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Conditional portfolio allocation: Does aggregate market liquidity matter?

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ABSTRACT

This paper investigates how aggregate liquidity influences optimal portfolio allocations across various US characteristic portfolios. We consider short-term allocation problems, with single and multiple risky assets, and use the nonparametric approach of Brandt (1999) to directly express optimal portfolio weights as functions of aggregate liquidity shocks. We find, first, that the effect of aggregate liquidity is positive and decreasing with the investment horizon. Second, at daily and weekly horizons, this effect is weaker on allocations in large stocks and gets stronger as we move toward small stocks, regardless of the other stock characteristics, suggesting that liquidity is the main concern of very short-term investors. Third, conditional allocations in risky assets decrease and exhibit shifts toward more liquid assets as aggregate liquidity worsens. Overall, conditioning on aggregate liquidity yields empirical results that are consistent with the so-called flight-to-safety and flight-to-liquidity episodes. Finally, we propose a simple tactical investment strategy and show how aggregate liquidity information can be exploited to enhance the out-of-sample performance of long-term strategies.

1. Introduction

We aim in this paper to examine the relation between aggregate market liquidity and optimal portfolio allocations. Aggregate market liquidity has been proved by many recent works to contain leading information about US future returns as well as real economy and macroeconomic conditions. However, to date, there has been no study that examines its impact on investment decisions. This paper intends to fill this gap in the literature by studying its implications on optimal portfolio allocation across various test portfolios including (a) the market portfolio, (b) 3 size-based portfolios, and (c) 20 double-sorted portfolios on the basis of size and other stock attributes including B/M, momentum, market beta, liquidity, and quality characteristics. In this work, we focus on short investment horizons (daily, weekly, monthly, and quarterly horizons) and consider conditional portfolio choice problems in the presence of a risk-free asset and both single and multiple risky assets. We build on the nonparametric method of Brandt (1999) to compute optimal conditional portfolio allocations as functions of the lagged aggregate liquidity level. The advantage of this method is that it computes optimal portfolio allocations directly from observing the signal and thereby avoids any model misspecification and estimation errors that can arise from any attempt to model return distributions. Additionally, it computes a solution for a CRRA-utility problem, which offers the advantage of considering any possible dependency between higher moments and the conditioning variable.

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We find strong evidence that aggregate liquidity influences optimal portfolio allocations. Our main findings can be summarized as follows. First, in line with the clientele effect (Amihud and Mendelson, 1986), the effect of aggregate liquidity is stronger at daily frequency and decreases with the investment horizon. Second, single risky asset settings show that, regardless of the portfolio B/M, momentum, market beta, and quality characteristics, the investor reacts more aggressively to aggregate liquidity shocks when investing in small stocks than when investing in large stocks. The only exceptions are allocations in large-illiquid stocks that have also strong sensitivity to liquidity shocks. This suggests that liquidity is the main concern of short-term investors. Third, multiple risky asset settings, without short selling, show that, regardless of the portfolio B/M, momentum, market beta, and quality characteristics, conditioning on aggregate liquidity yields mainly portfolio compositions with varying percentages of small stocks, large stocks, and the risk-free asset. In particular, the investor tends to gradually exit the market and shift toward large stocks as aggregate liquidity worsens. Overall, our results are in line with the flight-to-safety and the flight-to-liquidity episodes that have been documented in the literature (Beber et al., 2009; Longstaff, 2004; Vayanos, 2004). In addition, our findings give strong support to the assertion that investors have time-varying risk aversion and preferences for liquidity (Beber et al., 2009; Vayanos, 2004). Fourth, when short selling are allowed, the investor do not seem to exit the market as aggregate liquidity deteriorates. She instead engages in long/short strategies. Our results are robust to (i) different degrees of risk aversion, (ii) different sample periods, and (iii) alternative liquidity measures. Finally, in order to assess the economic value of exploiting information contained in aggregate liquidity, we propose a simple strategy that adapts to aggregate liquidity changes and assess its out-of-sample performance. All results indicate that our strategy is economically profitable and helps increasing return and reducing risk.

The remainder of the paper is organized as follows. Section 2 discusses relevant literature; Section 3 explains the investor's problem and describes Brandt's nonparametric technique; Section 4 presents data and preliminary analysis. We discuss, in Section 5, the empirical results on the effect of aggregate liquidity on optimal allocations and present robustness checks in Section 6. In Section 7, we propose a simple investment strategy based on aggregate liquidity signals and evaluate its out-of-sample performance. Section 8 concludes the paper.

2. Relevant literature

Our paper is closely related to the literature on portfolio allocation problems under return predictability. Since substantial empirical works found that US equity returns are partially predictable from some predictive variables such as dividend yield, term spread, and a variety of macroeconomic instruments, a number of studies have investigated the implications of those findings on optimal portfolio allocation policies. For example, Kandel and Stambaugh (1996), Balduzzi and Lynch (1999), Barberis (2000), and Campbell and Viceira (1999) use the dividend yield, and Brandt (1999) and Aît-Sahalia and Brandt (2001) use the lagged return, dividend yield, default spread, and term spread. In general, they conclude that optimal portfolio allocations are quite sensitive to variations in their conditioning variables and therefore investors may incur significant costs if they ignore time variation in those instruments. Along the same lines of the previous studies, we focus in this work on aggregate market liquidity as a predictive variable and examine its implications on portfolio allocation.

The concept of market liquidity, as a stock characteristic, is broadly defined as the ability of an asset to be transformed into cash without loss of value. Amihud and Mendelson (1986) were the first authors to confirm the existence of a negative relation between liquidity and asset returns. The effect of the asset's liquidity on optimal portfolio allocation has been addressed only in more recent studies. Longstaff (2001), for example, examines a portfolio choice problem where the investor has access to an illiquid risky asset that could not be traded immediately. Ghysels and Pereira (2008) study the effect of liquidity, as a stock characteristic, on optimal portfolio allocations in small and large stocks. Our work differs from these studies in that we consider liquidity as an aggregate state variable rather than a stock characteristic. Our aim, hence, is to investigate the effect of this aggregate liquidity on optimal portfolio allocation. Our motivation for this stems from three lines of research. First, there is a growing evidence that aggregate market liquidity is an important state variable affecting future returns. The notable works in this field are those of Amihud (2002), Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Liu (2006), and Watanabe and Watanabe (2008) among others. All these authors documented that aggregate liquidity is a priced state variable. For example, Amihud (2002) found that when aggregate liquidity falls, stock prices fall, leading to an increase in future expected returns. Amihud and Mendelson (2008) argues that "when market liquidity falls, investors anticipate that liquidity costs will remain high for a while because of the persistence of illiquidity, and higher expected liquidity costs should cause expected returns to rise and stock prices to fall." In addition, Pastor and Stambaugh (2003) and Sadka (2006) found that stocks exhibiting a greater sensitivity to aggregate market liquidity earn higher returns. They argue that asset prices include a compensation for the systematic liquidity risk. Second, besides the predictive power of innovations in aggregate liquidity to forecast expected returns, other supporting evidence comes from the role that market liquidity plays in financial markets. For example, Brunnermeier and Pedersen (2009) provide a theoretical framework that links market liquidity, funding liquidity, and asset prices. The model explains how shocks in the funding of liquidity providers, especially during periods of financial stress, can affect assets' market liquidity, leading asset prices to decline. This decline in prices, in turn, affects the ability of liquidity providers to raise funding, creating a downward liquidity spiral across asset classes and markets. Third, we also find support in recent macroeconomic research, such as the work of Næs et al. (2011). The authors highlight the importance of stock market liquidity as a state variable containing leading information about current and future real economy conditions. Using Granger tests, these authors found that, for both US and Norway markets, causality goes from stock market liquidity to real economy.

All these studies show that aggregate liquidity contains useful information about future investment opportunities. However, despite this predictability ability, its impact on investment decisions has not been adressed in previous studies. This paper seeks to fill this gap in the literature and explores the implications of considering aggregate liquidity in optimal portfolio problems with both single and multiple risky assets.

3. Conditional optimal portfolio allocations

3.1. Investor's problem

In this paper, we assess the ability of aggregate liquidity, as a state variable, to forecast optimal portfolio allocation. To this end, we consider a single-period investor who maximizes the conditional expectation of the utility of her wealth at the end of the period by trading in N risky assets and a risk-free asset. Furthermore, we assume that the investor's expectation is conditional on the aggregate liquidity level Z_t available at time t. Formally, the optimization setting is stated as:

$$\max_{x_t \in \mathbb{R}} E\left[u(W_{t+1}) \middle| Z_t\right] \tag{1}$$

subject to the budget equation:

$$W_{t+1} = W_t\left[x_t'\left(R_{t+1} - R_t^f 1_N\right) + R_t^f\right] \tag{2}$$

where R_{t+1} is an $N \times 1$ vector of gross returns on the N risky assets, R_t^f is the gross risk-free rate, 1_N is an $N \times 1$ vector of ones, x_t is an $N \times 1$ vector of portfolio weights in the N risky assets, W_t is the initial wealth normalized to one, and W_{t+1} is the terminal wealth. The objective function $u(.)$ measures the investor's utility of terminal wealth W_{t+1}. We use a CRRA utility function defined by

$$u(W) = \begin{cases} \dfrac{W^{1-\gamma}}{1-\gamma} \text{ if } \gamma > 0 \text{ and } \gamma \neq 1 \\ \ln(W) \text{ if } \gamma = 1 \end{cases} \tag{3}$$

where γ is the coefficient of relative risk aversion.

We choose a CRRA utility because it (i) is the commonly used utility function in many asset allocation studies, (ii) allows us to compute analytically the gradient and the hessian of the objective function due to its twice continuous differentiability property, and (iii) provides the advantage of incorporating preferences toward higher-order moments in a parsimonious manner as mentioned by Brandt (2009). Given the problem setting 1, optimal portfolio allocations are then characterized by the following N conditional Euler equations:

$$x_t : E\left[\frac{du(W_{t+1})}{dW_{t+1}}\left(R_{t+1} - R_t^f 1_N\right) \middle| Z_t\right] = 0 \tag{4}$$

3.2. Nonparametric approach: Brandt (1999)

The solution of the system of Euler Eq. (4) characterizes the optimal portfolio allocations as functions of the aggregate liquidity level Z_t. In spite of its multiple advantages, CRRA utility function does not allow for a closed form solution for x_t. Therefore, we rely on econometric methods to estimate x_t. One approach that has been extensively used by researchers is a two-step procedure. They develop a model that relates returns dynamics to forecasting variables in a first step, and then they solve for the optimal portfolio weights using implied conditional distributions of returns in a second step. However, Brandt (1999) points out that such an approach can lead to a severe model misspecification. He argues that portfolio weights are even easier to model than conditional return distributions and suggests estimating portfolio weights directly without further assumptions about returns dynamics using a nonparametric technique. In the following, we briefly present this method that we use to solve for the conditional optimal portfolio weights satisfying the FOCs in Eq. (4). For more details on the consistency of its estimators, see Brandt (1999).

If investment opportunities are constant, return distributions are independent of the state variable Z_t and so are the optimal portfolio weights. Using the method of moment, we can simply replace the unconditional expectation by the sample mean to get a consistent estimator of x_t as follows:

$$\hat{x} : \left\{x_t : \frac{1}{T}\sum_{t=1}^{T}\frac{du(W_{t+1})}{dW_{t+1}}\left(R_{t+1} - R_t^f 1_N\right) = 0\right\} \tag{5}$$

Now, supposing that investment opportunities are time-varying and are dependent on an observed state variable, Brandt (1999) suggests extending the traditional method of moment using a nonparametric approach. Called the conditional method of moments, this approach consists of replacing the conditional expectation by a locally weighted sample mean. For a given state reference $Z_t = Z$, the optimal portfolio weights estimator $\hat{x}(Z)$ of $x_t(Z)$ is

$$\hat{x}(Z) : \left\{ x_t : \frac{1}{Th_T} \sum_{t=1}^{T} K\left(\frac{Z_t - Z}{h_T}\right) * \frac{du(W_{t+1})}{dW_{t+1}} \left(R_{t+1} - R_t^f 1_N\right) = 0 \right\}, \tag{6}$$

where $K(.)$ is a weighting function that measures how close each observation Z_t is to the reference state Z and h is the window width (or bandwidth) that balances the bias-variance trade-off of the estimates. As we are interested in assigning greater weights to observations that are similar to the state reference, we choose a normal kernel density as our weighting function:

$$K(u) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u^2\right) \tag{7}$$

It is well known in the literature that the choice of the kernel function is not critical. However, the estimates are highly sensitive to the bandwidth selection. A large bandwidth will yield a small variance but a large bias in the estimation; while a small bandwidth will reduce the bias but increase the variance. Therefore, we follow the standard approach and choose bandwidths minimizing the mean squared errors of the estimates, which are of the form

$$h_T = \lambda\, \sigma(z) T^{-1/5}, \tag{8}$$

where $\sigma(z)$ denotes the standard deviations of the state variable, T is the sample size, and λ is a constant. The constant λ is the tuning parameter controlling the smoothness of the estimates. For each investment horizon, we use the same constant λ to obtain optimal weights for all the portfolio allocation settings considered in this paper. Following Brandt (1999), these values of λ are obtained by using the "leave-one-out cross validation" procedure and considering the benchmark portfolio choice setting where the investor has access to the market portfolio and a risk-free asset. Specifically, for each investment horizon, we proceed as follows. For every data point Z_t, we compute optimal weights in the market portfolio with and without removing the observation Z_t, and then we select λ that minimizes the sum of squared errors across all the data points.

4. Data and preliminary analysis

4.1. Data

In this paper, we examine the effect of aggregate liquidity on optimal allocations for daily, weekly, monthly, and quarterly horizons. To this end, we consider a total of 24 risky assets, including (a) the market portfolio, (b) 3 size-based portfolios, and (c) 20 double-sorted portfolios formed on the basis of size and other stock attributes including B/M, momentum, market beta, liquidity, and quality characteristics. The set of portfolios based on double sorts includes 4 size-B/M, 4 size-momentum, 4 size-market beta, 4 size-liquidity, and 4 size-quality portfolios.

The sample period is from 1963 through 2013. We obtained daily and monthly return time series on these test portfolios from different sources. Daily and monthly returns on the market portfolio (CRSP value-weighted index) are obtained from CRSP data. Daily and monthly returns on three size-based portfolios – small (bottom 30% caps stocks), medium (middle 40% caps stocks), and large (top 30% caps stocks) – as well as risk-free rates are obtained from Kenneth French's Data Library. Double-sorted portfolios are formed from independent sorts on size and B/M, momentum, market beta, or quality characteristics. Since size and liquidity are highly correlated, size-liquidity portfolios are formed from sequential sorts on size and then on liquidity. Our procedures to obtain daily and monthly returns on these double-sorted portfolios are described in detail in Appendix A. Finally, as we also consider weekly and quarterly horizons, we compute the portfolios' returns for these frequencies as follows. Weekly returns are computed by compounding daily returns from Wednesday to the following Wednesday. Quarterly returns are obtained from overlapping monthly returns in order to secure a sufficient number of observations for the nonparametric estimation that we consider in the next Sections.

We proxy for market (il)liquidity using the Amihud (2002) measure. Amihud (2002) defines his measure as the daily ratio of absolute stock return to its dollar volume ($|R_t|/Dvol_t$). Intuitively, this metric measures the "response of price to order flow." It has been widely used in the recent literature (Amihud, 2002; Acharya and Pedersen, 2005; Avramov et al., 2006; Watanabe and Watanabe, 2008; Korajczyk and Sadka, 2008; Hasbrouck, 2009 among others). In addition, Hasbrouck (2009) found that it is highly correlated with high frequency liquidity measures, and Goyenko et al. (2009) showed that the transaction costs and the price impact are well captured when using this measure. In order to compute aggregate market liquidity based on Amihud (2002) measure, we obtained daily data of stock prices, returns, volumes, and the number of shares outstanding from the Center of Research in Security Prices (CRSP). We, then, followed the standard literature and utilized only NYSE/AMEX common stocks with prices between \$2 and \$1000 over the sample period from 1963 through 2013. NASDAQ stocks are excluded because their volume measurement conventions are different. We started by computing daily liquidity measures for all eligible stocks. After that, we computed aggregate liquidity measure as the cross-sectional equally weighted average of individual Amihud's measures. To further estimate aggregate liquidity measures for weekly (from Wednesday to Wednesday) and monthly frequencies, we aggregated daily market-wide liquidity measures over weeks and months, respectively. Following Ghysels and Pereira (2008), time-aggregation is performed by taking weekly and monthly means.

The nonparametric method of Brandt (1999) requires that the conditioning state variable be stationary. This is not the case with our aggregate liquidity time series. Fig. 1a plots the time series of the raw aggregate Amihud (2002) liquidity measure at monthly frequency. The figure shows that the illiquidity measure is decreasing, indicating that aggregate market liquidity has increased over time. To eliminate non-stationarity, we follow Ghysels and Pereira (2008) and adjust aggregate liquidity time series by taking logs and subtracting a 6-month moving average. Our aggregate liquidity measures are redefined for daily, weekly, and monthly horizons as follows:

$$Z_t = -\left[\ln\left(l_{M,t}\right) - \frac{1}{S}\sum_{s=1}^{S}\ln\left(l_{M,t-s}\right)\right] \tag{9}$$

where $l_{M,t}$ denotes the raw aggregate Amihud (2002) measure at date t, S is a 6-month length that equals 126 for daily, 26 for weekly and 6 for monthly frequencies. We add the negative sign so that the measure represents liquidity rather than illiquidity. Furthermore, for practical concerns, our transformed aggregate liquidity time series is centered and scaled to have zero mean and variance 1. A negative value of Z indicates that the market is illiquid, and a positive value indicates that the market is liquid. In addition, any shift in portfolio weights can be interpreted as the response to a change in Z (in units of standard deviations). Fig. 1b shows the transformed time series (Z_t) at a monthly frequency. The figure shows no trend over time. Interestingly, the resulting time series seems to capture historical liquidity shocks that occurred in the US market during the past decades. The sharpest falls do correspond to the well-known financial events, such as the 1973 oil crisis, the 1987 crash, the 1997 Asian financial crisis, and subsequent LTCM collapse in 1998 and the 2007–2008 credit and liquidity crisis.

4.2. Preliminary analysis

Table 1 provides summary statistics for aggregate liquidity and future monthly returns on the 24 risky assets, described in subsection 4.2. By construction, our liquidity measure has mean zero and variance one. In addition, more than 90% of observations lie within two standard deviations of the mean zero. Regarding risky assets, overall, their monthly returns exhibit low correlation with the lagged aggregate liquidity measures.

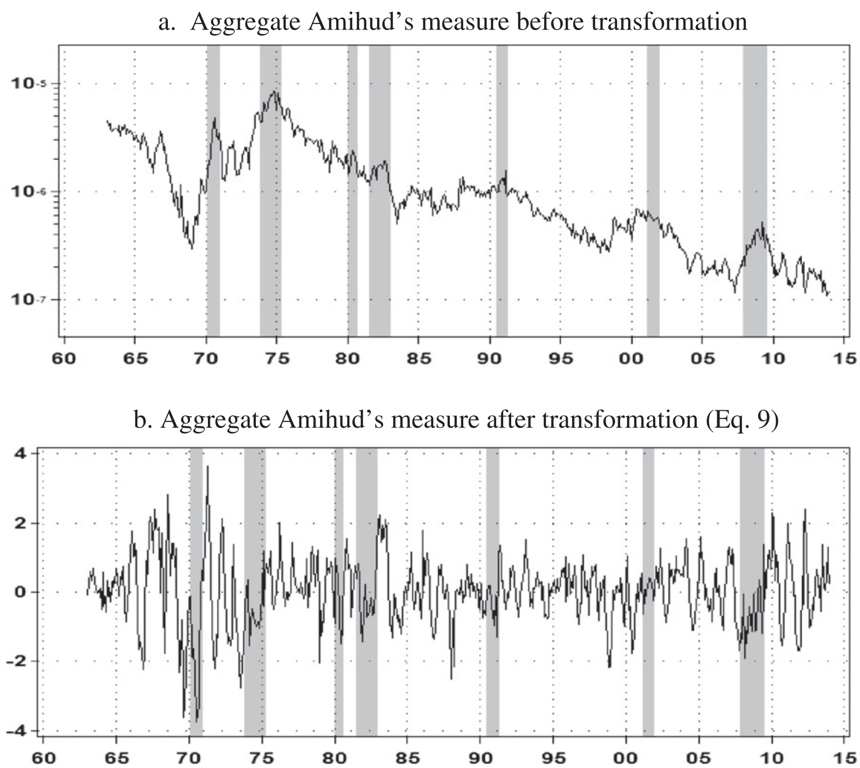

Fig. 1. Time series of monthly aggregate market liquidity. This figure plots the time series of monthly aggregate Amihud's measure before and after transformation. Before-transformation time series is computed by (1) averaging daily individual Amihud's measures ($|R_t|/dvol_t$) across all NYSE/AMEX common shares with prices between \$2 and \$1000, and then (2) taking the average across the corresponding month. After-transformation time series is obtained using Eq. (9). Plot *1.a.* displays the time series before transformation. Plot *1.b.* shows the time series after transformation. Note that we added a negative sign to the transformed measure so that a negative value can be interpreted as a negative shock to aggregate market liquidity.

Table 1
Descriptive statistics.
This table shows descriptive statistics of aggregate market liquidity and future excess returns ($R_{p,t+1}$) on 24 test portfolios including (a) the market portfolio, (b) 3 size-based portfolios and (c) 20 double-sorted portfolios on the basis of size and other stock attributes including B/M, momentum, market beta, liquidity. and quality characteristics. The portfolios are formed as described in subsection 4.1 and Appendix A. Aggregate market liquidity is proxied by the transformed aggregate Amihud's measure (Z_t) and is computed as described in Eq. (9). The statistics are computed with monthly observations from January 1963 to December 2013.

	Mean	Stdev	Skew.	Kurt.	Percentiles			Auto correlations				Correlation with Z
					5%	50%	95%	ρ_1	ρ_3	ρ_6	ρ_{12}	
	Monthly frequency											
Z_t	0.00	1.00	−0.24	1.06	−1.68	0.04	1.68	0.73	0.29	−0.13	0.13	1.00
Portfolio returns ($R_{p,t+1}$)												
Market	0.50	4.48	−0.56	2.05	−7.45	0.89	7.01	0.08	0.02	−0.05	0.03	0.01
Size-based portfolios												
Small	0.79	6.20	−0.35	2.21	−9.31	1.06	9.97	0.19	−0.03	−0.03	0.06	0.10
Medium	0.73	5.36	−0.55	2.26	−8.21	1.10	8.27	0.14	−0.02	−0.04	0.03	0.03
Large	0.48	4.32	−0.42	1.77	−7.20	0.82	6.95	0.05	0.03	−0.05	0.04	0.00
Double-sorted size-B/M portfolios												
Small growth	0.52	6.86	−0.36	1.82	−10.61	0.83	10.39	0.15	−0.04	−0.01	−0.01	0.04
Small value	1.07	5.59	−0.41	3.47	−8.09	1.40	8.94	0.18	−0.01	−0.08	0.13	0.09
Large growth	0.48	4.66	−0.35	1.88	−7.48	0.72	7.47	0.07	0.02	−0.04	0.03	−0.02
Large value	0.71	4.68	−0.42	2.53	−6.97	1.02	7.42	0.08	0.02	−0.10	0.08	0.03
Double-sorted size-MOM portfolios												
Small down	0.29	7.16	0.50	4.73	−10.87	0.21	11.37	0.19	−0.03	−0.06	0.06	0.05
Small up	1.23	6.21	−0.58	2.72	−9.70	1.68	9.81	0.14	−0.01	−0.02	0.02	0.07
Large down	0.32	5.90	0.28	3.02	−8.99	0.18	10.72	0.10	0.05	−0.05	0.03	−0.01
Large up	0.77	4.88	−0.48	2.01	−7.66	1.32	7.73	0.04	0.00	−0.04	0.03	0.03
Double-sorted size-beta portfolios												
Small low	0.76	4.61	−0.62	3.52	−6.80	1.06	7.34	0.15	−0.02	−0.02	0.10	0.08
Small high	0.89	6.79	−0.34	2.14	−10.28	1.06	11.17	0.14	−0.03	−0.07	0.04	0.03
Large low	0.49	3.93	−0.41	1.99	−6.57	0.75	6.13	0.02	0.05	−0.04	0.04	0.02
Large high	0.52	5.46	−0.40	1.54	−8.59	0.94	9.26	0.10	0.00	−0.07	0.01	0.00
Double-sorted size-liquidity portfolios												
Small illiquid	0.93	5.55	−0.60	3.55	−7.92	1.13	8.89	0.18	0.02	−0.05	0.10	0.12
Small liquid	0.74	6.08	−0.42	2.97	−9.07	1.15	9.17	0.16	−0.02	−0.07	0.06	0.04
Large illiquid	0.66	4.69	−0.54	3.20	−7.08	0.98	7.27	0.11	0.01	−0.07	0.04	0.02
Large liquid	0.44	4.18	−0.38	1.90	−6.66	0.63	6.76	0.03	0.03	−0.06	0.05	0.00
Double-sorted size-quality portfolios												
Small junk	0.03	7.36	−0.30	1.96	−11.73	0.43	11.34	0.19	−0.02	−0.03	0.04	0.08
Small quality	0.51	5.40	−0.46	2.81	−8.31	0.77	8.07	0.20	−0.02	−0.05	0.05	0.06
Large junk	−0.03	5.37	−0.62	2.12	−8.80	0.51	7.93	0.11	0.03	−0.05	0.02	0.03
Large quality	0.15	4.28	−0.40	1.55	−7.36	0.36	6.54	0.05	0.04	−0.03	0.04	−0.01

To provide a preliminary assessment of the effect of aggregate market liquidity on future expected returns, we consider the 24 test assets and estimate univariate predictive regressions of the form:

$$R_{p,t+1} = \alpha + \beta_{p,Z} Z_t + \varepsilon_t, \tag{10}$$

where $R_{p,t+1}$ denotes the one-period ahead excess return on asset p and Z_t stands for aggregate market liquidity as measured by the transformed aggregate Amihud's measure. We run the predictive regressions over multiple horizons including daily, weekly, monthly, and quarterly horizons. Regressions for quarterly horizons use overlapping monthly observations. It should be noted here that Amihud (2002) also studied the effect of aggregate market liquidity on future excess returns. However, the author investigated the effect of expected liquidity on future excess returns. We differ from Amihud in that we focus rather on the effect of aggregate liquidity shocks on future excess returns.

Table 2 exhibits slopes, t-statistics, and R^2 from regression (10) using excess returns on the 24 assets at different horizons. In order to correct for heteroskedasticity and autocorrelation, t-statistics were obtained using Newey and West (1987) standard errors. Several results emerge from Table 2. First, aggregate liquidity does not seem to predict future excess returns on the market portfolio for any of the investment horizons. Aggregate liquidity loadings, for the market portfolio, are small and statistically insignificant. Second, comparing regression results for small stocks to those of large stocks, we observe that, on one hand, there is

Table 2
The effect of aggregate market liquidity on expected future returns.
This table presents slopes, t-statistics, and R^2 from regressions of future excess returns ($R_{p,t+1}$) of 24 risky assets on aggregate market liquidity (Z_t) [$R_{p,t+1} = \alpha + \beta_{p,Z}Z_t + \varepsilon_t$]. The portfolios are formed as described in subsection 4.1 and Appendix A. Regressions are performed across different horizons, including 1-day (D), 1-week (W), 1-month (M), and 1-quarter (Q) horizons. The aggregate market liquidity is proxied by the transformed aggregate Amihud's measure and is computed for daily, weekly, and monthly horizons as described in Eq. (9). Quarterly regressions use overlapping monthly data. Panel A1 shows results for the market portfolio and three size-based portfolios (small, medium, and large). Panels A2–A6 exhibit outputs for size-B/M, size-momentum, size-beta, size-liquidity, and size-quality portfolios, respectively. To compute weekly returns, we compounded daily returns from Wednesday to the following Wednesday. Quarterly returns were obtained from overlapping monthly returns. The t-statistics, based on the Newey and West (1987) standard errors, are reported in brackets. Our sample covers the period 1963–2013.

	D	W	M	Q	D	W	M	Q	D	W	M	Q	D	W	M	Q
	$R_{p,t+1} = a + \beta_{p,Z}Z_t + \varepsilon_t$															
Panel A1: Market and size-based portfolios																
	Market				*Small*				*Medium*				*Large*			
$\beta_{p,Z}$	0.01	0.01	0.04	0.00	0.06	0.22	0.61	0.94	0.03	0.07	0.17	0.25	0.00	−0.02	−0.02	−0.09
	[0.78]	[0.18]	[0.23]	[−0.01]	[5.35]	[3.73]	[2.32]	[1.43]	[2.60]	[1.34]	[0.77]	[0.46]	[−0.12]	[−0.45]	[−0.11]	[−0.23]
R^2	0.0%	0.0%	0.0%	0.0%	0.3%	0.8%	1.0%	0.6%	0.1%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Panel A2: Double-sorted size-B/M portfolios																
	Small growth				*Small value*				*Large growth*				*Large value*			
$\beta_{p,Z}$	0.04	0.14	0.30	0.28	0.04	0.18	0.51	0.94	0.00	−0.03	−0.07	−0.28	0.01	0.02	0.15	0.22
	[3.64]	[2.08]	[1.03]	[0.39]	[4.10]	[3.39]	[2.28]	[1.65]	[−0.18]	[−0.61]	[−0.40]	[−0.62]	[0.65]	[0.46]	[0.81]	[0.50]
R^2	0.1%	0.2%	0.2%	0.0%	0.2%	0.6%	0.8%	0.7%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%
Panel A3: Double-sorted size-MOM portfolios																
	Small down				*Small up*				*Large down*				*Large up*			
$\beta_{p,Z}$	0.06	0.20	0.39	0.40	0.04	0.13	0.41	0.65	0.00	−0.01	−0.08	−0.17	0.01	0.01	0.14	0.36
	[4.38]	[2.69]	[1.29]	[0.57]	[3.77]	[2.23]	[1.62]	[1.01]	[0.04]	[−0.14]	[−0.33]	[−0.31]	[0.49]	[0.28]	[0.75]	[0.79]
R^2	0.2%	0.4%	0.3%	0.1%	0.1%	0.2%	0.4%	0.3%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.2%
Panel A4: Double-sorted size-beta portfolios																
	Small low				*Small high*				*Large low*				*Large high*			
$\beta_{p,Z}$	0.03	0.14	0.38	0.73	0.04	0.12	0.24	0.16	0.00	0.00	0.09	0.22	0.00	0.00	0.01	−0.17
	[3.69]	[2.81]	[2.05]	[1.48]	[3.04]	[1.69]	[0.83]	[0.23]	[0.38]	[−0.02]	[0.58]	[0.59]	[0.25]	[−0.07]	[0.03]	[−0.34]
R^2	0.2%	0.4%	0.7%	0.7%	0.1%	0.2%	0.1%	0.0%	0.0%	0.0%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%
Panel A5: Double-sorted size-liquidity portfolios																
	Small illiquid				*Small liquid*				*Large illiquid*				*Large liquid*			
$\beta_{p,Z}$	0.06	0.22	0.64	1.16	0.04	0.12	0.26	0.41	0.02	0.05	0.09	0.08	0.00	−0.02	0.01	0.03
	[5.61]	[4.04]	[2.73]	[1.95]	[3.05]	[1.78]	[0.99]	[0.65]	[2.30]	[1.08]	[0.48]	[0.17]	[−0.26]	[−0.39]	[0.04]	[0.07]
R^2	0.4%	0.9%	1.3%	1.1%	0.1%	0.2%	0.2%	0.1%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Panel A6: Double-sorted size-quality portfolios																
	Small junk				*Small quality*				*Large junk*				*Large quality*			
$\beta_{p,Z}$	0.04	0.14	0.60	0.85	0.04	0.13	0.32	0.42	0.00	0.00	0.15	0.21	0.00	−0.02	−0.02	−0.10
	[3.45]	[2.03]	[1.99]	[1.17]	[3.47]	[2.29]	[1.36]	[0.75]	[0.31]	[−0.07]	[0.70]	[0.42]	[0.08]	[−0.49]	[−0.13]	[−0.24]
R^2	0.1%	0.2%	0.7%	0.4%	0.1%	0.3%	0.3%	0.2%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%

no evidence of predictability for large stocks whereas for small stocks the evidence of predictability is very strong. The magnitude of aggregate liquidity loadings for small stocks, are higher and their t-statistics are significant while loadings for large stocks, are too low and their t-statistics are insignificant. Third, considering regression outputs for size-B/M, size-momentum, size-beta, size-liquidity, and size-quality portfolios, the general picture that emerges from Table 2 is that the predictive power of aggregate liquidity for future returns is concentrated among small stocks while the relationship between aggregate liquidity and future returns among large stocks is insignificant. Fourth, the predictability power of aggregate liquidity shocks for small stock returns is short-lived. It is stronger for the very short horizon (daily) and gradually dissipates at longer horizons (weekly and monthly) to completely disappear for quarterly horizon. In addition, among small stocks, small-illiquid and small-value stocks are the most affected by aggregate liquidity shocks. They exhibit the highest loadings, largest t-statistics, and highest R^2 values.

5. The effect of aggregate liquidity on optimal portfolio allocations

The purpose of our study is to explore the relationship between lagged aggregate liquidity shocks and optimal portfolio choice. In this section, we empirically investigate this relationship by considering conditional portfolio weights in various test portfolios including (a) the market portfolio, (b) 3 size-based portfolios, and (c) 20 double-sorted portfolios on the basis of size and other stock attributes including B/M, momentum, market beta, liquidity, and quality characteristics. The portfolios are formed as described in subsection 4.1 and Appendix A. We performed double-sorting procedure in order to disentangle the effect of aggregate liquidity shocks on portfolio weights in size-sorted portfolios from its effect on optimal weights in portfolios based on the other characteristics. We consider different investment horizons including 1-day, 1-week, 1-month, and 1-quarter horizons. Aggregate liquidity shocks are estimated by the transformed aggregate Amihud's measure (Z_t) and are computed for 1-day, 1-week, and 1-month horizons as described in subsection 4.1. Portfolio choice settings for quarterly horizons use overlapping monthly observations in order to secure a sufficient number of observations for nonparametric estimation.

We perform our analysis in two steps. In the first step, we focus on portfolio choice problems with a risk-free asset and a single risky asset. Our objective, via these single risky asset settings, is to analyze the effect of aggregate liquidity shocks on single allocations in (a) the market portfolio, (b) 3 size-based portfolios, and (c) 4 size-B/M, 4 size-momentum, 4 size-beta, 4 size-liquidity, and 4 size-quality portfolios. In the second step, we extend our analysis to the multiple risky assets settings, where the investor has access to a risk-free asset and either (a) 3 size-based portfolios or (b) 4 size-B/M, 4 size-momentum, 4 size-beta, 4 size-liquidity, or 4 size-quality portfolios. We aim by this extension to study the effect of aggregate liquidity shocks on optimal portfolio composition. For multiple risky assets settings, portfolio choice problems are solved for the case when short selling is allowed as well as for the case when short selling is not allowed ($0 \le x_t \le 1$).

Despite the large body of empirical works conducted over the past decades, the issue of the appropriate choice of the relative risk aversion level that reflects innate views of the market is still debatable. We rely, therefore, on the work of Mehra and Prescott (1985), who suggest that the conventional range of risk aversion should be less than 10. Furthermore, following studies such as Brandt (1999), Barberis (2000), and Guidolin and Timmermann (2005), we assume, for all the results in this section, a CRRA utility function with a relative risk aversion $\gamma = 5$.

We rely on the nonparametric method of Brandt (1999) to directly explain portfolio weights as functions of aggregate liquidity shocks. More specifically, optimal weights are obtained by solving Eq. (6)and using aggregate liquidity (Z_t) as the forecasting variable. For each portfolio choice setting, we present the results in a figure and a companion table. Each figure plots the optimal portfolio weight (composition) as a function of aggregate liquidity shocks for daily, weekly, monthly, and quarterly investment horizons. The corresponding table summarizes the results from the figure. In particular, each table presents optimal portfolio weights (compositions) at aggregate liquidity levels $Z = -2$ (two-standard deviation below the mean), $Z = 1$ (one-standard deviation below), $Z = 0$ (the mean), $Z = 1$ (one-standard deviation above the mean), and for $Z = 2$ (two-standard deviation above).

5.1. Portfolio allocation in the presence of a single risky asset

In this section, we focus on portfolio choice problems with a risk-free asset and one risky asset. Our aim here is to investigate how aggregate liquidity shocks affect optimal allocations in different characteristic portfolios. Section 5.1.1 discusses the results for

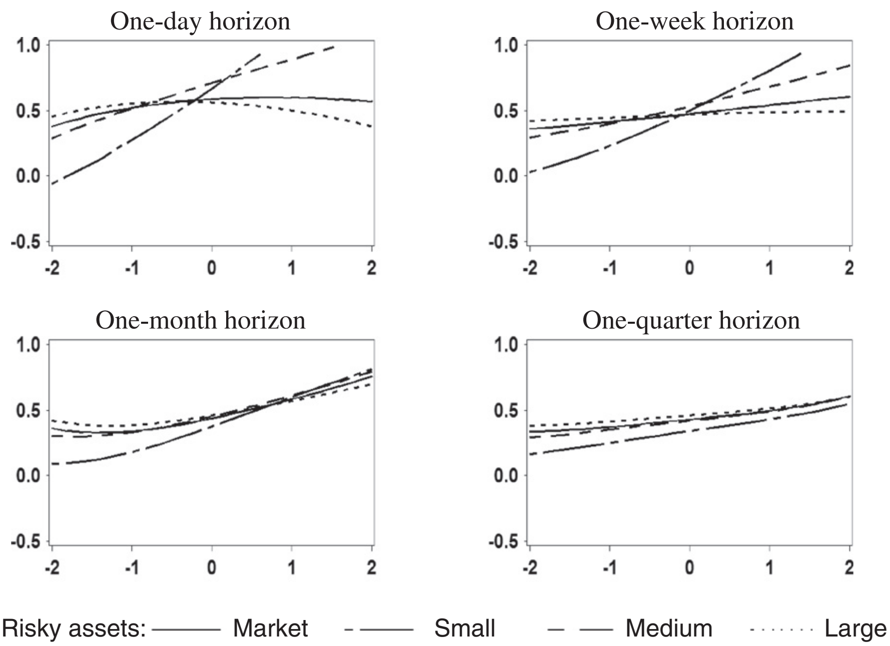

Fig. 2. Conditional allocations in the market and size-based portfolios. This figure plots optimal portfolio allocations as functions of aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth between the risk-free asset and a risky asset. The risky asset can be the market portfolio (market) or a size-based portfolio (small, medium, or large stocks). The portfolios are formed as described in subsection 4.1. The investment horizons are 1-day, 1-week, 1-month, or one-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day, 1-week, and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Each curve shows conditional portfolio weight in the corresponding risky asset (solution to Eq. (6)) as a function of the aggregate market liquidity level (Z). To compute weekly returns, we compounded daily returns from Wednesday to the following Wednesday. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

the case when the risky asset is either the market portfolio or a size-based portfolio. Section 5.1.2 discusses the outputs from the cases when the risky asset is one of the double-sorted portfolios. In order to give further insights on the sensitivity of optimal portfolio weights to changes in aggregate liquidity, we also compute their first derivatives as follows:

$$\left.\frac{\partial x(Z)}{\partial Z}\right|_{Z=\bar{z}} \approx \frac{x(\bar{z}+0.01)-x(\bar{z}-0.01)}{0.02} \tag{11}$$

5.1.1. Conditional allocations in the market and size-based portfolios

We start our analysis by considering a portfolio choice problem with a risk-free asset and one risky asset. The risky asset can be either the market portfolio or a size-based portfolio (small, medium, or large). Fig. 2 depicts optimal portfolio allocations in the risky asset as functions of the lagged aggregate liquidity shock and Table 3 summarizes the results.

Several observations can be made. First, comparing conditional (solutions to Eq. (6)) and unconditional (solutions to Eq. (5)) weights yields an interesting result. The availability of aggregate liquidity information causes the investor to overweight the risky assets when the market is highly liquid and to dynamically underweight the risky assets as the market is getting illiquid. At monthly frequency, for instance, unconditional allocations are 0.49 in the market portfolio and 0.40, 0.49, and 0.51 in small, medium, and large stocks, respectively. However, conditioning on market liquidity yields time-varying weights. On one hand, following a month with high liquidity ($Z = 2$), the conditional weights are 0.76 in the market portfolio and 0.81, 0.80, and 0.70 in small, medium, and large stocks, respectively. On the other hand, following a month with high illiquidity ($Z = -2$), the conditional allocations in the same risky assets becomes only 0.36 in the market portfolio and 0.09, 0.31, and 0.42 in small, medium, and large stocks, respectively. This suggests that aggregate liquidity information can serve as a signal to the investor to move toward the safer asset in times of economic distress, which is right in line with the flight-to-safety phenomenon documented in many recent empirical works (Longstaff, 2004; Vayanos, 2004). It should be noted that, although our predictive regressions shows that aggregate liquidity is only a weak predictor of excess returns on the market portfolio and medium and large stocks, our results here are not surprising. Previous studies such as Kandel and Stambaugh (1996) and Brandt (1999) shows that even weaker predictor can have substantial influence on CRRA investors' decisions.

Second, for daily and weekly horizons, All slopes for optimal weights in large stocks are close to zero. However, the slopes are high for optimal weights in medium stocks and becomes even higher for optimal weights in small stocks. This suggests that the sensitivity of optimal weights, to changes in aggregate liquidity, increases as we move from large toward small stocks. One

Table 3
Conditional allocations in the market and size-based portfolios.
This table shows estimates of optimal portfolio allocations conditional on the aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth between the risk-free asset and a risky asset. The risky asset can be the market portfolio (market) or a size-based portfolio (small, medium, or large stocks). The portfolios are formed as described in subsection 4.1. The investment horizons are 1-day, 1-week, 1-month, or 1-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day, 1-week, and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Each panel shows conditional portfolio weights (solutions to Eq. (6)) and unconditional portfolio weights (solutions to Eq. (5)) in the corresponding risky asset. The conditional weights are computed for aggregate liquidity levels $Z = -2$ (two-standard deviation below the mean), $Z = -1$ (one-standard deviation below), $Z = 0$ (the mean), $Z = 1$ (one-standard deviation above the mean), and for $Z = 2$ (two-standard deviation above). The slope at each liquidity level is obtained from Eq. (11) and is presented in curly braces. To compute weekly returns, we compounded daily returns from Wednesday to the following Wednesday. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

Assets	Conditional weight					Uncond. weight	Conditional weight					Uncond. weight
	$Z = -2$	$Z = -1$	$Z = 0$	$Z = 1$	$Z = 2$		$Z = -2$	$Z = -1$	$Z = 0$	$Z = 1$	$Z = 2$	
	One-day horizon						*One-week horizon*					
Market	0.38	0.52	0.59	0.60	0.57	0.49	0.36	0.41	0.47	0.54	0.61	0.46
	{0.19}	{0.10}	{0.04}	{−0.01}	{−0.04}		{0.05}	{0.06}	{0.07}	{0.07}	{0.06}	
Small	−0.06	0.28	0.67	1.11	1.56	0.62	0.03	0.23	0.50	0.81	1.13	0.49
	{0.31}	{0.36}	{0.42}	{0.45}	{0.45}		{0.17}	{0.24}	{0.30}	{0.32}	{0.32}	
Medium	0.29	0.52	0.71	0.89	1.07	0.63	0.29	0.40	0.53	0.68	0.85	0.52
	{0.26}	{0.21}	{0.19}	{0.18}	{0.17}		{0.09}	{0.12}	{0.15}	{0.16}	{0.16}	
Large	0.45	0.56	0.56	0.50	0.38	0.46	0.42	0.45	0.47	0.49	0.49	0.45
	{0.16}	{0.05}	{−0.03}	{−0.09}	{−0.14}		{0.02}	{0.02}	{0.02}	{0.01}	{−0.01}	
	One-month horizon						*One-quarter horizon*					
Market	0.36	0.34	0.44	0.59	0.76	0.49	0.34	0.37	0.43	0.50	0.61	0.45
	{−0.10}	{0.05}	{0.13}	{0.16}	{0.19}		{0.00}	{0.05}	{0.06}	{0.08}	{0.15}	
Small	0.09	0.18	0.38	0.60	0.81	0.40	0.16	0.25	0.34	0.43	0.55	0.34
	{0.01}	{0.16}	{0.22}	{0.22}	{0.21}		{0.06}	{0.10}	{0.09}	{0.10}	{0.15}	
Medium	0.31	0.33	0.45	0.61	0.80	0.49	0.29	0.35	0.42	0.49	0.61	0.43
	{−0.04}	{0.08}	{0.15}	{0.17}	{0.20}		{0.04}	{0.07}	{0.07}	{0.08}	{0.15}	
Large	0.42	0.39	0.46	0.57	0.70	0.51	0.38	0.41	0.46	0.51	0.60	0.48
	{−0.12}	{0.03}	{0.10}	{0.12}	{0.14}		{−0.00}	{0.05}	{0.05}	{0.06}	{0.12}	

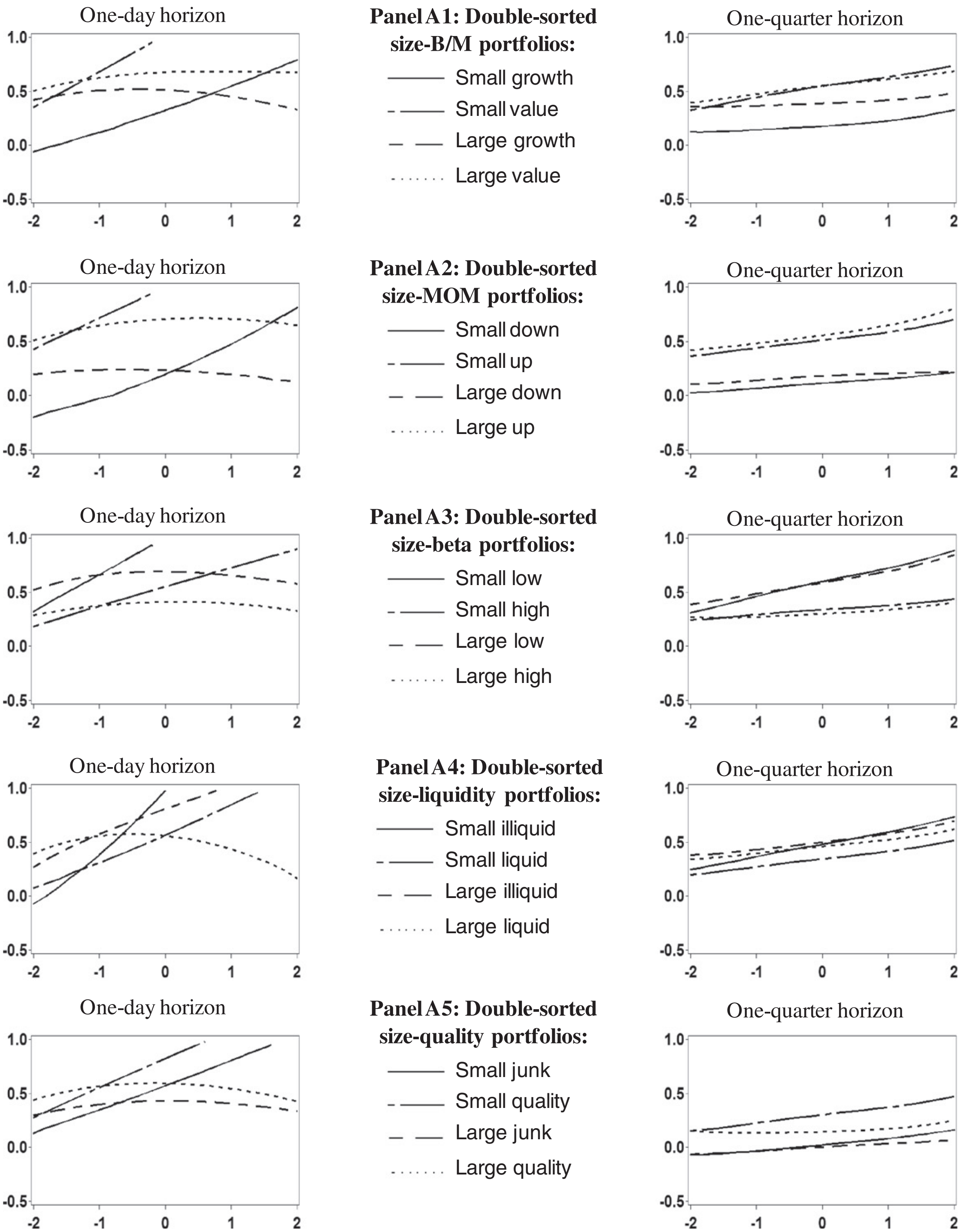

Fig. 3. Conditional allocations in size-B/M, size-momentum, size-beta, size-liquidity, and size-quality portfolios. This figure plots optimal portfolio allocations as functions of aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth between the risk-free asset and a risky asset. The risky asset can be one of the following double-sorted portfolios: a size-B/M (Panel A1), a size-momentum (Panel A2), a size-beta (Panel A3), a size-liquidity (Panel A4), or a size-quality (Panel A5) portfolio. The portfolios are formed as described in subsection 4.1 and Appendix A. The investment horizons are 1-day or 1-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure, and is computed for 1-day and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Each curve shows conditional portfolio weight in the corresponding risky asset (solution to Eq. (6) as a function of the aggregate market liquidity level (Z)). Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

explanation of this is that the effect of changes in aggregate liquidity is stronger for small stocks and gets weaker for large stocks. Furthermore, since size is also a proxy for liquidity (Amihud, 2002), we conclude, therefore, that liquidity is a greater concern for investors allocating their wealth to illiquid assets than for those investing in liquid assets.

Third, the effect of aggregate liquidity on optimal weights decreases with the investment horizon. For instance, daily allocations vary from −0.6 and 0.29 in small and medium portfolios at $Z = -2$ to reach 1.56 and 1.07 in small and medium portfolios at $Z = 2$, while quarterly allocations vary from 0.16 and 0.29 in small and medium portfolios at $Z = -2$ to reach 0.55 and 0.61 in

Table 4

Conditional allocations in size-B/M, size-momentum, size-beta, size-liquidity, and size-quality portfolios.

This table shows estimates of optimal portfolio allocations conditional on the aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth between the risk-free asset and a risky asset. The risky asset can be one of the following double-sorted portfolios: a size-B/M (Panel A1), a size-momentum (Panel A2), a size-beta (Panel A3), a size-liquidity (Panel A4), or a size-quality (Panel A5) portfolio. The portfolios are formed as described in subsection 4.1 and Appendix A. The investment horizons are 1-day or 1-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Each panel shows conditional portfolio weights (solutions to Eq. (6)) and unconditional portfolio weights (solutions to Eq.(5)) in the corresponding risky asset. The conditional weights are computed for aggregate liquidity levels $Z = -2$ (two-standard deviation below the mean), $Z = -1$ (one-standard deviation below), $Z = 0$ (the mean), $Z = 1$ (one-standard deviation above the mean), and for $Z = 2$ (two-standard deviation above). The slope at each liquidity level is obtained from Eq. (11) and is presented in curly braces. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

Risky asset	*One-day horizon*						*One-quarter horizon*					
	Conditional weight					Uncond. weight	Conditional weight					Uncond. weight
	$Z = -2$	$Z = -1$	$Z = 0$	$Z = 1$	$Z = 2$		$Z = -2$	$Z = -1$	$Z = 0$	$Z = 1$	$Z = 2$	
Panel A1: Double-sorted size-B/M portfolios												
Small growth	−0.06	0.12	0.32	0.55	0.79	0.28	0.13	0.14	0.18	0.23	0.33	0.20
	{0.20}	{0.17}	{0.21}	{0.24}	{0.25}		{−0.01}	{0.03}	{0.04}	{0.07}	{0.14}	
Small value	0.36	0.68	1.03	1.37	1.70	0.96	0.33	0.45	0.55	0.64	0.74	0.54
	{0.32}	{0.34}	{0.35}	{0.34}	{0.31}		{0.10}	{0.12}	{0.09}	{0.09}	{0.13}	
Large growth	0.42	0.51	0.51	0.45	0.33	0.42	0.36	0.37	0.39	0.42	0.48	0.41
	{0.14}	{0.04}	{−0.03}	{−0.09}	{−0.15}		{−0.02}	{0.02}	{0.02}	{0.04}	{0.10}	
Large value	0.50	0.63	0.68	0.69	0.68	0.60	0.40	0.48	0.55	0.61	0.69	0.54
	{0.17}	{0.08}	{0.02}	{−0.01}	{−0.00}		{0.06}	{0.08}	{0.07}	{0.06}	{0.10}	
Panel A2: Double-sorted size-MOM portfolios												
Small down	−0.20	−0.02	0.19	0.47	0.81	0.20	0.03	0.07	0.12	0.16	0.22	0.12
	{0.16}	{0.18}	{0.25}	{0.31}	{0.37}		{0.02}	{0.05}	{0.04}	{0.05}	{0.07}	
Small up	0.43	0.71	1.00	1.29	1.54	0.91	0.36	0.44	0.51	0.59	0.70	0.52
	{0.30}	{0.29}	{0.29}	{0.27}	{0.24}		{0.06}	{0.08}	{0.07}	{0.09}	{0.16}	
Large down	0.20	0.24	0.23	0.20	0.13	0.19	0.11	0.14	0.18	0.21	0.22	0.18
	{0.07}	{0.02}	{−0.02}	{−0.05}	{−0.05}		{−0.00}	{0.05}	{0.03}	{0.02}	{0.03}	
Large up	0.51	0.65	0.71	0.71	0.65	0.60	0.42	0.48	0.56	0.65	0.80	0.58
	{0.19}	{0.09}	{0.03}	{−0.03}	{−0.09}		{0.04}	{0.07}	{0.08}	{0.12}	{0.19}	
Panel A3: Double-sorted size-beta portfolios												
Small low	0.32	0.66	1.00	1.33	1.63	0.90	0.31	0.46	0.60	0.72	0.89	0.58
	{0.35}	{0.34}	{0.33}	{0.31}	{0.30}		{0.14}	{0.15}	{0.12}	{0.13}	{0.20}	
Small high	0.18	0.37	0.55	0.73	0.90	0.49	0.24	0.29	0.34	0.38	0.44	0.34
	{0.20}	{0.18}	{0.18}	{0.17}	{0.17}		{0.03}	{0.06}	{0.04}	{0.04}	{0.08}	
Large low	0.52	0.66	0.69	0.66	0.58	0.58	0.39	0.49	0.59	0.70	0.85	0.58
	{0.22}	{0.08}	{−0.01}	{−0.06}	{−0.09}		{0.08}	{0.11}	{0.10}	{0.12}	{0.19}	
Large high	0.29	0.38	0.41	0.40	0.33	0.33	0.27	0.27	0.30	0.34	0.41	0.32
	{0.12}	{0.06}	{0.01}	{−0.04}	{−0.09}		{−0.04}	{0.02}	{0.03}	{0.05}	{0.09}	
Panel A4: Double-sorted size-liquidity portfolios												
Small illiquid	−0.07	0.38	0.98	1.65	2.27	0.90	0.25	0.37	0.48	0.60	0.74	0.48
	{0.42}	{0.52}	{0.66}	{0.67}	{0.55}		{0.11}	{0.12}	{0.11}	{0.12}	{0.17}	
Small liquid	0.07	0.31	0.56	0.85	1.11	0.50	0.20	0.27	0.35	0.41	0.52	0.35
	{0.24}	{0.23}	{0.27}	{0.28}	{0.24}		{0.05}	{0.08}	{0.07}	{0.08}	{0.14}	
Large illiquid	0.27	0.58	0.81	1.03	1.23	0.70	0.38	0.43	0.50	0.58	0.70	0.52
	{0.38}	{0.26}	{0.22}	{0.21}	{0.18}		{0.01}	{0.07}	{0.07}	{0.09}	{0.15}	
Large liquid	0.39	0.56	0.56	0.44	0.16	0.42	0.34	0.40	0.46	0.52	0.62	0.47
	{0.27}	{0.07}	{−0.06}	{−0.19}	{−0.28}		{0.03}	{0.07}	{0.06}	{0.07}	{0.13}	
Panel A5: Double-sorted size-quality portfolios												
Small junk	0.13	0.35	0.57	0.81	1.05	0.52	−0.07	−0.03	0.02	0.08	0.16	0.03
	{0.20}	{0.21}	{0.23}	{0.24}	{0.24}		{0.01}	{0.05}	{0.06}	{0.07}	{0.10}	
Small quality	0.28	0.56	0.82	1.08	1.32	0.73	0.15	0.23	0.30	0.37	0.47	0.30
	{0.29}	{0.27}	{0.27}	{0.25}	{0.24}		{0.05}	{0.08}	{0.07}	{0.08}	{0.13}	
Large junk	0.30	0.40	0.43	0.41	0.33	0.34	−0.06	−0.04	0.00	0.03	0.07	0.00
	{0.14}	{0.07}	{0.00}	{−0.05}	{−0.09}		{0.01}	{0.04}	{0.04}	{0.03}	{0.04}	
Large quality	0.44	0.57	0.60	0.55	0.43	0.48	0.15	0.14	0.14	0.17	0.25	0.18
	{0.19}	{0.07}	{−0.01}	{−0.09}	{−0.14}		{−0.05}	{0.00}	{0.02}	{0.04}	{0.11}	

small and medium portfolios at $Z = 2$. This finding is consistent with the Amihud and Mendelson's (1986) clientele effect. It suggests that investors with longer investment horizons are less concerned about the liquidity of their portfolios. Ghysels and Pereira (2008) report similar results for small and large stocks when conditioning allocations on liquidity as a stock characteristic.

5.1.2. Conditional allocations in size-B/M, size-momentum, size-beta, size-liquidity, and size-quality portfolios

In this section, we further investigate the effect of aggregate liquidity on optimal allocations in other characteristic portfolios, including B/M, momentum, market beta, liquidity, and quality characteristics. We, thus, re-run our analysis by considering a portfolio choice problem with a riskless asset and one risky asset. The risky asset can be one of the 20 double-sorted test portfolios, described in subsection 4.1 and Appendix A. Fig. 3 depicts optimal portfolio weights in the risky assets as functions of aggregate liquidity level, and Table 4 summarizes the results. To save space, only the outputs from daily and quarterly horizons are presented in Fig. 3 and Table 4. Panels A1–A5 display results for 4 size-BM, 4 size-MOM, 4 size-beta, 4 size-liquidity, and 4 size-quality portfolios, respectively.

Several observations can be made. First, on one hand, the investor with very short horizon aggressively underweights (overweights) small stocks during periods following negative (positive) liquidity shocks. On the other hand, CRRA investor's allocations in large stocks do not seem to be affected by the lagged liquidity shock. This result remains valid and independent of the B/M, momentum, market beta, and quality characteristics of the portfolios. The only exception are allocations in large-illiquid stocks that are also sensitive to the lagged liquidity shock. This confirms our earlier conclusion that liquidity is the main concern of short-term investors. Second, looking at daily optimal portfolio weights in small stocks, we can notice that the slopes of the conditional weights in small-value, small-low market beta, and small-illiquid portfolios are relatively higher than those of conditional weights in small-growth, small-high market beta, and small-liquid portfolios. These results indicate that the CRRA investor reacts more aggressively to aggregate liquidity shocks when investing in the former portfolios than when investing in the latter. Third, the effect of aggregate liquidity on optimal weights in small stocks remains positive but considerably reduces with the investment horizon in general. Furthermore, at the quarterly horizon, aggregate liquidity does not seem to differently affect conditional allocations in small and large stocks. Conditional weights in large-illiquid stocks are also no more highly sensitive to aggregate liquidity shocks. In line with the hypothesis of clientele effect, these results indicate that longer-term investors are less concerned about the liquidity of their portfolios when aggregate liquidity changes.

Table 5

Conditional portfolio composition in the presence of size-based portfolios.

This table shows estimates of the optimal portfolio composition conditional on the aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth among the risk-free asset and three size-based portfolios (small, medium, and large stocks). The portfolios are formed as described in subsection 4.1. The investment horizons are 1-day, 1-week, 1-month, or 1-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day, 1-week, and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Panel A shows results for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panel B exhibits results for the case when short selling is allowed. Each panel shows conditional portfolio compositions (solutions to Eq. (6)) and unconditional portfolio compositions (solutions to Eq. (5)). Conditional portfolio compositions are computed for aggregate market liquidity levels $Z = -2$ (two-standard deviation below the mean), $Z = -1$ (one-standard deviation below), $Z = 0$ (the mean), $Z = 1$ (one-standard deviation above the mean), and for $Z = 2$ (two-standard deviation above). To compute weekly returns, we compounded daily returns from Wednesday to the following Wednesday. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

Assets	*Panel A: short selling is not allowed*						*Panel B: short selling is allowed*					
	Conditional weight					Uncond. weight	Conditional weight					Uncond. weight
	$Z = -2$	$Z = -1$	$Z = 0$	$Z = 1$	$Z = 2$		$Z = -2$	$Z = -1$	$Z = 0$	$Z = 1$	$Z = 2$	
	One-day horizon											
Small	0.00	0.00	0.00	1.00	1.00	0.26	−3.58	−2.33	−0.14	1.81	4.12	−0.02
Medium	0.00	0.08	0.71	0.00	0.00	0.38	3.66	2.83	1.11	0.10	−1.17	1.13
Large	0.46	0.48	0.00	0.00	0.00	0.00	0.06	−0.12	−0.30	−0.99	−1.85	−0.53
Risk-free	0.54	0.44	0.29	0.00	0.00	0.36	0.86	0.62	0.33	0.08	−0.10	0.42
	One-week horizon											
Small	0.00	0.00	0.02	0.81	1.00	0.12	−3.21	−1.90	−0.25	1.53	3.44	−0.16
Medium	0.00	0.18	0.52	0.00	0.00	0.40	3.78	2.65	1.18	−0.36	−2.11	1.09
Large	0.42	0.26	0.00	0.00	0.00	0.00	−0.40	−0.48	−0.49	−0.53	−0.52	−0.51
Risk-free	0.58	0.56	0.46	0.19	0.00	0.48	0.83	0.73	0.56	0.36	0.19	0.58
	One-month horizon											
Small	0.00	0.00	0.00	0.60	0.81	0.00	−1.94	−1.34	−0.17	1.01	1.89	−0.23
Medium	0.00	0.26	0.45	0.00	0.00	0.49	2.77	2.17	0.89	−0.38	−1.24	1.01
Large	0.42	0.09	0.00	0.00	0.00	0.00	−0.48	−0.53	−0.34	−0.17	−0.15	−0.38
Risk-free	0.58	0.65	0.55	0.40	0.19	0.51	0.65	0.70	0.62	0.54	0.50	0.60
	One-quarter horizon											
Small	0.00	0.00	0.00	0.38	0.55	0.00	−1.09	−0.73	−0.26	0.22	0.58	−0.32
Medium	0.10	0.35	0.42	0.06	0.00	0.43	1.67	1.43	0.98	0.47	0.25	1.09
Large	0.26	0.00	0.00	0.00	0.00	0.00	−0.22	−0.37	−0.37	−0.32	−0.45	−0.41
Risk-free	0.64	0.65	0.58	0.56	0.45	0.57	0.64	0.67	0.65	0.63	0.62	0.64

5.2. Portfolio allocation in the presence of multiple risky assets

We have, so far, considered only conditional weights in single risky assets. We now extend our analysis and investigate conditional weights in multiple risky assets. Our aim here is to examine the effect of aggregate liquidity shocks on the optimal portfolio composition. More specifically, Section 5.2.1 discusses results for portfolio choice settings with a risk-free asset and 3 size-

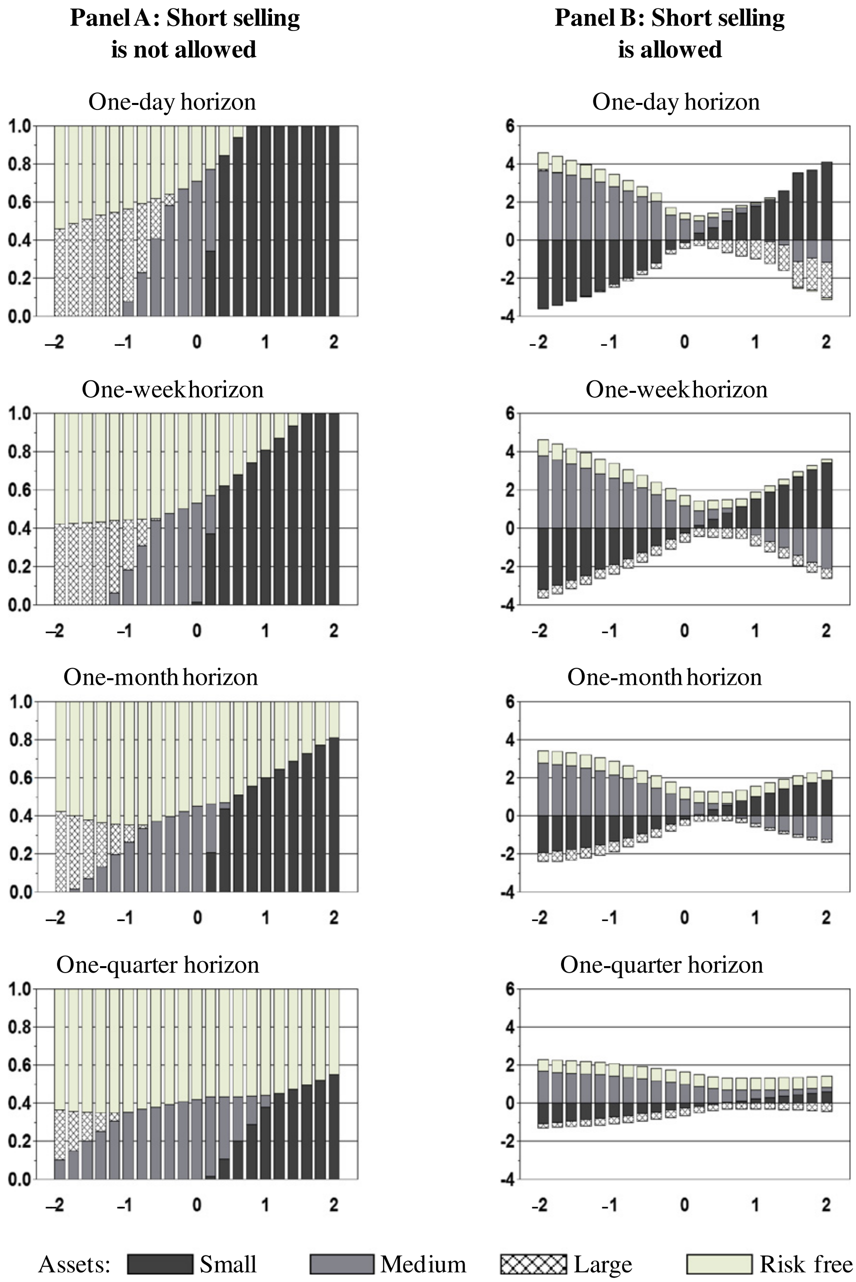

Fig. 4. Conditional portfolio composition in the presence of size-based portfolios. This figure plots optimal portfolio composition as a function of aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth among the risk-free asset and three size-based portfolios (small, medium and large stocks). The portfolios are formed as described in subsection 4.1. The investment horizons are 1-day, 1-week, 1-month, or 1-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day, 1-week, and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Panel A shows conditional portfolio compositions for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panel B presents portfolio compositions for the case when short selling is allowed. Each bar shows the optimal portfolio composition (solution to Eq. (6)) conditional on the aggregate market liquidity level (Z)). To compute weekly returns, we compounded daily returns from Wednesday to the following Wednesday. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

based portfolios (small, medium, and large) as risky assets. Section 5.2.1 discusses outputs from portfolio choice settings with a risk-free asset and either 4 size-B/M, 4 size-momentum, 4 size-beta, 4 size-liquidity, or 4 size-quality portfolios. Furthermore, we solve portfolio choice problems for the case when short selling is allowed as well as for the case when short selling is not allowed ($0 \le x_t \le 1$).

5.2.1. Conditional portfolio composition in the presence of size-based portfolios

Table 5 and Fig. 4 show allocation results when the investor has access to the risk-free asset and 3 size-based portfolios (small, medium, and large) as risky assets. Panel A shows conditional portfolio compositions for the case when short selling is not allowed ($0 \le x_t \le 1$). Panel B presents portfolio compositions for the case when short selling is allowed.

Let's first consider the case when short selling is not allowed. Four main conclusions can be drawn from the outputs in Panel A (Table 5 and Fig. 4). First, in spite of the presence of multiple risky assets, our conditional method still yields decreasing weights in the risky assets as aggregate market liquidity worsens. This finding is consistent with the flight-to-safety phenomenon. The aggregate liquidity level can, hence, serve as a signal, for the investor, to decide on the amount of wealth to allocate to the risky assets. In the case of a daily horizon for instance, this amount ranges from 43% when the market is highly illiquid ($Z = -2$) to 100% of wealth when the market is highly liquid ($Z = 2$) ; allowing, hence, the investor to reap the advantages of risky assets when they exhibit high performance and to dynamically exit the market as investment conditions are becoming unfavorable. Second, what is more important about the outputs of these settings is the composition of the risky assets. We can see how the investor gradually shifts from small to large stocks as aggregate liquidity worsens. This is consistent with the flight-to-liquidity episodes reported in Næs et al. (2011) and Ben-David et al. (2012). The authors find that during financial crisis, institutional investors shift their portfolios toward larger stocks. Third, the effect of aggregate liquidity on optimal weights is stronger for the very short horizon (daily) and gets weaker as the investment horizon lengthens. For instance, at daily frequency, the amount of wealth invested in risky assets ranges from 43% when the market is highly illiquid ($Z = -2$) to 100% of wealth when the market is highly liquid ($Z = 2$), while at quarterly frequency, this amount ranges from 30% when the market is highly illiquid to 45% of wealth when the market is highly liquid. Fourth, comparing the outputs of conditional and unconditional settings, we observe that the latter allocates more wealth to medium stocks while the conditional setting targets small stocks when the market is liquid and large stocks when the market gets illiquid. We interpret this finding in the sense that, when information about market liquidity is not available, the medium portfolio represents a diversified portfolio that can hedge against market liquidity shocks. Whereas, learning from aggregate liquidity about future market conditions can help the investor to gain from small stocks when the market is highly liquid and to move to larger stocks when market liquidity dries up, which provides a better hedge than medium stocks.

Turning to the case when short selling is allowed. The outputs from Panel B (Table 5 and Fig. 4) suggest three main conclusions. First, following positive shocks to aggregate liquidity, the investor tends to short large and medium stocks and long small stocks. However, she does not seem to exit the market as aggregate liquidity worsens. She, instead, shorts small stocks and buys medium stocks and the risk-free asset. This long/short strategy allows the investor to hedge against liquidty dry-ups. If liquidity dries up, it will affect small stocks more than medium stocks. As a result, losses due to liquidity from medium stocks can be compensated by gains due liquidity from shorted small stocks. This suggests that CRRA investor plays the role of a liquidity provider (demander) during liquid (illiquid) periods. Second, the investor takes larger short positions in response to larger aggregate liquidity shocks (both negative and positive shocks). Especially, the investor tends to short heavily small stocks after large negative shocks (liquidity crises). This finding provides, hence, empirical evidence of the existence of price pressure on small stocks during liquidity crises. Overall, our findings are consistent with those reported in Shkilko et al. (2012). The authors document that, during liquidity crises, short selling activities increase and that « short sellers switch from their usual role as liquidity providers to demanding liquidity ». Third, the magnitude of short positions decreases with the investment horizon. Very short-term (daily and weekly) investor tends to engage heavily in short selling while a longer-term (monthly and quarterly) investor also engages in short selling but with a lower degree.

5.2.2. Conditional portfolio composition in the presence of size-B/M, size-momentum, size-beta, size-liquidity, or size-quality portfolios

In this section, we further investigate the effect of aggregate liquidity on optimal allocations among a risk-free asset and four risky assets that capture both size and other stock attributes including B/M, momentum, market beta, liquidity,and quality characteristics. We re-run our analysis by considering portfolio choice problems with a risk-free asset and either 4 size-B/M, 4 size-momentum, 4 size-beta, 4 size-liquidity, or 4 size-quality portfolios. Fig. 5 depicts optimal portfolio compositions as functions of aggregate liquidity level, and Table 6 summarizes the results. To save space, only the outputs from daily and quarterly horizons are presented in Fig. 5 and Table 6. Panels A1–A5 and B1–B5 display results for 4 size-B/M, 4 size-momentum, 4 size-beta, 4 size-liquidity, and 4 size-quality portfolios, respectively. Panels A1–A5 present results for the case when short selling is not allowed ($0 \le x_t \le 1$). Panels B1–B5 are for the case when short selling is allowed.

We begin our analysis by considering the case of portfolio choice problems with short selling constraints. Panels A1–A5 show that some of our previous results hold in all the portfolio settings with the double-sorted portfolios. First, in line with the flight-to-safety phenomenon, for all portfolio settings, optimal weights in the risky assets decreases as aggregate liquidity worsens. Second, regardless of portfolio characteristics in terms of B/M, momentum, market beta, and quality, very short-term investor dynamically switches from small to large stocks as aggregate liquidity deteriorates. For the case of size-liquidity portfolios, the investor switches from small-illiquid, to large-illiquid and then to large-liquid stocks as the market gets illiquid. This is consistent with the flight-to-liquidity assertion during bad times, suggesting that liquidity is the main concern of very short-term investors. Third,

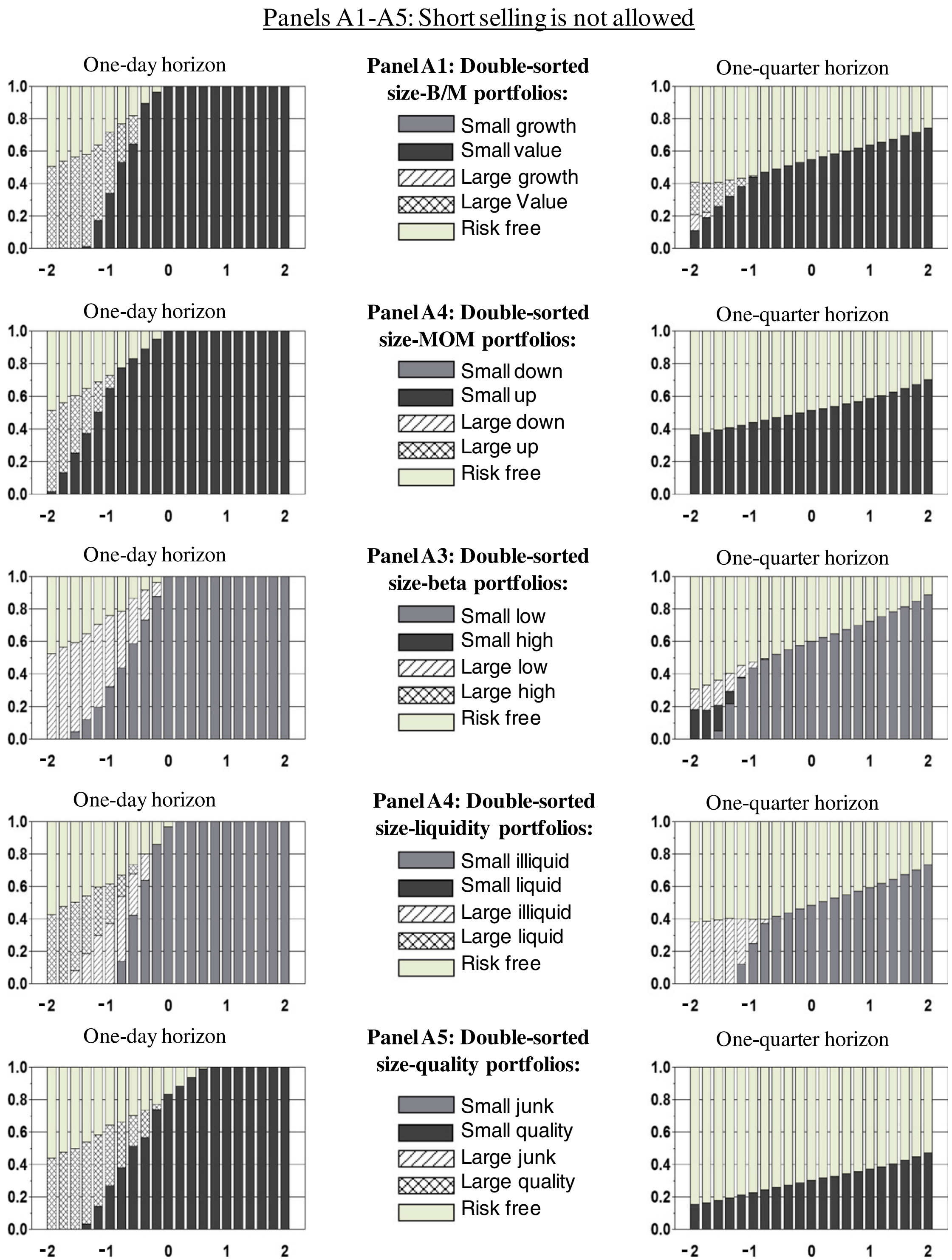

Fig. 5. Conditional portfolio composition in the presence of size-B/M, size-momentum, size-beta, size-liquidity, or size-quality portfolios. This figure plots optimal portfolio composition as a function of aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investor allocates her wealth among the risk-free asset and four risky assets. The risky assets can be either 4 size-B/M (Panels A1, B1), 4 size-momentum (Panels A2, B2), 4 size-beta (Panels A3, B3), 4 size-liquidity (Panels A4, B4), or 4 size-quality (Panels A5, B5) double-sorted portfolios. The portfolios are formed as described in subsection 4.1 and Appendix A. The investment horizons are 1-day or 1-quarter horizons. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for one-day and one-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Panels A1–A5 present plots for the case when short selling is not allowed ($0 \le x_t \le 1$). Panels B1–B5 display plots for the case when short selling is allowed. Each bar shows the optimal portfolio composition (solution to Eq. (6)) conditional on aggregate market liquidity level (Z). Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

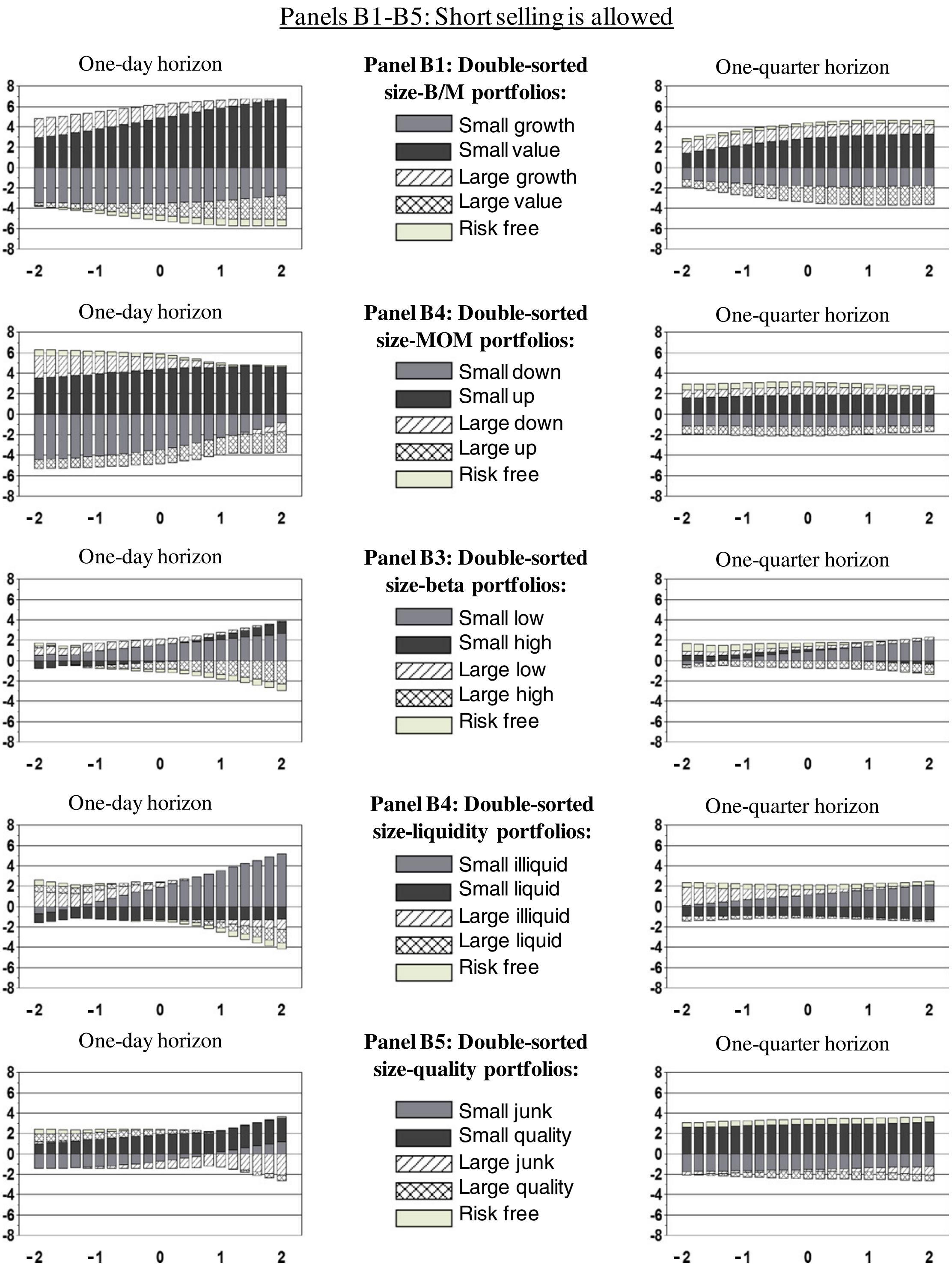

Fig. 5 (*continued*).

Table 6

Conditional portfolio composition in the presence of size-B/M, size-momentum, size-beta, size-liquidity, or size-quality portfolios.

This table shows estimates of the optimal portfolio composition conditional on the aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investment horizons are 1-day or 1-quarter horizons. The investor allocates her wealth among the risk-free asset and four risky assets. The risky assets can be either 4 size-B/M (Panels A1, B1), 4 size-momentum (Panels A2, B2), 4 size-beta (Panels A3, B3), 4 size-liquidity (Panels A4, B4), or 4 size-quality (Panels A5, B5) double-sorted portfolios. The portfolios are formed as described in subsection 4.1 and Appendix A. Panels A1–A5 present results for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panels B1–B5 are for the case when short selling is allowed. The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Each panel shows conditional portfolio compositions (solutions to Eq. (6)) and unconditional portfolio compositions (solutions to Eq. (5)). Conditional portfolio compositions are computed for aggregate market liquidity levels $Z = -2$ (two-standard deviation below the mean), $Z = 0$ (the mean), and for $Z = 2$ (two-standard deviation above). Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

	Short-sales are not allowed								*Short-sales are allowed*							
Portfolio	Conditional weight			Uncond. weight	Conditional weight			Uncond. weight	Conditional weight			Uncond. weight	Conditional weight			Uncond. weight
	$Z = -2$	$Z = 0$	$Z = 2$		$Z = -2$	$Z = 0$	$Z = 2$		$Z = -2$	$Z = 0$	$Z = 2$		$Z = -2$	$Z = 0$	$Z = 2$	
	Double-sorted size-B/M portfolios															
	Panel A1								Panel B1							
	One-day horizon				One-quater horizon				One-day horizon				One-quater horizon			
Small growth	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−3.43	−3.49	−2.73	−3.40	−1.19	−1.81	−1.74	−1.60
Small value	0.00	1.00	1.00	0.96	0.11	0.55	0.74	0.54	2.94	4.86	6.72	4.85	1.44	2.88	3.31	2.57
Large growth	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	1.87	1.34	−0.04	1.20	1.11	1.24	0.94	1.14
Large value	0.50	0.00	0.00	0.00	0.20	0.00	0.00	0.00	−0.33	−1.21	−2.34	−1.28	−0.68	−1.59	−1.88	−1.39
Risk-free	0.50	0.00	0.00	0.04	0.59	0.45	0.26	0.46	−0.05	−0.50	−0.61	−0.37	0.32	0.28	0.37	0.28
	Double-sorted size-MOM portfolios															
	Panel A2								Panel B2							
	One-day horizon				One-quater horizon				One-day horizon				One-quater horizon			
Small down	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−4.43	−3.44	−0.82	−3.06	−1.14	−1.19	−1.10	−1.18
Small up	0.02	1.00	1.00	0.91	0.36	0.51	0.70	0.52	3.52	4.40	4.70	4.19	1.61	1.83	1.87	1.82
Large down	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.18	1.13	−0.85	0.98	0.76	0.82	0.55	0.77
Large up	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.86	−1.40	−2.09	−1.48	−0.81	−0.91	−0.60	−0.85
Risk-free	0.48	0.00	0.00	0.09	0.64	0.49	0.30	0.48	0.59	0.31	0.06	0.37	0.58	0.45	0.28	0.44
	Double-sorted size-beta portfolios															
	Panel A3								Panel B3							
	One-day horizon				One-quater horizon				One-day horizon				One-quater horizon			
Small low	0.00	1.00	1.00	0.90	0.00	0.60	0.89	0.58	0.54	1.54	2.69	1.55	−0.42	0.91	2.00	0.86
Small high	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.00	−0.75	−0.13	1.10	−0.08	0.54	0.17	−0.36	0.11
Large low	0.53	0.00	0.00	0.00	0.13	0.00	0.00	0.00	0.75	0.59	0.12	0.48	0.39	0.33	0.33	0.26
Large high	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	−0.70	−2.27	−0.79	−0.27	−0.75	−0.83	−0.60
Risk-free	0.47	0.00	0.00	0.10	0.69	0.40	0.11	0.42	0.28	−0.30	−0.64	−0.16	0.76	0.34	−0.14	0.37
	Double-sorted size-liquidity portfolios															
	Panel A4								Panel B4							
	One-day horizon				One-quater horizon				One-day horizon				One-quater horizon			
Small illiquid	0.00	0.97	1.00	0.90	0.00	0.48	0.74	0.48	−0.74	1.92	5.16	2.01	0.09	1.16	2.12	1.13
Small liquid	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−0.85	−1.28	−1.26	−1.18	−0.92	−0.92	−1.30	−1.05
Large illiquid	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.00	1.46	0.43	−0.94	0.28	1.82	0.53	0.00	0.78
Large liquid	0.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.09	−1.36	−0.09	−0.46	−0.22	−0.17	−0.29
Risk-free	0.57	0.03	0.00	0.10	0.62	0.52	0.26	0.52	0.51	−0.16	−0.60	−0.02	0.47	0.45	0.35	0.43
	Double-sorted size-quality portfolios															
	Panel A5								Panel B5							
	One-day horizon				One-quater horizon				One-day horizon				One-quater horizon			
Small junk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	−1.43	−0.74	1.20	−0.41	−1.75	−1.53	−1.25	−1.48
Small quality	0.00	0.83	1.00	0.73	0.15	0.30	0.47	0.30	0.98	1.89	2.40	1.66	2.58	2.90	3.12	2.83
Large junk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	−0.67	−2.08	−0.77	−0.30	−0.20	−0.83	−0.40
Large quality	0.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.74	0.44	−0.56	0.27	0.04	−0.70	−0.58	−0.46
Risk-free	0.56	0.17	0.00	0.27	0.85	0.70	0.53	0.70	0.48	0.08	0.04	0.25	0.43	0.53	0.54	0.51

consistent with the clientele hypothesis, the effect of aggregate liquidity on optimal weights decreases with the investment horizon. It is stronger for daily horizon and gets weaker for quarterly horizon.

Turning to the case when short selling is allowed. Overall, Panels B1–B5 show that optimal weights with short selling are different from the weights without short selling. Especially, the investor does not seem to exit the market as aggregate liquidity worsens. She instead tends to engage in long/short strategies. However, the investor does not short all small stock portfolios as aggregate liquidity deteriorates. Following illiquid periods, she rather shorts (longs) small growth (value), small low-momentum (high-momentum), small high-beta (low-beta), and small-junk (quality) stocks. Furthermore, she intensifies short selling following larger shocks. Finally, for all portfolio choice settings, the magnitude of short selling highly reduces at quarterly horizon; which is in line with our previous finding that the effect of aggregate liquidity decreases with the investment horizon.

6. Robustness checks

In the previous section, we investigated the effect of aggregate liquidity on optimal allocations in various characteristic portfolios. Overall, regardless of the portfolio B/M, momentum, market beta, and quality characteristics, the availability of aggregate liquidity information yields mainly portfolio compositions with varying percentages of small stocks, large stocks, and the risk-free asset. For that reason, we restrict our robustness checks to the case when the investor has access to the risk-free asset and single (multiple) size-based portfolio(s) as risky assets. We explore the robustness of our results along a number of dimensions. In particular, we consider (i) different degrees of risk aversion, (ii) different sample periods, and (iii) two alternative liquidity measures. To save space, the outputs from these checks are only presented in figures. Tables summarizing these results are available upon request. Panel A's plots, in each figure, show single allocations in the corresponding risky asset (market, small, medium or large) as a function of aggregate liquidity (Z). Panels B and C present plots for allocation problems in the presence of the risk-free asset and three risky assets (small, medium, and large). Panel B shows conditional portfolio compositions for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panel C presents portfolio compositions for the case when short selling is allowed. Each bar, in plots of Panels B and C, shows optimal portfolio compositions conditional on the aggregate liquidity level (Z).

6.1. Different degrees of risk aversion tests

So far, we performed our analysis mainly for an investor with a coefficient of relative risk aversion of 5. In this section, we check the robustness of our main findings to different degrees of risk aversion. In particular, we consider allocation problems for an aggressive investor with a lower degree of risk aversion ($\gamma = 2$) as well as for a conservative investor with a higher degree of risk aversion ($\gamma = 10$). To save space, we present, in Fig. 6, only the plots from settings with daily and quarterly horizons.

The outputs from single risky asset settings (Panel A) show that both the aggressive and the conservative investors are sensitive to aggregate liquidity when allocating wealth in size-based portfolios. In line with our previous findings, overall, the effect of liquidity is positive and weakens with time horizon. Furthermore, both investors have greater sensitivity to aggregate liquidity when allocating their wealth to small stocks than when investing in large stocks. The only difference between the investors' reactions is that the aggressive investor is more sensitive to aggregate liquidity than the conservative investor, especially when investing in small and medium stocks. Turning to the multiple risky assets settings. When short selling is not allowed (Panel B), the conservative investor shows a flight-to-safety and to liquidity as the market is getting illiquid. However, the aggressive investor do not exit the market in response to unfavorable changes in aggregate liquidity. She only flees from small to large stocks but remains invested 100% in the market. When short selling is allowed (Panel C), both investors engage in short selling. They short (long) small stocks in response to a negative (positive) change in aggregate liquidity. Furthermore, they intensify short selling following larger shocks. Overall, both investors respond in the same way to changes in aggregate liquidity. They only differ in that the aggressive investor has greater sensitivity to aggregate liquidity than does the conservative investor.

6.2. Sub-period tests

To understand the effect of aggregate liquidity over time, we further split our entire sample period into two sub-periods 1963–1989 and 1990–2013 and separately estimate conditional portfolio weights. Fig. 7 exhibits plots corresponding to the two sub-periods. To save space, we present, in Fig. 7, only the plots from settings with weekly and quarterly horizons.

Comparing outputs from the two sub-samples, a number of common findings seem to be robust to the sample period. First, Panel A shows that, for both sub-periods, the effect of aggregate liquidity is stronger for short horizon (weekly) and weakens at longer horizons (quarterly). Furthermore, At short horizon (weekly), the effect of liquidity on optimal weights is weaker for large stocks and gets stronger as we move toward small stocks. Second, regarding multiple risky assets' settings, Panels B and C display similar patterns in both sub-periods. On one hand, when short selling is not allowed (Panel B), unfavorable changes in aggregate liquidity cause the investor to gradually and dynamically pull money out of the market (flight-to-safety) and to move investments from small stocks toward large stocks (flight-to-liquidity). On the other hand, when short selling is allowed (Panel C), in both sub-periods, the investor engages in short selling. She shorts (longs) small stocks in response to a negative (positive) change in aggregate liquidity.

The main difference between the outputs from the two sub-periods is that optimal allocations, in the second period 1990–2013, are less sensitive to aggregate liquidity than those in the first period 1963–1989. In particular, single risky asset settings reveal that the investor, in the second period, reacts less aggressively to changes in aggregate liquidity; especially when

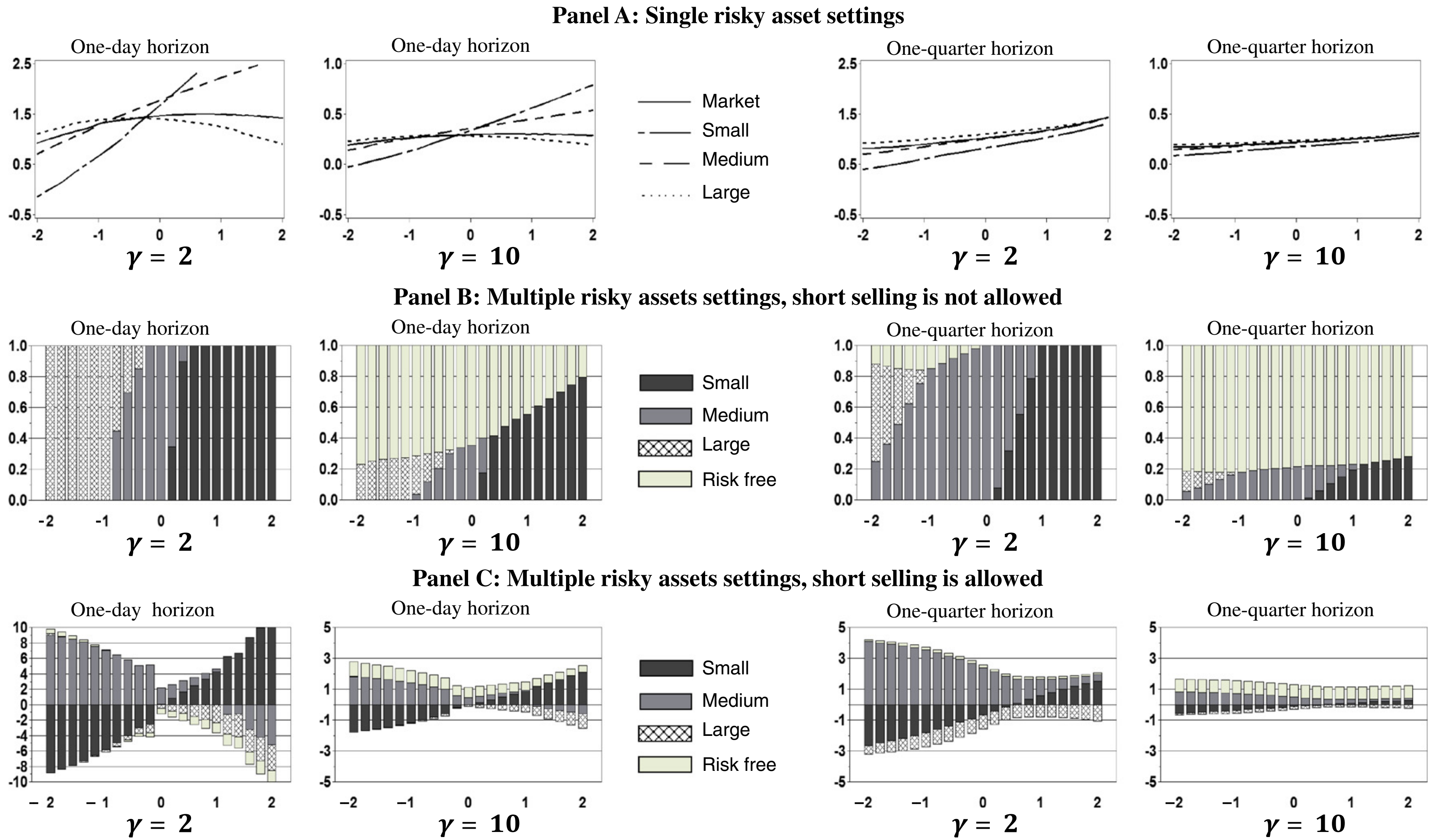

Fig. 6. Robustness checks: Different risk aversion levels. This figure plots optimal portfolio allocations as functions of aggregate market liquidity level (Z) for single-period investors with constant relative risk aversion $\gamma = 2$ and $\gamma = 10$. The investment horizons are 1-day or 1-quarter horizons. Panel A shows plots for the case when investors allocate their wealth between the risk-free asset and a single risky asset. The risky asset, in Panel A, can be the market portfolio (market) or a size-based portfolio (small, medium, or large stocks). The portfolios are formed as described in subsection 4.1. Each curve, in Panel A's plots, shows conditional portfolio weight in the corresponding risky asset (solution to Eq. (6)) as a function of aggregate market liquidity level (Z). Panels B and C present plots for the case when investors allocate their wealth among the risk-free asset and three size-based portfolios (small, medium, and large stocks). Panel B shows conditional portfolio compositions for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panel C presents portfolio compositions for the case when short selling is allowed. Each bar, in plots of Panels B and C, shows the optimal portfolio composition (solution to Eq.(6)) conditional on aggregate market liquidity level (Z). The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-day and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

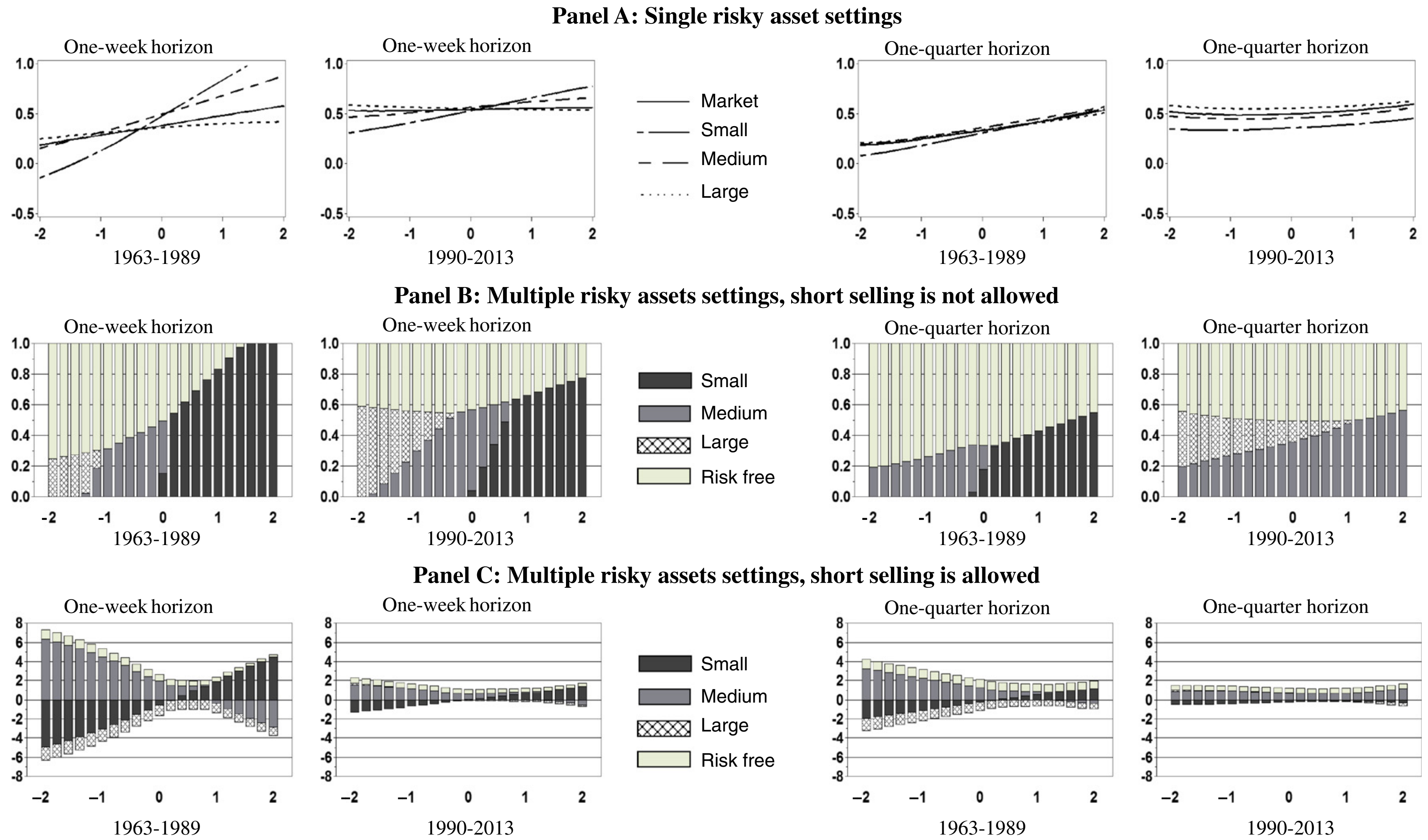

Fig. 7. Robustness checks: Sub-period analysis. This figure plots optimal portfolio allocations as functions of aggregate market liquidity level (Z) for a single-period investor with a constant relative risk aversion $\gamma = 5$. Portfolio allocations are estimated using two sub-periods: 1963–1989 and 1990–2013. The investment horizons are 1-week or 1-quarter horizons. Panel A shows plots for the case when the investor allocates her wealth between the risk-free asset and a single risky asset. The risky asset, in Panel A, can be the market portfolio (market) or a size-based portfolio (small, medium, or large stocks). The portfolios are formed as described in subsection 4.1. Each curve, in Panel A's plots, shows conditional portfolio weight in the corresponding risky asset (solution to Eq. (6)) as a function aggregate market liquidity level (Z). Panels B and C present plots for the case when the investor allocates her wealth among the risk-free asset and three size-based portfolios (small, medium, and large stocks). Panel B shows conditional portfolio compositions for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panel C presents portfolio compositions for the case when short selling is allowed. Each bar, in plots of Panels B and C, shows the optimal portfolio composition (solution to Eq. (6)) conditional on aggregate market liquidity level (Z). The aggregate liquidity is proxied by the transformed aggregate Amihud's measure and is computed for 1-week and 1-month horizons as described in Eq. (9). Portfolio choice problems for quarterly horizons use overlapping monthly observations. To compute weekly returns, we compounded daily returns from Wednesday to the following Wednesday. Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

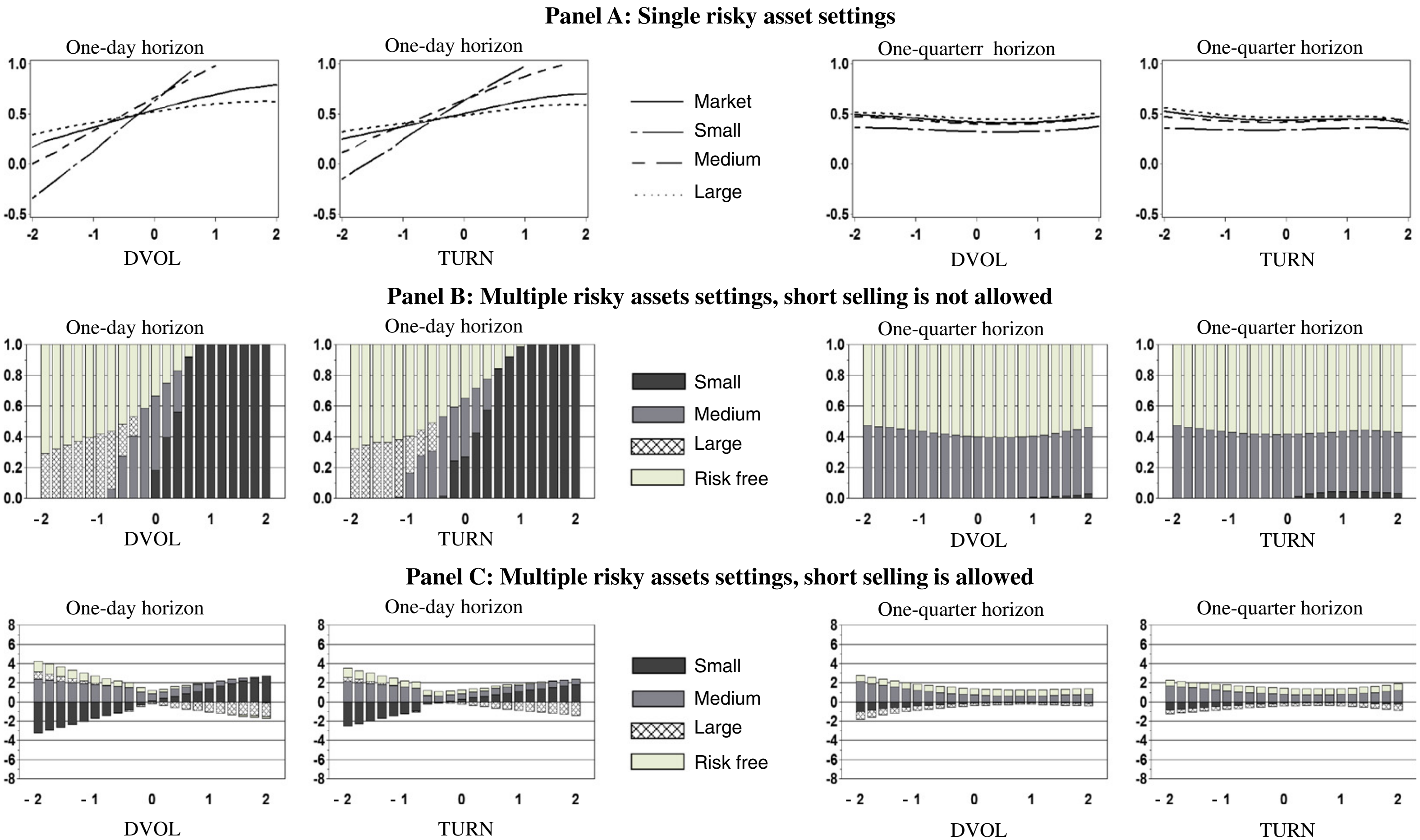

Fig. 8. Robustness checks: Alternative liquidity measures. This figure plots optimal portfolio allocations as functions of aggregate market liquidity level for a single-period investor with a constant relative risk aversion $\gamma = 5$. The investment horizons are 1-day or 1-quarter horizons. The aggregate market liquidity is proxied by the transformed aggregate dollar volume (*DVOL*) or by the transformed aggregate share turnover (*TURN*). The two alternative aggregate liquidity measures are computed for 1-day and 1-month horizons as described in subsection 6.3. Portfolio choice problems for quarterly horizons use overlapping monthly observations. Panel A shows plots for the case when the investor allocates her wealth between the risk-free asset and a single risky asset. The risky asset, in Panel A, can be the market portfolio (market) or a size-based portfolio (small, medium, or large stocks). The portfolios are formed as described in subsection 4.1. Each curve, in Panel A's plots, shows conditional portfolio weight in the corresponding risky asset (solution to Eq. (6)) as a function of aggregate market liquidity level (*DVOL* or *TURN*). Panels B and C present plots for the case when the investor allocates her wealth among the risk-free asset and three size-based portfolios (small, medium, and large stocks). Panel B shows conditional portfolio compositions for the case when short selling is not allowed ($0 \leq x_t \leq 1$). Panel C presents portfolio compositions for the case when short selling is allowed. Each bar, in plots of Panels B and C, shows the optimal portfolio composition (solution to Eq. (6)) conditional on aggregate market liquidity level (*DVOL* or *TURN*). Quarterly returns are obtained from overlapping monthly returns. Our sample covers the period 1963–2013.

Table 7
Liquidity-responsive strategy: An out-of-sample performance evaluation.
This table summarizes the out-of-sample performance of a naive fixed mix strategy and a liquidity-responsive strategy. Both strategies are rebalanced monthly. The naive fixed mix strategy buys 50% small stocks and 50% large stocks, at the beginning of each month. Liquidity-responsive strategy is based on aggregate liquidity signals and proceeds as follows. At the beginning of each month, the strategy buys either (1) the aggressive strategy (100% small stocks) if the last month's aggregate liquidity was positive or (2) the conservative strategy (50% large stocks, 50% risk-free asset) if the last month's aggregate liquidity was negative. Aggregate market liquidity is proxied by the transformed (but not standardized) aggregate Amihud's measure (Z_t) and is computed for monthly horizon as described in Eq. (9). Panel A displays performance statistics assuming no transaction costs. Panel B exhibits performance metrics assuming proportional transaction costs of 50 basis points (bp). The investment strategies are evaluated over the full period 1963–2013 and the two sub-periods 1990–2013 and 2007–2013.

	Panel A: Before-transaction-costs returns						Panel B: After-transaction-costs returns					
	1963–2013		1990–2013		2007–2013		1963–2013		1990–2013		2007–2013	
	Strategic asset allocation	*Liquidity resp. strategy*	*Strategic asset allocation*	*Liquidity resp. strategy*	*Strategic asset allocation*	*Liquidity resp. strategy*	*Strategic asset allocation*	*Liquidity resp. strategy*	*Strategic asset allocation*	*Liquidity resp. strategy*	*Strategic asset allocation*	*Liquidity resp. strategy*
Avg. monthly return (%)	1.1	1.4	1.0	1.2	0.7	1.0	1.0	1.2	1.0	1.0	0.7	0.7
Annual avg. return (%)	12.6	16.3	11.9	14.8	8.7	11.5	12.5	13.9	11.8	12.2	8.6	8.8
Annualized std. deviation (%)	17.2	16.1	16.9	14.9	19.4	15.1	17.2	16.3	16.9	15.1	19.4	15.2
Annulized downside deviation (%)	10.5	8.8	10.4	8.2	12.2	8.6	10.5	9.2	10.4	8.6	12.2	8.9
Beta	1.1	0.8	1.1	0.8	1.1	0.7	1.1	0.8	1.1	0.8	1.1	0.7
Annualized Sharpe ratio (%)	44.3	70.3	51.6	78.3	39.9	69.8	43.8	55.0	51.1	60.1	39.6	51.5
Annualized Sortino ratio (%)	72.7	128.2	84.2	142.6	63.4	122.5	71.8	97.6	83.3	106.0	62.8	88.0
Annualized information ratio (%)	32.1	50.0	28.4	42.7	18.3	36.9	30.4	26.9	26.7	16.9	16.6	8.3
Annual avg. alpha (%)	1.2	6.4	1.1	6.3	0.3	5.5	1.1	4.1	1.0	3.6	0.2	2.8
Annualized M2 return (%)	11.8	15.8	11.1	15.2	8.0	13.4	11.7	13.5	11.0	12.4	8.0	10.1
Annualized Treynor ratio (%)	7.1	13.9	8.3	15.6	7.3	14.7	7.1	11.0	8.2	12.2	7.2	11.0

investing in small stocks. Furthermore, multiple risky asset settings without short selling show that, in the second period, the investor tends to move less aggressively money out of the market as a reaction to negative shocks to aggregate liquidity. In addition, when short selling is allowed, the investor also engages in short selling with a lower degree. To sum up, both single and multiple risky assets settings indicate that the effect of liquidity on optimal portfolio weights has decreased over time but still remains considerable. One explanation for this decline is that the liquidity of stocks especially small stocks has been improved over time.

6.3. Alternative liquidity measures

Because liquidity is not observable, there is some concern that the documented evidence of the effect of aggregate liquidity on optimal portfolio weights might be related to the use of Amihud (2002) liquidity measure. To test the robustness of our results to alternative liquidity measures, we further use two additional measures, namely, dollar volume and turnover. Daily dollar volume of a stock is computed as the number of shares traded in a given day multiplied by the day's stock price. Brennan et al. (1998) found that stock returns are cross-sectionally decreasing in stock dollar volume, which is consistent with the negative liquidity-return relationship. Daily share turnover is defined as the ratio of the number of shares traded in a given day to the total number of shares outstanding at the end of the day. In line with the negative liquidity-return relationchip, many studies found that stock returns are cross-sectionally negatively related to stock turnover (e.g., Chordia et al., 2001; Datar et al., 1998).

Based on the same sample used in the Amihud (2002) liquidity measure, we started by computing individual dollar volumes and share turnovers. And then, Daily aggregate dollar volume was obtained by adding together individual dollar volumes of all eligible stocks. And, daily aggregate turnover was computed as the value-weighted average of all individual share turnovers. For weekly and monthly aggregate measures, time aggregation is done by averaging across weeks and months, respectively. We then detrend and standardize the time series as shown in Eq. (9), but without adding the negative sign.

Aggregate dollar volume and turnover are positively correlated with the transformed aggregate Amihud's measure (Z). The correlation coefficients between the transformed Amihud's measure and aggregate dollar volume and turnover are 0.49 and 0.23, respectively. Fig. 8, displays plots corresponding to the results based on the two alternative liquidity measures. As we can notice, conditioning allocation problems on both liquidity measures yields very similar patterns as those resulting from using the Amihud (2002) measure. These results prove that the documented evidence of the effect of aggregate liquidity on optimal portfolio weights is robust to alternative liquidity measures and is not driven by the use of a particular liquidity measure.

7. Liquidity-responsive strategy as a tactical asset allocation tool

The in-sample analysis provides evidence that optimal asset allocation among size-based portfolios depends on the evolution of aggregate market liquidity. From a practical perspective, however, the key issue is whether liquidity-responsive strategies would be economically profitable. We address this issue by considering a simple liquidity-responsive strategy that makes use of information contained in aggregate liquidity signals. The out-of-sample performance of this strategy is then compared, on a risk-adjusted basis, to that of a naive fixed mix strategy (i.e. an investment strategy that maintains the same mix of assets over time).

From the previous sections, we can draw two simple rules of investing: (1) If the aggregate liquidity in the last period improved, invest a large proportion of wealth in small stocks the following period. (2) If the aggregate liquidity in the last period deteriorated, invest a large proportion of wealth in the risk-free asset and favor large stocks over small stocks.

Based on these two simple rules, we limited our analysis to a monthly rebalancing and implemented our liquidity-responsive strategy as follows. At the beginning of each month, the liquidity-responsive strategy buys either

(1) the aggressive strategy (100% small stocks) if the last month's aggregate liquidity was positive, or
(2) the conservative strategy (50% large stocks, 50% risk-free asset) if the last month's aggregate liquidity was negative.

To implement the strategy above, we estimate aggregate liquidity using the transformed (but not standardized) aggregate Amihud's measure. The strategy is designed to benefit from the high potential growth of small stocks during months following positive shocks to aggregate liquidity and to move defensively to the conservative strategy during months following negative shocks to aggregate liquidity. We compare the out-of-sample performance of this liquidity-responsive strategy to that of a naive fixed mix strategy targeting a capital allocation of 50% small stocks, 50% large stocks. To this end, we compute a number of common risk metrics and risk-adjusted performance measures for both investment strategies, over the full sample periods 1963–2013 as well as over the two sub-periods 1990–2013 and 2007–2013. The risk metrics considered are, namely, the standard deviation (to measure the total risk), the downside deviation (that only considers the dispersion of returns below the risk-free return), and the beta (that measures the systematic risk). Regarding risk-adjusted performance measures, we compute the Sharpe, Sortino, Information, and Treynor ratios as well as The Jensen's alpha and the M-squared return for both strategies. In addition, since liquidity-responsive strategy is expected to generate a relatively higher rate of portfolio turnover, its performance may be hardly affected by transaction costs. To take this into account, we examine its out-of-sample performance using both before- and after-transaction-costs returns. As in DeMiguel et al. (2009) and Kirby and Ostdiek (2012), we account for transaction costs by assuming proportional transaction costs of 50 basis points per transaction. Following the authors, we compute the portfolio strategy return net of transaction costs, for a period t, by subtracting the cost of rebalancing to the desired weights in period $t + 1$ from the portfolio strategy before-transaction-costs returns for period t. Under these assumptions, the after-transaction-costs returns are given by:

$$R^a_{p,t} = \left[1 + R^b_{p,t}\right]\left[1 - 0.5\%\left|w_{s,t} - \frac{w_{s,t-1}\left(1 + R_{s,t}\right)}{\left(1 + R^b_{p,t}\right)}\right| w_{l,t} - 0.5\%\left|\frac{w_{l,t-1}\left(1 + R_{l,t}\right)}{\left(1 + R^b_{p,t}\right)}\right|\right] - 1, \tag{12}$$

where $R^b_{p,t}$ and $R^a_{p,t}$ stand for before- and after-transaction-costs returns on the portfolio strategy p. $R_{s,t}$ and $R_{l,t}$ denote the returns on small and large stocks. $w_{s,t-1}$, $w_{l,t-1}$ are the desired weights in small and large stocks in period t and $w_{s,t}$, $w_{l,t}$ are the desired weights in small and large stocks in period $t + 1$.

Table 7 summarizes performance statistics of the liquidity-responsive strategy as compared to those of the fixed mix strategy. Panel A provides performance statistics assuming no transaction costs. Panel B shows performance statistics after transaction costs were discounted. First, consider the case assuming no transaction costs. The liquidity-responsive strategy achieved an annual average return of 16.3% against 12.6% for the fixed-mix strategy during the full sample period 1963–2013 and annual average returns of 14.8% and 11.5% against 11.9% and 8.7% during the sub-periods 1990–2013 and 2007–2013, respectively. Compared to the benchmark strategy, our strategy not only achieved higher returns but also had lower risk. The liquidity-responsive strategy exhibits a beta and annualized standard deviation and downside risk smaller than those of the fixed-mix strategy for the full sample period as well as for the two sub-periods. For instance, over the full sample period, our strategy exhibits a beta of 0.8 against 1.1, an annualized standard deviation of 16.1% against 17.2%, and an annualized downside risk of 8.8% against 10.5% over the full testing period. Results also indicate that our strategy achieved higher returns with lower risk for both sub-samples 1990–2013 and 2007–2013. Furthermore, for all computed risk-adjusted performance measures, the liquidity-responsive strategy records higher risk-adjusted returns relative to the benchmark strategy. For instance, over the full sample period, our strategy generates higher annualized Sharpe and Sortino ratios of 70.3% against 44.3%, and 128.2% against 72.7%, respectively. The strategy also exhibits a higher annual average alpha of 6.4% against 1.2% and a higher annualized M-squared return of 15.8% against 11.8%.

Second, to examine whether investors can earn positive abnormal profits on this strategy, it is important to assess its performance after accounting for transaction costs. Panel B exhibits after-transaction-costs performance statistics for both strategies. As expected, liquidity-responsive strategy entails higher costs than the fixed mix strategy. Transaction costs associated with our strategy reduced the annual return by 2.4%, 2.6%, and 2.7% over the sample periods 1963–2013, 1990–2013, and 2007–2013, respectively. While transaction costs associated with the fixed mix strategy reduced the annual return only by 0.1% over the three sample periods. However, despite the high transaction costs, our strategy still achieves higher returns, lower risk, and superior risk-adjusted performance than the benchmark strategy; for all the three periods.

We conclude, therefore, that our simple strategy that makes use of information contained in the aggregate liquidity signals is economically profitable. This is because the principle that underpins the liquidity-responsive strategy is to reduce exposure to risky and illiquid assets (small stocks) when liquidity dries-up and to increase that exposure when the market is highly liquid.

8. Conclusion

A large body of studies has provided evidence that aggregate market liquidity is an important state variable for future investment opportunities. In this paper, we address the question of how changes in aggregate liquidity influences optimal portfolio allocations. Using data on the US equity market, we express optimal allocations in various characteristic portfolios as functions of aggregate market liquidity. Our results show that the effect of aggregate liquidity depends on the asset and the investment horizon. Interestingly, the availability of aggregate liquidity information causes the investor to gradually exit the market and shift toward liquid assets as aggregate market liquidity worsens. Overall, our results are in line with the flight-to-safety and the flight-to-liquidity episodes and give support to the assertion that investors' risk aversion and preference for liquidity are time-varying.

Furthermore, we assess, in an out-of-simple test, the economic value of a simple investment strategy that uses information contained in aggregate liquidity signals. Results clearly indicate the superior performance of such a liquidity-responsive strategy. Overall, it can be stated that aggregate market liquidity can play an important role in the investment decision process since it contains leading information about future investment opportunities. We therefore claim that its signals could be a valuable guide to investors and portfolio managers on how to actively reallocate investments across asset classes to potentially increase returns and reduce exposure to market liquidity risk.

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Appendix A

Double-sorted portfolios are formed from the intersections of the 2 × 3 independent sorts on size and the B/M, momentum, market beta, or quality characteristic. Since size and liquidity are highly correlated, size-liquidity portfolios are formed from the 2 × 3 sequential sorts on size and then on liquidity.

We obtained daily and monthly returns on the 4 size-B/M (small-growth, small-value, large-growth, and large-value) and the 4 size-momentum (small-down, small-up, large-down, and large-up) portfolios from Kenneth French's Data Library.

The 4 size-beta (small-low beta, small-high beta, large-low beta, and large-high beta) portfolios are obtained using CRSP data and are computed as follows. At the end of each year between 1962 and 2012, we identified NYSE/AMEX/NASDAQ common stocks with prices between $5 and $1000 and 60 non-missing monthly returns over the most recent 5 years. For each eligible stock, we use the most recent 5 years' data and estimate its market beta by regressing the share monthly excess returns on the Carhart (1997) four factors.

$$r_{i,t}^{e} = \alpha_{i,y} + \beta_{i,y}^{Mkt}\, MKT_t + \beta_{i,y}^{smb} SMB_t + \beta_{i,y}^{hml} HML_t + \beta_{i,y}^{mom} MOM_t + \varepsilon_{i,t} \tag{A1}$$

where $r_{i,t}^{e}$ stands for the stock i's excess return, MKT_t, SMB_t, HML_t, and MOM_t are the market, size, value and momentum factors, respectively. $\beta_{i,y}^{Mkt}$, $\beta_{i,y}^{smb}$, $\beta_{i,y}^{hml}$, and $\beta_{i,y}^{mom}$ denote, respectively, the historical exposures of the stock i to the market, size, value, and momentum factors; as estimated at the end of year y. We, then, at the end of each year, sorted independently eligible stocks on the basis of their size and market beta and allocated them into 2 × 3 value-weighted portfolios using NYSE breakpoints. The size breakpoint is the median NYSE market equity. The market beta breakpoints are the 30th and 70th NYSE percentiles. The post-formation of daily (monthly) returns on these portfolios during the next year are linked across years to form a daily (monthly) return series for each portfolio.

The 4 size-liquidity (small-illiquid, small-liquid, large-illiquid, and large-liquid) portfolios are obtained using CRSP data and are computed as follows. At the end of each year between 1962 and 2012, we identified NYSE/AMEX common stocks with prices between $5 and $1000 and at least 100 valid daily returns, prices and volumes over the year. We follow Lou and Sadka (2011) and measure the liquidity level of eligible stocks as the average of their daily Amihud's (2002) ratio over the year. In formal terms, we compute the (il)liquidity level of a stock i at the end of year y as given by the following equation:

$$ILLIQ_{i,y} = \frac{1}{D_{i,y}} \left[\sum_{d=1}^{D_{i,y}} \frac{\left| r_{i,d,y} \right|}{Dvol_{i,d,y}} \right] \tag{A2}$$

where $ILLIQ_{i,y}$ denotes the (il)liquidity level measure of stock i at the end of year y. $D_{i,y}$ is the stock i's number of trading days in year y. $r_{i,d,y}$ and $Dvol_{i,d,y}$ are, respectively, the daily return and the dollar volume of stock i on the trading day d in year y. We, next, divided stocks into 2 × 3 matrix using sequentially sorts on size and then on liquidity. The size breakpoint is the median NYSE market equity. The liquidity breakpoints are the 30th and 70th NYSE percentiles within the corresponding size groups. The post-formation of daily (monthly) returns on these portfolios during the next year are linked across years to form a daily (monthly) return series for each portfolio.

Monthly returns on the 4 size-quality portfolios (small-junk, small-quality, large-junk, and large-quality) are obtained from Andrea Frazzini's web site.[3] Unfortunately, the authors do not provide daily returns of their portfolios. In order to compute daily returns on 4 size-quality portfolios, we use, thus, a procedure very similar to the one used to form size-beta portfolios. The only differences consist in (i) using the Carhart (1997) four-factor augmented with quality factor instead of the Carhart (1997) four-factor model and (ii) sorting stocks on their quality-beta instead of their market beta.

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