42^c	0.26	0.03	0.23	0.08	0.23
pos. (sign.)	25 (1)		15 (3)		19 (4)		18 (4)		16 (4)		13 (3)		14 (3)		16 (3)	
neg. (sign.)	1 (0)		11 (2)		7 (1)		7 (0)		10 (0)		13 (0)		12 (1)		10 (3)	

This table reports the slope coefficients and corresponding standard errors of model (3) linking anomaly returns (for size and value) to liquidity. The parameters are estimated using the ordinary least squares (OLS) method and quantile regression (QR) with $q \in \{0.25, 0.50, 0, 75\}$. The standard errors (SE) for the OLS case follow Newey and West (1987). For QR, we obtain Gould (1992) bootstrap standard errors based on 400 bootstrap draws. a, b and c imply significance at the 1%, 5% and 10% level, respectively. For a better overview, we count the number of positive and negative slope coefficients across all portfolios (countries and aggregates) and the number of significant outcomes (at the 5% level).

Table 4: Ordinary least squares and quantile regression results − Size and value

	Momentum								Beta							
	OLS		QR 25		QR 50		QR 75		OLS		QR 25		QR 50		QR 75	
	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE
Australia	0.26	0.63	−0.49	0.60	0.70	0.73	1.51^a	0.61	-1.43^b	0.84	0.23	0.78	−0.98	0.83	-2.03^b	1.14
Austria	-1.31^b	0.63	-1.56^a	0.65	−0.65	0.83	0.41	1.02	-1.76^c	1.09	-1.74^b	0.92	−0.61	1.15	0.09	1.23
Belgium	0.46	0.64	0.07	0.79	0.18	0.53	0.99^b	0.56	0.14	0.46	-1.32^c	0.82	−0.10	0.43	0.84^c	0.55
Canada	-1.36^b	0.72	-1.50^b	0.71	−0.19	0.64	0.68	1.08	0.70	0.59	−0.18	0.45	0.99^a	0.41	3.08^a	0.66
Denmark	0.07	0.23	0.17	0.39	0.02	0.33	0.14	0.30	−0.02	0.19	−0.23	0.26	−0.07	0.18	0.36	0.29
Finland	−0.02	0.33	0.50	0.63	-0.32^c	0.23	-0.41^c	0.26	0.57^b	0.33	0.68^c	0.43	0.33	0.45	−0.02	0.48
France	0.31	0.39	−0.01	0.46	0.17	0.34	0.70^b	0.36	1.13^a	0.33	0.89^c	0.67	0.89^b	0.41	1.53^a	0.31
Germany	1.35^c	1.05	0.36	0.56	1.60^a	0.49	2.60^a	0.92	1.25^c	0.80	0.03	1.06	1.32^c	0.84	3.19^a	1.07
Hong Kong	-2.72^b	1.26	-4.39^b	1.94	−0.46	1.04	1.02	0.90	0.86	1.43	-1.57^b	0.81	1.03	1.11	4.68^a	1.21
Ireland	−1.12	1.66	−1.39	1.61	-2.30^b	1.22	0.22	2.70	0.84	2.14	2.13	2.09	2.17	1.95	1.55	3.30
Italy	−0.07	0.25	−0.17	0.25	−0.18	0.25	0.18	0.32	0.26^c	0.18	0.32^c	0.22	0.07	0.27	0.22	0.29
Japan	0.04	0.39	0.02	0.40	−0.09	0.23	0.33	0.55	0.87^a	0.36	0.84^c	0.53	1.27^a	0.36	1.31^a	0.55
Netherlands	0.60	0.79	−0.84	0.87	0.67	0.74	2.54^a	0.97	0.73	0.62	0.15	0.85	1.29^b	0.61	1.03	0.96
New Zealand	0.23	0.59	1.71^b	0.87	0.72	0.65	-1.13^c	0.86	−0.74	0.96	-1.44^a	0.47	0.70	0.90	−1.17	1.55
Norway	0.21	0.63	0.06	0.80	0.18	0.76	−0.38	0.83	0.02	0.66	0.33	0.78	0.19	0.74	0.09	0.74
Singapore	-0.88^c	0.62	−0.72	0.68	−0.01	0.51	1.11^a	0.40	1.21^a	0.40	0.79^b	0.38	1.50^a	0.44	2.17^a	0.44
Spain	0.07	0.55	0.10	0.71	0.21	0.64	0.32	0.57	0.13	0.53	0.74	1.03	0.70^b	0.40	−0.04	0.54
Sweden	0.39	0.65	0.04	0.88	0.28	0.47	0.85^c	0.64	0.12	0.60	−0.34	0.73	−0.21	0.73	0.64^c	0.48
Switzerland	0.32	0.71	-0.93^c	0.64	0.39	0.66	1.20^b	0.62	1.49^b	0.65	−0.32	0.69	1.67^a	0.67	3.08^a	0.67
United Kingdom	−0.36	0.52	−0.90	0.77	-0.51^c	0.34	−0.09	0.68	−0.07	0.65	−0.37	1.07	0.94^b	0.49	1.91^b	0.92
United States	-1.37^b	0.64	-1.56^a	0.64	−0.30	0.43	0.25	0.58	-1.08^a	0.42	-1.21^b	0.53	-0.67^b	0.29	-1.14^a	0.45
World	−0.59	0.59	-1.5^b	0.82	0.07	0.42	1.25^a	0.39	−0.02	0.44	0.49	0.61	0.39	0.43	0.49	0.53
World ex US	0.02	0.80	−0.03	0.75	−0.17	0.58	0.49	0.76	0.40	0.69	−0.23	0.67	1.02^c	0.71	2.16^a	0.84
Europe	0.36	0.58	−0.13	0.78	0.60	0.48	0.82^b	0.39	1.21^b	0.53	1.53^a	0.56	1.77^a	0.64	2.04^b	0.94
North America	-1.38^b	0.65	-1.52^a	0.63	−0.22	0.47	0.24	0.56	-0.98^a	0.42	-0.87^c	0.55	-0.62^b	0.29	-1.09^b	0.47
Pacific	0.33	0.40	−0.08	0.57	−0.02	0.31	0.21	0.35	1.30^a	0.35	1.81^a	0.36	1.79^a	0.36	1.20^b	0.59
pos. (sign.)	15 (0)		9 (1)		13 (1)		22 (9)		18 (7)		14 (3)		19 (10)		20 (11)	
neg. (sign.)	11 (5)		17 (6)		13 (1)		4 (0)		8 (3)		12 (4)		7 (2)		6 (3)	

This table reports the slope coefficients and corresponding standard errors of model (3) linking anomaly returns (for momentum and beta) to liquidity. The parameters are estimated using the ordinary least squares (OLS) method and quantile regression (QR) with $q \in \{0.25, 0.50, 0, 75\}$. The standard errors (SE) for the OLS case follow Newey and West (1987). For QR, we obtain Gould (1992) bootstrap standard errors based on 400 bootstrap draws. a, b and c imply significance at the 1%, 5% and 10% level, respectively. For a better overview, we count the number of positive and negative slope coefficients across all portfolios (countries and aggregates) and the number of significant outcomes (at the 5% level).

Table 5: Ordinary least squares and quantile regression results − Momentum and beta

To circumvent these problems, Hamilton (1989) proposed to model s_t as a Markov chain with the transition matrix

$$\begin{bmatrix} P(s_t = 0|s_{t-1} = 0) & P(s_t = 1|s_{t-1} = 0) \\ P(s_t = 0|s_{t-1} = 1) & P(s_t = 1|s_{t-1} = 1) \end{bmatrix} = \begin{bmatrix} p_{00} & p_{01} = 1 - p_{00} \\ p_{10} = 1 - p_{11} & p_{11} \end{bmatrix} \tag{5}$$

where p_{ij} $(i, j = 0, 1)$ denotes the probability that state i will be followed by state j, which depends on the past only through the most recent value s_{t-1}. Clearly, the transition probabilities satisfy $p_{i0} + p_{i1} = 1$. The Markovian state variable allows capturing frequent changes of the model structure, and its transition probabilities determine the persistence of each regime.

The parameters of the model $\theta = [\phi, \varphi, \sigma, p_{00}, p_{11}]$ can be estimated via maximum likelihood (see Engel and Hamilton, 1990). Standard error calculation typically follows White (1980). As a by-product, the parameter estimation delivers so-called filtering probabilities $\hat{\pi}_t = P(s_t = 0|\Omega^t, \hat{\theta}) = 1 - P(s_t = 1|\Omega^t, \hat{\theta})$, which are based on past and current information. We use these probabilities in regressions of the type

$$\hat{\pi}_t = \upsilon + \omega l_t + \epsilon_t, \tag{6}$$

where, after additionally computing Newey and West (1987) standard errors, ω can be used to investigate the link between the probability of a low-return regime and liquidity. A positive slope coefficient suggests attenuation because, in this case, a high (low) probability of a low return is on average accompanied by high (low) liquidity.

Table 6 presents our estimation results for model (6). For the US, we observe negative (size and value) and positive slopes (momentum and beta). Because only the momentum slope is significant, we have significant attenuation only for this anomaly. On an international scale, we have 7, 11, 22 and 10 (3, 3, 10 and 4 significant) attenuations for size, value, momentum and beta, respectively. Thus, in comparison to Section 3.1.1, the different econometric approach has delivered a crucially higher number of significant return declines (only) for momentum. However, the overall picture of no significant negative relationship between anomaly returns and liquidity continues to hold.

3.2 Panel regressions

While our previous estimations focused on the time-series dimension, this section introduces a panel setting incorporating both a time-series and a cross-sectional perspective to answer the question

	Size		Value		Momentum		Beta	
	Slope	SE	Slope	SE	Slope	SE	Slope	SE
Australia	0.121^{b}	0.059	-0.009	0.033	0.025	0.032	0.099^{b}	0.048
Austria	0.008	0.022	-0.001	0.015	0.016^{c}	0.012	0.018	0.043
Belgium	-0.006	0.012	0.030^{b}	0.016	0.034^{c}	0.023	-0.004	0.006
Canada	-0.093^{b}	0.048	-0.038^{b}	0.021	0.089^{b}	0.040	-0.166^{a}	0.045
Denmark	-0.051^{a}	0.019	0.000	0.015	0.006	0.006	-0.004^{c}	0.002
Finland	-0.012^{b}	0.007	0.004	0.007	-0.004	0.005	0.002	0.006
France	-0.009	0.013	0.002	0.002	0.019^{c}	0.012	-0.020^{b}	0.010
Germany	0.038^{b}	0.019	-0.013^{c}	0.009	0.055^{b}	0.024	-0.103^{a}	0.032
Hong Kong	-0.085^{b}	0.037	0.013	0.017	0.211^{a}	0.058	-0.085^{b}	0.040
Ireland	-0.015	0.015	-0.022	0.025	0.008	0.012	-0.022	0.022
Italy	0.008	0.007	-0.020^{b}	0.011	0.006	0.008	-0.008^{a}	0.003
Japan	0.007	0.006	0.012	0.010	-0.009	0.020	-0.065^{a}	0.021
Netherlands	-0.043^{b}	0.021	0.052^{b}	0.030	0.035^{b}	0.018	0.013^{c}	0.009
New Zealand	0.027^{c}	0.020	0.004	0.007	0.074^{b}	0.045	0.022	0.039
Norway	-0.008	0.013	-0.005	0.008	-0.009	0.018	-0.042	0.059
Singapore	-0.047^{b}	0.022	-0.006	0.008	0.022	0.019	-0.006	0.010
Spain	-0.029	0.035	0.041^{b}	0.022	0.018^{c}	0.014	-0.004	0.005
Sweden	-0.010	0.009	0.010	0.043	0.018	0.022	-0.030^{c}	0.020
Switzerland	-0.296^{a}	0.089	-0.025	0.027	0.050^{b}	0.024	0.005	0.007
United Kingdom	-0.045^{b}	0.025	-0.042^{b}	0.026	0.051^{b}	0.025	0.073^{b}	0.042
United States	-0.015	0.015	-0.018	0.021	0.029^{c}	0.021	0.075^{b}	0.041
World	-0.027	0.024	-0.032^{b}	0.019	0.070^{b}	0.035	0.061	0.072
World ex US	-0.037^{c}	0.026	-0.061^{b}	0.034	0.119^{a}	0.050	-0.029^{b}	0.014
Europe	-0.004	0.023	-0.020	0.019	0.078^{b}	0.037	-0.131^{a}	0.046
North America	-0.016	0.015	-0.023	0.021	0.030^{c}	0.022	0.076^{b}	0.043
Pacific	0.032^{b}	0.016	0.005	0.008	-0.021	0.024	-0.087^{a}	0.034
pos. (sign.)	7 (3)		11 (3)		22 (10)		10 (4)	
neg. (sign.)	19 (8)		15 (5)		4 (0)		16 (9)	

This table reports the slope coefficients and corresponding Newey and West (1987) standard errors of model (6), where the (filtered) probability of a low-return regime is regressed on liquidity. a, b and c imply significance at the 1%, 5% and 10% level, respectively. For a better overview, we count the number of positive and negative slope coefficients across all portfolios (countries and aggregates) and the number of significant outcomes (at the 5% level).

Table 6: Markov switching probabilities and liquidity

of whether higher liquidity levels are associated with lower anomaly returns.[24] We start with the general panel model

$$r_{i,t} = \alpha + \beta l_{i,t} + \epsilon_{i,t}, \tag{7}$$

where $i = 1, ..., N$ represents a country and $t = 1, ..., T$ is a time index. The simplest way of obtaining the parameters of such a model is to use pooled OLS estimation (see Wooldridge, 2002). For this approach, the sample is interpreted as containing $N \cdot T$ cross-sectional observations. Over all i and t, the error term needs to have a conditional mean of zero, i.e., $E(\epsilon_{i,t}|l_{i,t}) = 0$, and has to be free of heteroscedasticity, i.e., $E(\epsilon_{i,t}^2) = \sigma^2$, and correlation, i.e., $E(\epsilon_{i,t}\epsilon_{j,s}) = 0$ for $i \neq j$ or $t \neq s$. If these assumptions hold, the estimation procedure is consistent and efficient.

[24] We do not take the hypothesis of Chordia et al. (2014) stated in Section 1 literally because it should be the level and not the growth rate of share turnover affecting prices. Consider two markets A and B, where A has a higher initial liquidity level than B. Thus, if both countries experience the same growth rate in a given month, it is unlikely that arbitrage pressure will be the same because liquidity is still higher in market A.

Another approach to panel estimation is to assume that there is unobserved heterogeneity across the countries, captured by v_i, and to split the error term in $\epsilon_{i,t} = v_i + u_{i,t}$, where $u_{i,t}$ is a classic disturbance (see Wooldridge, 2002; Greene, 2018). This yields

$$r_{i,t} = \alpha + \beta l_{i,t} + (v_i + u_{i,t}). \tag{8}$$

If the individual effects v_i are allowed to be correlated with the regressor, we have the fixed effects model. Obviously, because of the inherited endogeneity, the direct application of the pooled estimation procedure would cause inconsistent estimates for the parameters of such a model. The natural way of dealing with the unobserved heterogeneity is to use the within estimator, which eliminates v_i and yields consistent estimates under the assumption of strict exogeneity, i.e., $E(u_{i,t}|l_{i,t}, v_i) = 0$, $t = 1, ..., T$. Averaging (8) over all t for each i, we have $\bar{r}_i = v_i + \beta\bar{l}_i + \bar{u}_i$, which can be subtracted from (8) to obtain $(r_{i,t} - \bar{r}_i) = \beta(l_{i,t} - \bar{l}_i) + (u_{i,t} - \bar{u}_i)$, i.e., a model for the country-specific deviations of the variables from their time-averaged values. Pooled estimation of this model yields the slope parameter β. This procedure is consistent even if the true model is a pooled model or the following random effects model. However, in the two latter cases, it is not efficient.

If we treat v_i in (8) as a random variable, uncorrelated with the regressor, we obtain the random effects model and no endogeneity problem arises. A pooled generalised least squares (GLS) procedure can provide efficient estimates of the random effects model (see Wooldridge, 2002; Greene, 2018). Here, we simply have to estimate the transformed model $r_{i,t} - \hat{\nu}\bar{r}_i = (1 - \hat{\nu})\alpha + \beta(l_{i,t} - \hat{\nu}\bar{l}_i) + w_{i,t}$, where $w_{i,t} = (1 - \hat{\nu})v_i + (u_{i,t} - \hat{\nu}\bar{u}_i)$ and $\hat{\nu} = 1 - \hat{\sigma}_u(\hat{\sigma}_u^2 + T\hat{\sigma}_v^2)^{-0.5}$.[25]

In Table 7 we present the slope parameter estimation results for these models, which we order from the most restrictive to the most general. That is, we start with the simple pooled model, followed by the random effects model (estimated via GLS) and the fixed effects model (estimated via the within estimator). We denote these models A, B and C, respectively. Furthermore, we include two additional generalisations, which are models D and E. To obtain model D, we extend the standard fixed effects model C (with country-specific effects v_i) by adding time-specific effects z_t. That is, we estimate the more general model $r_{i,t} = \alpha + \beta l_{i,t} + (v_i + z_t + u_{i,t})$. To this end, the within estimation procedure is modified by additionally subtracting country-averaged values. In model E, we address that panel datasets often exhibit all sorts of dependencies and that erroneously

[25]Note that $\hat{\nu} = 0$ corresponds to pooled OLS and $\hat{\nu} = 1$ to the within estimator.

ignoring such patterns can lead to biased statistical inference (see Hoechle, 2007).[26] We supplement model D by the nonparametric covariance matrix estimator of Driscoll and Kraay (1998), which produces heteroscedasticity consistent standard errors that are robust to very general forms of cross-sectional and temporal dependence. Specifically, besides heteroscedasticity and correlation within a country, it allows contemporary correlation between countries.[27]

	Pooled	Random effects	Fixed effects		
			CFE	CFE, TFE	CFE, TFE, DK
Model	A	B	C	D	E
Size					
Slope	0.095	0.095	0.198^a	0.102	0.102
SE	0.059	0.059	0.074	0.102	0.109
Value					
Slope	0.014	0.015	0.017	−0.027	−0.027
SE	0.070	0.073	0.087	0.119	0.164
Momentum					
Slope	−0.042	−0.054	−0.076	−0.165	−0.165
SE	0.088	0.095	0.110	0.129	0.152
Beta					
Slope	0.131	0.208^b	0.307^a	0.220	0.220
SE	0.088	0.098	0.110	0.149	0.181

This table reports the slope coefficient estimates and corresponding standard errors (SE) for our panel models testing the link between anomaly returns and liquidity. We cover the simple pooled estimation, a random and a fixed effect setting. The latter approach is specified with country-fixed effects (CFE), time-fixed effects (TFE) and Driscoll and Kraay (1998) standard errors (DK), which take into account heteroscedasticity and correlation within a country and cross-sectional correlation between countries. *a*, *b* and *c* imply significance at the 1%, 5% and 10% level, respectively.

Table 7: Panel estimation results

Starting with the size portfolios, we find positive and insignificant slope coefficients for the pooled and random effects models. Furthermore, the slope is positive and significant for the fixed effects model C but loses significance when time-fixed effects and corrected standard errors are considered. For the value (momentum) portfolios, we have negative slopes for the two more general fixed effects models D and E (all models). However, they are insignificant. Finally, the beta anomaly is characterised by significantly positive links to liquidity when the random and basic fixed models B and C are employed. However, for the more general settings D and E, the detected link vanishes similar to the size anomaly.

In summary, our finding of mainly insignificant panel regression coefficients does not provide persuasive evidence of anomaly return attenuation related to higher liquidity. Put differently, liquidity does not appear to be the key driver for the dynamics of arbitrage portfolio returns. The

[26] Petersen (2009) argues that a substantial fraction of articles in leading finance journals fails to adjust standard errors correctly.

[27] An application of the Pesaran (2004) test confirms the existence of cross-sectional dependence. An F test of the time-dummy coefficients of the extended fixed effects model D supports the inclusion of time-fixed effects. Detailed test results are presented in Table A2 of the appendix.

results in our appendix show that, for all of our estimators, this holds regardless of whether we use the original variables or detrended values.

3.3 Robustness checks

To ensure that our regression results are not driven by some specifics of our dataset or our methodology, we conduct several sensitivity checks.[28]

First, we use alternative measures for the willingness and ability of speculators to put arbitrage capital at risk. Specifically, we follow Jacobs (2015) by (i) capturing overall expected volatility and uncertainty via suitable option-based volatility indices because higher expected volatility leads to tighter funding constraints for speculators (see Brunnermeier and Pedersen, 2009), (ii) calculating Ted spreads because they are a widespread measure for funding liquidity (see Ang et al., 2011) and (iii) measuring constraints related to transaction costs via bid-ask spreads (as estimated in Corwin and Schultz, 2012). However, our results do not qualitatively change.[29]

Second, the standard method for calculating the book-to-market ratio uses lagged book data and aligns price data using the same lag, ignoring recent price movements (see Fama and French, 1992). However, recent research argues that, while this was entirely reasonable, particularly in the early days of the literature, when momentum was not a literal or figurative factor, it is now suboptimal (see Asness and Frazzini, 2013). It shows that book-to-market ratios based on more timely prices more accurately forecast true, unobservable book-to-market ratios at fiscal year-end and that value portfolios based on such measures earn significantly higher alphas than portfolios derived from the standard method. To analyse the impact of such alternative portfolio construction on our results, we repeat our regressions for the alternative value factor also contained in the AQR dataset. However, our overall conclusions still hold.

Finally, even though our data selection is consistent, meaning that the returns cover an investment period of one month and liquidity is captured over the corresponding full month (instead of just the end of the month), we test whether our results are different when, in two modified settings, (besides contemporaneous liquidity) lags of the liquidity variable are included in our models. Here, our focus lies on the cumulative liquidity coefficients. In a first setting, we include four lags. In a second one, we follow Chordia et al. (2014) by extending our OLS time-series regressions by

[28] For brevity and because the results allow conclusions virtually identical to Sections 3.1 and 3.2, we limit ourselves to verbally summarising their design and outcome. Detailed results are available upon request.

[29] This is not surprising because correlations between different types of liquidity measures are partially quite high (see Lesmond et al., 1999).

the transfer function approach of Liu (2006) automatically detecting statistically relevant higher lags. We still cannot find persuasive evidence of a significant relation between anomaly returns and liquidity. This is not surprising because it is hard to imagine that (not shock-like) trades of up to ten months ago (as identified by the transfer function approach) are highly economically relevant for current prices.

4 Conclusion

In a recent study of the US stock market, Chordia et al. (2014) show that higher liquidity (in the form of higher trading activity and lower transaction costs) has (i) created an environment in which arbitrageurs can more efficiently exploit capital market anomalies and (ii) that the reduced limits to arbitrage have indeed led to an attenuation of many well-known anomalies. In this article, we extend their study in two important ways. First, we analyse the robustness of their time-series evidence for the US market by using a more advanced econometric methodology (including quantile regressions and Markov regime-switching models). Second, we visit an international setting by analysing whether such tendencies can be observed for size, value, momentum and beta arbitrage portfolios in a wide variety of other developed stock markets. Within this extended sample, we also use panel methods to test for the existence of a significant cross-sectional link between anomaly portfolio returns and market liquidity.

Using a novel dataset covering three decades, we find that the recent worldwide regime of increased liquidity, apart from some exceptions, is not accompanied by robustly significant decreases of anomalous returns in the US and the majority of other markets. We cannot establish a persistent negative link between arbitrage portfolio returns and share turnover in both the time-series and the cross-sectional dimension. These results suggest that aggregate liquidity may be a measure too coarse for our purposes or that liquidity in general may not be the key driver of the dynamics of international anomaly portfolios. For example, it may be relevant to distinguish between different kinds of money flows because recent research indicates that aggregate flows to mutual funds (dumb money) and hedge fund flows (smart money) tend to have different effects on markets (see Akbas et al., 2015). Furthermore, it is widely argued that investor sentiment may influence capital market anomalies (see Fong and Toh, 2014; Jacobs, 2015). Thus, repeating our international analysis with decomposed liquidity variables and/or investor sentiment measures (such as the one developed by

Baker and Wurgler, 2006) may be a fruitful endeavour.[30] Because our analysis is limited to four anomalies, future research may also extend it to a wider selection of capital market effects (such as the ones related to the 50 variables summarised by Subrahmanyam, 2010).

While our study has an aggregate portfolio perspective, the previous literature has often focused on the empirical relation between individual asset returns and liquidity. For example, several studies have documented higher returns for illiquid assets because investors expect to be compensated for high transaction costs and potential trading barriers (see Amihud and Mendelson, 1986, 1991, for stocks and bonds, respectively). Furthermore, more recent studies show that market-wide liquidity is an especially important determinant of individual asset returns because it contributes to assets' systematic risk (see Chordia et al., 2000; Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Brockman et al., 2009). In light of our results on trending liquidity and insignificant relations, future research could also revisit these studies because their key findings may no longer hold in regimes with very high general liquidity levels.

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[30] One might also think of comparing more alternative measures of liquidity than covered by our robustness checks (for a starting point, see Schestag et al., 2016; Fong et al., 2017).

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Appendix

	World	World ex US	Europe	North America	Pacific
Australia	x	x			x
Austria	x	x	x		
Belgium	x	x	x		
Canada	x	x		x	
Denmark	x	x	x		
Finland	x	x	x		
France	x	x	x		
Germany	x	x	x		
Greece	x	x	x		
Hong Kong	x	x			x
Ireland	x	x	x		
Israel	x	x	x		
Italy	x	x	x		
Japan	x	x			x
Netherlands	x	x	x		
Norway	x	x	x		
New Zealand	x	x			x
Portugal	x	x	x		
Singapore	x	x			x
Spain	x	x	x		
Sweden	x	x	x		
Switzerland	x	x	x		
United Kingdom	x	x	x		
United States	x			x	

This table reports the constituents of the value-weighted portfolio aggregates used in our main analysis. Source of the table is the website www.aqr.com/library/data-sets/betting-against-beta-equity-factors-monthly.

Table A1: Constituents of portfolio aggregates

	Size		Value		Momentum		Beta	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
F test	4.03	0.00	4.81	0.00	12.99	0.00	5.26	0.00
Pesaran test	−12.17	0.00	−11.96	0.00	−11.83	0.00	−11.77	0.00

This table presents the test statistics and corresponding p-values for two tests concerning the extended fixed effects models D and E of Section 3.2. First, we conduct an F test focusing on the null hypothesis of zero-valued time dummy coefficients. Second, we apply the Pesaran (2004) test of the null hypothesis of cross-sectional independence.

Table A2: Tests for time-fixed effects and cross-sectional dependence

	Size								Value							
	OLS		QR 25		QR 50		QR 75		OLS		QR 25		QR 50		QR 75	
	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE
Australia	−0.79	0.82	-1.67^{c}	1.05	−0.68	1.18	0.19	1.19	0.04	0.74	0.52	0.90	−0.42	0.84	−0.83	1.34
Austria	0.39	0.58	−1.03	1.00	1.63^{a}	0.62	1.68^{a}	0.59	0.14	0.63	−0.12	0.86	0.00	0.71	0.20	0.65
Belgium	−0.26	0.69	0.26	0.82	−0.05	0.53	-1.46^{c}	1.00	−0.88	0.70	−0.74	0.77	−0.90	0.93	-1.66^{b}	0.85
Canada	0.15	0.54	0.08	0.75	0.64	0.51	0.95^{b}	0.48	0.90^{c}	0.70	−0.21	0.70	1.24^{b}	0.61	1.67^{b}	0.85
Denmark	0.47^{a}	0.19	0.20	0.40	0.09	0.27	0.48^{b}	0.26	0.12	0.24	−0.20	0.46	0.07	0.28	0.13	0.35
Finland	−0.10	0.27	−0.28	0.42	−0.11	0.24	−0.22	0.45	-0.71^{b}	0.41	-1.39^{a}	0.54	-0.61^{b}	0.36	0.04	0.43
France	0.00	0.29	−0.12	0.47	−0.08	0.40	−0.13	0.43	0.34	0.35	0.09	0.60	0.40	0.38	0.21	0.37
Germany	0.51	0.56	−0.27	0.50	0.85	0.75	1.08	1.09	0.56	0.51	−0.01	0.57	0.14	0.43	0.76	0.68
Hong Kong	−0.04	1.10	-1.92^{c}	1.36	0.34	1.28	2.15^{b}	1.26	−0.54	0.75	−0.66	1.04	-1.27^{c}	0.95	0.75	1.00
Ireland	0.41	1.23	−0.84	1.43	−0.51	1.63	0.80	1.19	-1.92^{c}	1.28	0.14	1.66	-2.51^{b}	1.10	−0.63	1.44
Italy	0.41	0.32	0.41	0.44	0.47^{b}	0.28	0.52	0.58	0.65^{b}	0.37	1.25^{a}	0.47	0.45	0.53	0.10	0.44
Japan	0.34	0.49	0.21	0.66	0.60	0.56	0.63	0.60	0.76^{b}	0.34	0.52	0.51	1.22^{a}	0.44	0.97^{b}	0.47
Netherlands	0.52	0.42	0.44	0.55	−0.13	0.52	1.19^{b}	0.64	0.08	0.74	−0.33	0.88	0.58	0.74	1.09	1.09
New Zealand	0.90^{c}	0.70	0.67	0.67	0.73	0.76	1.08^{b}	0.62	−0.43	1.00	0.63	1.09	0.23	1.00	−1.51	1.23
Norway	0.61^{c}	0.43	0.44	0.42	0.30	0.39	0.59	0.81	1.30^{a}	0.53	1.11^{c}	0.75	0.62	0.67	1.72^{a}	0.66
Singapore	0.25	0.59	-1.48^{a}	0.46	-0.75^{c}	0.52	0.24	0.72	1.69^{a}	0.45	0.37	0.51	0.85^{b}	0.47	1.86^{a}	0.42
Spain	0.40	0.48	0.76	0.76	0.67	0.66	0.06	0.66	0.16	0.62	−0.04	0.84	0.08	0.70	−0.31	1.06
Sweden	−0.04	0.37	0.00	0.47	−0.03	0.33	−0.17	0.63	0.29	0.68	−0.58	0.67	−0.50	0.60	0.34	0.81
Switzerland	0.53	0.59	0.20	0.76	0.99^{c}	0.70	1.01^{a}	0.43	0.38	0.65	−0.94	0.79	0.61	0.81	0.55	0.82
United Kingdom	0.06	0.42	−0.38	0.53	0.15	0.52	1.20^{c}	0.79	0.90^{a}	0.35	1.03^{a}	0.40	1.22^{a}	0.34	0.44	0.41
United States	0.37	0.64	-1.85^{a}	0.77	−0.58	0.64	1.09	0.88	0.01	0.66	−0.89	0.70	−0.09	0.86	2.08^{b}	0.99
World	0.50	0.46	−0.37	0.52	−0.20	0.41	1.08^{b}	0.54	0.34	0.50	−0.41	0.49	0.65^{c}	0.40	1.46^{b}	0.70
World ex US	0.19	0.43	−0.32	0.54	0.29	0.44	0.86^{b}	0.48	0.16	0.48	0.53	0.49	0.53^{b}	0.32	−0.03	0.62
Europe	0.12	0.41	0.30	0.53	0.43	0.35	0.20	0.78	0.40	0.38	0.63^{c}	0.40	0.73^{b}	0.33	0.65^{b}	0.36
North America	0.34	0.65	-1.75^{b}	0.84	-0.81^{c}	0.60	0.79	0.66	0.07	0.67	-1.10^{c}	0.71	0.13	0.79	2.35^{a}	0.91
Pacific	0.00	0.47	0.64^{c}	0.41	0.50	0.55	0.23	0.61	0.31	0.26	0.47	0.44	0.37	0.47	0.55^{b}	0.24
pos. (sign.)	19 (1)		12 (0)		15 (2)		22 (9)		21 (5)		12 (2)		18 (6)		20 (9)	
neg. (sign.)	5 (0)		13 (3)		11 (0)		4 (0)		5 (1)		14 (1)		7 (2)		6 (1)	

Extending the results of Table 4, we include a time trend in our simple liquidity model. This approach is identical to regressing the linearly detrended original variables on each other (see Wooldridge, 2009, chpt. 10).

Table A3: Dealing with non-stationarity: Ordinary least squares and quantile regression results − Size and value

	Momentum								Beta							
	OLS		QR 25		QR 50		QR 75		OLS		QR 25		QR 50		QR 75	
	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE	Slope	SE
Australia	0.36	1.01	0.63	0.91	0.25	1.64	0.83	1.08	0.05	0.95	0.27	0.86	−0.55	1.13	−0.38	1.06
Austria	-1.34^{b}	0.72	-2.01^{a}	0.65	−0.18	0.79	1.15	1.10	−1.30	1.13	-1.74^{c}	1.10	0.38	1.12	0.19	1.03
Belgium	0.98	1.01	0.09	1.16	0.87	0.73	2.1^{a}	0.82	0.75	0.69	−0.14	1.29	0.88^{c}	0.63	1.13	0.91
Canada	-1.53^{c}	1.05	−1.12	1.41	−0.60	0.86	0.34	1.52	−0.64	0.83	-1.53^{b}	0.71	−0.12	0.58	2.23^{b}	1.23
Denmark	−0.09	0.27	0.07	0.45	0.03	0.42	−0.18	0.33	−0.12	0.24	-0.38^{c}	0.29	−0.20	0.28	0.62^{b}	0.34
Finland	0.15	0.43	0.07	0.80	−0.29	0.29	0.32	0.41	1.14^{a}	0.43	0.46	0.50	0.79^{c}	0.51	1.15^{b}	0.58
France	0.38	0.46	−0.03	0.51	0.24	0.41	0.71^{c}	0.44	1.10^{a}	0.41	0.79	0.75	0.74^{c}	0.48	1.82^{a}	0.41
Germany	1.18	1.07	−0.19	0.71	1.11^{b}	0.54	2.73^{a}	0.96	1.06^{c}	0.82	−0.28	1.08	1.36^{c}	0.90	3.06^{a}	1.04
Hong Kong	-2.75^{b}	1.28	-4.36^{b}	1.94	−0.47	1.08	0.73	0.98	0.71	1.43	-1.71^{b}	0.99	1.28	1.17	5.17^{a}	1.31
Ireland	−1.14	1.63	−1.47	1.53	-2.52^{b}	1.28	−0.87	1.78	1.11	2.08	2.24	2.05	2.42^{c}	1.81	2.99	2.80
Italy	−0.22	0.38	−0.43	0.47	-0.56^{c}	0.40	−0.06	0.54	0.77^{a}	0.32	0.70^{a}	0.30	0.32	0.40	0.80^{c}	0.52
Japan	−0.12	0.75	−0.49	0.94	0.13	0.49	0.77	0.85	1.14^{b}	0.61	1.75^{b}	0.86	1.59^{b}	0.72	2.00^{a}	0.73
Netherlands	0.88	0.84	−0.70	0.90	1.45^{c}	0.92	3.15^{a}	1.00	0.62	0.64	0.21	0.97	1.28^{b}	0.65	1.25^{c}	0.95
New Zealand	0.56	0.76	1.35	1.13	1.12	0.93	0.11	0.71	−1.11	1.24	-2.46^{a}	0.82	0.81	1.21	0.97	1.39
Norway	−0.05	0.63	−0.07	0.60	−0.40	0.71	−0.61	0.94	−0.34	0.66	−0.29	0.67	−0.47	0.75	0.05	0.78
Singapore	-1.63^{b}	0.79	-1.32^{b}	0.80	−0.47	0.64	0.53	0.63	1.46^{a}	0.51	0.72^{b}	0.37	1.62^{a}	0.52	2.40^{a}	0.47
Spain	−0.66	0.78	0.24	1.01	−0.30	0.76	-2.52^{a}	0.87	0.77	0.73	1.35	1.12	1.21^{b}	0.64	0.90	0.84
Sweden	−0.07	0.74	−0.73	0.64	0.08	0.51	1.62^{b}	0.81	0.20	0.67	−0.45	0.79	0.12	0.72	0.90	0.73
Switzerland	0.33	0.76	-1.12^{b}	0.66	0.19	0.75	1.45^{b}	0.69	1.98^{a}	0.72	−0.34	0.75	2.07^{a}	0.80	3.94^{a}	0.79
United Kingdom	−0.35	0.54	−0.91	0.86	-0.60^{c}	0.37	−0.30	0.67	0.00	0.64	−0.25	1.10	0.88^{b}	0.53	2.18^{a}	0.87
United States	-1.91^{c}	1.42	-3.59^{b}	1.64	−0.34	0.86	2.93^{b}	1.36	-2.25^{a}	0.88	-3.89^{a}	1.02	-1.62^{a}	0.65	−0.63	0.92
World	−0.89	1.01	-2.56^{b}	1.46	−0.08	0.75	1.96^{b}	0.93	−0.48	0.69	−0.89	1.01	0.33	0.59	1.50^{b}	0.82
World ex US	0.06	0.80	−0.16	0.79	−0.39	0.54	0.73	0.74	0.43	0.71	−0.48	0.65	0.73	0.67	2.27^{b}	0.99
Europe	0.14	0.68	0.09	0.94	0.06	0.58	0.54	0.54	0.92^{b}	0.55	1.14^{b}	0.68	1.45^{a}	0.58	1.70^{b}	0.91
North America	-1.98^{c}	1.41	-4.02^{a}	1.55	−0.23	0.92	2.21^{b}	1.32	-2.21^{a}	0.88	-3.81^{a}	1.06	-1.29^{b}	0.63	−0.32	1.12
Pacific	0.13	0.55	−0.95	0.81	−0.22	0.49	0.16	0.53	1.11^{a}	0.44	1.27^{a}	0.37	1.70^{a}	0.46	1.66^{b}	0.73
pos. (sign.)	11 (0)		7 (0)		11 (1)		20 (8)		17 (8)		11 (5)		20 (8)		23 (14)	
neg. (sign.)	15 (3)		19 (7)		15 (1)		6 (1)		8 (2)		15 (5)		6 (2)		3 (0)	

Extending the results of Table 5, we include a time trend in our liquidity model. This approach is identical to regressing the linearly detrended original variables on each other (see Wooldridge, 2009, chpt. 10).

Table A4: Dealing with non-stationarity: Ordinary least squares and quantile regression results − Momentum and beta

	Size		Value		Momentum		Beta	
	Slope	SE	Slope	SE	Slope	SE	Slope	SE
Australia	0.111	0.100	0.068	0.097	0.032	0.042	−0.021	0.043
Austria	−0.003	0.023	0.000	0.016	0.023^c	0.017	0.002	0.044
Belgium	−0.001	0.019	−0.004	0.023	0.048^c	0.036	-0.014^c	0.010
Canada	-0.082^c	0.055	−0.044	0.040	0.115^a	0.049	-0.101^c	0.078
Denmark	-0.081^a	0.022	−0.025	0.025	0.018^b	0.009	−0.001	0.004
Finland	0.003	0.009	−0.009	0.012	−0.002	0.005	−0.005	0.007
France	−0.010	0.014	0.004	0.004	0.024^c	0.015	-0.028^b	0.013
Germany	0.045^b	0.020	-0.017^c	0.011	0.055^b	0.024	-0.112^a	0.034
Hong Kong	-0.084^b	0.036	0.018	0.017	0.215^a	0.059	-0.088^b	0.040
Ireland	−0.014	0.015	−0.016	0.024	0.008	0.012	−0.023	0.022
Italy	−0.005	0.011	−0.015	0.015	0.010	0.009	-0.031^b	0.014
Japan	0.009	0.010	−0.009	0.013	0.024	0.038	-0.052^c	0.033
Netherlands	-0.031^c	0.023	0.055^b	0.030	0.042^b	0.020	0.013^c	0.009
New Zealand	−0.016	0.026	0.004	0.007	0.037	0.033	0.015	0.042
Norway	-0.018^b	0.011	−0.011	0.009	0.001	0.018	0.021	0.057
Singapore	-0.073^a	0.031	−0.015	0.012	0.030^c	0.021	-0.024^c	0.018
Spain	−0.042	0.041	-0.078^b	0.044	0.029^c	0.020	−0.016	0.016
Sweden	−0.011	0.011	−0.040	0.051	0.042^b	0.024	-0.059^b	0.028
Switzerland	-0.232^a	0.087	-0.036^c	0.027	0.056^b	0.026	−0.003	0.008
United Kingdom	-0.045^b	0.025	-0.047^b	0.028	0.052^b	0.026	0.074^b	0.039
United States	-0.086^a	0.033	-0.115^b	0.060	0.069^c	0.043	0.284^a	0.071
World	-0.109^a	0.040	-0.085^b	0.049	0.149^a	0.054	0.194^b	0.097
World ex US	-0.039^c	0.026	-0.059^b	0.033	0.120^a	0.050	-0.028^b	0.014
Europe	−0.014	0.024	-0.045^b	0.027	0.102^b	0.044	-0.158^a	0.050
North America	-0.087^a	0.033	-0.114^b	0.062	0.070^c	0.043	0.288^a	0.074
Pacific	0.027	0.024	-0.023^b	0.013	0.010	0.037	-0.070^c	0.044
pos. (sign.)	5 (1)		6 (1)		25 (11)		8 (4)	
neg. (sign.)	21 (9)		20 (8)		1 (0)		18 (7)	

Modifying our estimations of Table 6, we regress probabilities on detrended liquidity instead of plain liquidity. That is, we first regress liquidity on time and then use the residuals of this regression as the explanatory variable in the probability model (see Wooldridge, 2009, chpt. 10). Note that, in contrast to Tables A3 and A4, we do not simply add a time variable to our model because such an approach would also detrend the probabilities which cannot have a standard linear trend because of their natural boundaries.

Table A5: Dealing with non-stationarity: Markov switching probabilities and liquidity

	Pooled	Random effects	Fixed effects		
			CFE	CFE, TFE	CFE, TFE, DK
Model	A	B	C	D	E
Size					
Slope	0.112	0.112	0.219^b	0.221	0.221
SE	0.076	0.076	0.094	0.128	0.139
Value					
Slope	0.135	0.135	0.135	−0.004	−0.004
SE	0.090	0.090	0.111	0.149	0.214
Momentum					
Slope	−0.070	−0.070	−0.165	−0.172	−0.172
SE	0.112	0.112	0.139	0.161	0.192
Beta					
Slope	0.309^a	0.309^a	0.441^a	0.584^a	0.584^b
SE	0.113	0.113	0.139	0.185	0.235

This table presents the liquidity coefficients resulting after including a time trend variable in each of our panel specifications of Table 7.

Table A6: Dealing with non-stationarity: Panel estimation results