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Stock liquidity and corporate cash holdings

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ABSTRACT

This paper investigates the effects of stock liquidity on corporate cash holdings in the U.S. We show that firms with liquid stocks hold less cash after controlling for several firm characteristics, industry and year fixed effects. To mitigate endogenous concerns, we further employ decimalization in the U.S. stock market as an exogenous shock and find the increase in stock liquidity causes firms to reduce cash holdings.

1. Introduction

Previous studies show that firms hold cash for several reasons, such as transaction motives, precautionary motives and agency motives (Opler et al., 1999; Bates et al., 2009). In static trade off theory, corporate cash holdings are determined by the marginal cost of liquidity assets shortage and the opportunity cost of holding liquidity assets. In agency theory, entrenched managers prefer to hold excess cash. Since cash allows managers to make investment without the monitoring and punishment from the capital market.

In this paper, we argue that stock liquidity has a negative effect on corporate cash holdings. First, stock liquidity reduces the cost of equity issuing and debt financing (Butler et al., 2005; Huang et al., 2015), lowering the cost of liquidity assets shortage. Second, stock liquidity can enhance corporate governance through both increasing blockholder intervention and amplifying threat of exit (Edmans et al., 2013), making managers less entrenched. Hence, according to static trade off theory and agency theory, firms with liquid stocks will hold less cash.

Our study has two main contributions. First, to our knowledge, this study is the first attempt to investigate the impact of stock liquidity on corporate cash holdings. Second, we use decimalization as a quasi-natural experiment to effectively mitigate endogenous concerns in our tests.

2. Data and variables

We obtain our data from two data sources. Accounting variables are from COMPUSTAT and intra-day stock data is from TAQ. The sample period is from 1993 to 2013 and we exclude financial firms and utility firms. Following Opler et al. (1999), we measure cash holdings as the ratio of cash and short-term investments to net assets. We use the negative natural logarithm of the annual dollar effective spread as our liquidity measure. The annual dollar effective spread is calculated as the equally-weighted average of the daily

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Table 1
Descriptions of variables.

Variable	Descriptions	Compustat items
Dependent variable		
CASH	Cash holdings scaled by net assets	#1/(#6 - #1)
Independent variable		
LIQ	- log(annual dollar effective spread)	
Control variables		
SIZE	The natural logarithm of net assets	log (#6 - #1)
MB	Market value of net assets scaled by book value of net assets	(#6 - #1 - #60 + #25 × #199)/(#6 - #1)
CF	Cash flow scaled by book value of net assets	(#13 - #15 - #16 - #21)/(#6 - #1)
NWC	Net working capital net of cash scaled by book value of net assets	(#179 - #1)/(#6 - #1)
CAPEX	Capital expenditures scaled by book value of net assets	#128/(#6 - #1)
LEV	Long term debt plus debt in current liabilities scaled by book value of net assets	(#9 + #34)/(#6 - #1)
SIGMA	Average standard deviations of cash flow over 20 years for firms with the same 2-digit SIC	
DIV	A dummy variable equal to one if the firm paid a common dividend and zero otherwise	#21 > 0
R&D	The ratio of research and development expense to sales	#46/#12
ACQ	Expenditures on acquisitions scaled by book value of net assets	#129/(#6 - #1)
PRICE	The close price at the end of the fiscal year	#199
INDUSTRY	Two-digit SIC industry dummy variables	
YEAR	Year dummy variables	

Table 2
Summary statistics.

Variable	Obs.	Mean	Std	P25	Median	P75
CASH	48,932	0.312	0.790	0.018	0.068	0.238
LIQ	48,932	2.858	1.087	2.026	2.827	3.815
SIZE	48,932	5.471	2.295	3.757	5.372	7.079
MB	48,932	3.597	7.421	1.167	1.688	2.973
CF	48,932	0.092	0.696	−0.105	−0.050	0.008
NWC	48,932	0.051	0.327	−0.054	0.072	0.229
CAPEX	48,932	0.079	0.085	0.026	0.051	0.099
LEV	48,932	0.239	0.268	0.015	0.181	0.358
SIGMA	48,932	0.167	0.183	0.058	0.106	0.196
DIV	48,932	0.320	0.467	0.000	0.000	1.000
R&D	48,932	0.100	0.566	0.000	0.002	0.030
ACQ	48,932	0.029	0.071	0.000	0.000	0.015
PRICE	48,932	20.490	21.280	5.310	13.840	28.560

dollar effective spread over a fiscal year for a stock. The daily dollar effective spread is defined as the simple average of the dollar effective spreads for each matched quote/trade[1] over a trading day for each stock in our sample. Our control variables include firm size, market-to-book ratio, cash flow, net working capital, capital expenditures, leverage, industry cash flow volatility, dividend dummy, R&D and acquisitions expenditures, all of which have been shown having effects on corporate cash holdings in literature. Additionally, we control the close price at the end of the fiscal year to remove the influence of price level on the dollar effective spread. We also include year dummy variables and 2-digit SIC industry dummy variables to control year fixed effects and industry fixed effects in our regression tests. Table 1 gives the detailed descriptions for these variables. Summary statistics for variables are listed in Table 2. The average (median) cash holding is equal to approximately 31.2% (6.8%) of net assets. The stock liquidity measure LIQ has a mean value of 2.858 and a median value of 2.827 (The mean (median) of the annual dollar effective spread is 10 (5) cents in our sample, which is comparable to Holden and Jacobsen, 2014).

3. Empirical results

Our baseline model for testing the effects of liquidity on cash holdings is as follows:

$$\mathrm{CASH}_{i,t} = a + b{*}LIQ_{i,t} + c{*}Control_{i,t} + INDUSTRY + YEAR + \varepsilon_{i,t} \tag{1}$$

We predict that the coefficient of LIQ is significantly negative, indicating that firms with liquid stocks will hold less cash.

Table 3 shows the regression results and the sample period is from 1993 to 2013. In Model 1 and Model 2, the independent variable is contemporaneous liquidity and in Model 3 and Model 4, the independent variable is lagged liquidity. In all regressions, the coefficient of liquidity is significantly negative, indicating that firms with liquid stocks hold less cash.

[1] We use the WRDS derived WCT files that have matched trades and NBBO quotes. They are located on wrds-cloud.wharton.upenn.edu under /wrds/nyse/sasdata/wrds_taqs_ct directory. Following Holden and Jacobsen (2014) we also filter trades with "crossed" or "locked" NBBO quotes.

Table 3
Regression results of baseline model.

Variable	(1)	(2)	(3)	(4)
LIQ_t	−0.034***	−0.055***		
	(0.002)	(0.004)		
LIQ_{t-1}			−0.025***	−0.038***
			(0.002)	(0.004)
SIZE	−0.042***	−0.036***	−0.043***	−0.039***
	(0.002)	(0.002)	(0.002)	(0.002)
MB	0.040***	0.039***	0.040***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)
CF	0.321***	0.309***	0.289***	0.279***
	(0.015)	(0.016)	(0.016)	(0.016)
NWC	−0.386***	−0.429***	−0.369***	−0.408***
	(0.022)	(0.025)	(0.022)	(0.025)
CAPEX	0.341***	0.629***	0.216***	0.480***
	(0.046)	(0.055)	(0.047)	(0.057)
LEV	−0.178***	−0.160***	−0.156***	−0.140***
	(0.017)	(0.018)	(0.017)	(0.018)
SIGMA	0.121***	−0.339***	0.093***	−0.315***
	(0.016)	(0.041)	(0.015)	(0.040)
DIV	−0.007*	0.001	−0.003	0.004
	(0.004)	(0.004)	(0.003)	(0.004)
R&D	0.039**	0.033**	0.033*	0.026
	(0.016)	(0.015)	(0.017)	(0.017)
ACQ	−0.140***	−0.114***	−0.111***	−0.098***
	(0.020)	(0.020)	(0.020)	(0.020)
PRICE	0.001***	0.000**	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.449***		0.417***	
	(0.015)		(0.015)	
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
Obs.	48,932	48,932	43,312	43,312
adj. R^2	0.606	0.616	0.592	0.602

Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Stock liquidity and corporate cash holdings may be jointly determined by firms' unobservable characteristics, or there may be a reverse causality. To mitigate such concerns, we employ decimalization as an exogenous shock to stock liquidity. Over the period, August 28, 2000–January 29, 2001, NYSE and AMEX changed the minimum tick size from $1/16 to pennies. NASDAQ decimalized shortly after, over the period, March 12, 2001–April 9, 2001. Decimalization reduced investors' trading cost and enhanced stock liquidity. Moreover, since this event can't be affected by firm behaviours, decimalization provides an ideal setting for our tests.

We construct our treatment group and control group following Fang et al. (2014). We first sort firms into tertiles based on their liquidity change from pre-decimalization year ($t-1$) to post-decimalization year ($t+1$). The top tertile includes firms having a largest increase in liquidity and the bottom tertile includes firms experiencing a smallest increase in liquidity. We then drop the middle tertile and estimate a probit model to predict whether a given firm belongs to the treatment group (top tertile). All control variables in Eq. (1) as well as the liquidity measure at the pre-decimalization year are included in our probit model. Then, we use the predicted probability to conduct nearest-neighbour propensity score matching and obtain our final treatment group and control group.

Table 4 reports the matching diagnostic test. As shown in Table 4, in pre-match sample, firm characteristics have strong predictive power for whether a firm belongs to the latent treatment group, while, in post-match sample, firm characteristics have no predictive power. Table 5 shows that in post-match sample, all the differences of firm characteristics between the treatment group and the control group are not significant. Overall, Tables 4 and 5 indicate that our propensity score matching successfully remove the observable differences between treatment firms and control firms.

We then conduct the following DID test using the post-match sample:

$$CASH_{i,t} = a{*}After_t + b{*}Treat_i + c{*}Treat_i{*}After_t + d{*}Control_{i,t} + INDUSTRY + YEAR + \varepsilon_{i,t} \tag{2}$$

After is a dummy variable equal to one if the year is after decimalization, and zero otherwise. Treat is a dummy variable equal to one (zero) for firms in the treatment (control) group. Since firms in the treatment group experience largest increase in liquidity after decimalization, we predict the coefficient of interaction term is significantly negative.

Table 6 reports the results of DID regressions and the sample period is three years before and after decimalization. The coefficient of interaction term is significantly negative for all of the four models, indicating that firms experiencing largest increase in liquidity will significantly reduce cash holdings.

Table 4
Matching diagnostic.

Variable	Pre-match	Post-match
LIQ_{t-1}	−0.270***	0.014
	(0.088)	(0.103)
$SIZE_{t-1}$	0.397***	−0.021
	(0.036)	(0.046)
MB_{t-1}	0.029**	0.002
	(0.012)	(0.010)
CF_{t-1}	0.728***	0.056
	(0.139)	(0.157)
NWC_{t-1}	−0.208	−0.055
	(0.209)	(0.232)
$CAPEX_{t-1}$	2.312***	−0.397
	(0.492)	(0.613)
LEV_{t-1}	−0.897***	−0.082
	(0.170)	(0.259)
$SIGMA_{t-1}$	0.849**	−0.330
	(0.401)	(0.515)
DIV_{t-1}	−0.689***	0.246
	(0.095)	(0.139)
$R\&D_{t-1}$	0.061	0.151
	(0.199)	(0.288)
ACQ_{t-1}	1.260**	−0.480
	(0.534)	(0.681)
$PRICE_{t-1}$	0.015***	−0.001
	(0.004)	(0.004)
Intercept	−2.075***	0.087
	(0.274)	(0.307)
Industry FE	Yes	Yes
Obs.	1,650	736
p-value of X^2	0.000	0.999
Pseudo R^2	0.339	0.006

Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5
Post-matching differences.

Variable	Treatment	Control	Difference	t-Statistic
LIQ_{t-1}	1.920	1.907	0.013	0.33
$SIZE_{t-1}$	5.214	5.207	0.007	0.05
MB_{t-1}	3.065	2.790	0.274	0.66
CF_{t-1}	0.054	0.030	0.024	0.82
NWC_{t-1}	0.102	0.109	−0.006	−0.36
$CAPEX_{t-1}$	0.086	0.088	−0.002	−0.39
LEV_{t-1}	0.228	0.235	−0.007	−0.46
$SIGMA_{t-1}$	0.142	0.144	−0.002	−0.25
DIV_{t-1}	0.293	0.242	0.052	1.58
$R\&D_{t-1}$	0.047	0.035	0.012	0.79
ACQ_{t-1}	0.031	0.034	−0.003	−0.64
$PRICE_{t-1}$	15.304	14.866	0.438	0.40

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

4. Robustness

Another concern is that our DID results may be spuriously driven by the dot-com crash. As previously noted, the tick size change from $1/16 to decimals in 2001 coincided with the bursting of the dot-com bubble, leading to a large price drop on Nasdaq and a recession in the U.S. Firms experiencing large price drop may have the largest decrease in liquidity. Meanwhile, firms whose stock prices dropped more during the recession may hold more cash for precautionary motive. Hence, our PSM-DID results in Table 6 may be contaminated by this confounding factor. To alleviate this concern, we repeat the tests in Tables 4, 5, and 6 for high-tech firms and manufacturing firms, separately. Our industry classification here follow Fama and French 10-industryclassification scheme.[2] Since

[2] More details about Fama and French 10-industry classification scheme please see French's data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_ind_port.html).

Table 6
DID regressions.

Variable	(1)	(2)	(3)	(4)
After	0.017	0.028		
	(0.017)	(0.018)		
Treat	0.036*	0.039*	0.032	0.035
	(0.022)	(0.022)	(0.022)	(0.022)
Treat*After	−0.109***	−0.111***	−0.105***	−0.107***
	(0.022)	(0.022)	(0.022)	(0.021)
Control	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES
Year FE	NO	NO	YES	YES
Obs.	3,766	3,766	3,766	3,766
adj. R^2	0.476	0.482	0.477	0.484

Control variables are the same as in Table 3. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 7
Matching diagnostic for high-tech firms and manufacturing firms.

	Panel A: High-tech		Panel B: Manufacturing	
Variable	Pre-match	Post-match	Pre-match	Post-match
LIQ_{t-1}	−1.229***	0.098	−0.094	−0.001
	(0.205)	(0.248)	(0.231)	(0.245)
$SIZE_{t-1}$	0.473***	0.027	0.519***	−0.069
	(0.075)	(0.094)	(0.101)	(0.143)
MB_{t-1}	0.035**	0.004	0.351**	0.073
	(0.017)	(0.015)	(0.159)	(0.207)
CF_{t-1}	0.293	0.110	1.934*	−2.091
	(0.217)	(0.298)	(1.045)	(1.754)
NWC_{t-1}	−0.267	0.268	−1.721***	1.045
	(0.349)	(0.480)	(0.646)	(0.959)
$CAPEX_{t-1}$	4.993***	−1.506	1.859	0.733
	(1.186)	(1.502)	(2.564)	(3.063)
LEV_{t-1}	−0.549	−0.356	−0.900	0.648
	(0.383)	(0.522)	(0.616)	(0.897)
$SIGMA_{t-1}$	−1.833	0.955	−0.475	−0.548
	(1.622)	(2.161)	(0.639)	(0.808)
DIV_{t-1}	−1.175***	0.527	−0.379*	0.047
	(0.324)	(0.438)	(0.202)	(0.296)
$R\&D_{t-1}$	−0.405	0.193	12.870	−5.265
	(0.419)	(0.481)	(8.136)	(11.899)
ACQ_{t-1}	0.908	−0.133	3.091*	−0.900
	(0.848)	(1.459)	(1.686)	(2.338)
$PRICE_{t-1}$	0.001	−0.003	−0.006	0.005
	(0.007)	(0.007)	(0.010)	(0.012)
Intercept	−0.401	−0.303	−2.921***	0.048
	(0.543)	(0.638)	(0.636)	(0.792)
Industry FE	Yes	Yes	Yes	Yes
Obs.	452	170	276	108
p-value of X^2	0.000	0.976	0.000	0.970
Pseudo R^2	0.429	0.019	0.384	0.031

Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

the bursting of the dot-com bubble has much less influence on the manufacturing industry than the high-tech industry. If our previous DID results are not spuriously driven by such cofounding event, we expect to see significant treatment effects not only in the high-tech subsample but also in the manufacturing subsample.

Panel A and Panel B of Table 7 report the matching diagnostic test for the high-tech subsample and the manufacturing subsample, respectively. As shown in Table 7, none of the matching variables are statistically significant in post-match sample (column 2 and 4) for both subsamples. Table 8 also indicates that in post-match sample, all the differences of firm characteristics between treatment firms and control firms are insignificant for both the high-tech subsample (Panel A) and the manufacturing subsample (Panel B). Overall, Tables 7 and 8 show that our matching scheme effectively alleviate the observable differences between the treatment group and the control group for both subsamples.

We then re-run the DID regressions using these two post-match subsamples, separately. Panel A and Panel B of Table 9 report the DID results for the high-tech subsample and the manufacturing subsample, respectively. The coefficient of interaction term is

Table 8
Post-matching differences for high-tech firms and manufacturing firms.

Panel A: High-tech Variable	Treatment	Control	Difference	t-Statistic
LIQ_{t-1}	1.650	1.656	−0.006	−0.07
$SIZE_{t-1}$	4.903	4.743	0.160	0.63
MB_{t-1}	5.198	4.579	0.619	0.46
CF_{t-1}	0.008	0.024	−0.016	−0.21
NWC_{t-1}	0.110	0.086	0.024	0.52
$CAPEX_{t-1}$	0.084	0.098	−0.014	−1.08
LEV_{t-1}	0.138	0.164	−0.026	−0.80
$SIGMA_{t-1}$	0.168	0.167	0.001	0.15
DIV_{t-1}	0.106	0.059	0.047	1.11
$R\&D_{t-1}$	0.050	0.037	0.013	0.37
ACQ_{t-1}	0.037	0.037	0.000	0.01
$PRICE_{t-1}$	18.940	17.760	1.180	0.39
Panel B: Manufacturing				
Variable	Treatment	Control	Difference	t-Statistic
LIQ_{t-1}	1.922	1.952	−0.030	−0.26
$SIZE_{t-1}$	5.975	5.941	0.034	0.11
MB_{t-1}	1.504	1.443	0.061	0.39
CF_{t-1}	0.055	0.077	−0.022	−1.29
NWC_{t-1}	0.191	0.165	0.026	0.98
$CAPEX_{t-1}$	0.063	0.059	0.004	0.47
LEV_{t-1}	0.296	0.302	−0.006	−0.15
$SIGMA_{t-1}$	0.144	0.170	−0.026	−0.86
DIV_{t-1}	0.574	0.574	0.000	0.00
$R\&D_{t-1}$	0.007	0.008	−0.001	−0.35
ACQ_{t-1}	0.029	0.031	−0.002	−0.20
$PRICE_{t-1}$	19.370	17.030	2.340	0.79

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 9
DID regressions for high-tech firms and manufacturing firms.

Panel A: High-tech Variable	(1)	(2)	(3)	(4)
After	0.097***	−0.003		
	(0.037)	(0.042)		
Treat	0.096	0.077	0.077	0.071
	(0.061)	(0.059)	(0.060)	(0.060)
Treat*After	−0.167**	−0.146**	−0.140**	−0.136**
	(0.065)	(0.062)	(0.064)	(0.062)
Control	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES
Year FE	NO	NO	YES	YES
Obs.	792	792	792	792
adj. R^2	0.527	0.531	0.534	0.533
Panel B: Manufacturing				
Variable	(1)	(2)	(3)	(4)
After	0.039**	0.035*		
	(0.019)	(0.021)		
Treat	0.014	0.008	0.014	0.008
	(0.027)	(0.028)	(0.029)	(0.028)
Treat*After	−0.103***	−0.103***	−0.103***	−0.104***
	(0.029)	(0.029)	(0.030)	(0.030)
Control	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES
Year FE	NO	NO	YES	YES
Obs.	592	592	592	592
adj. R^2	0.239	0.275	0.240	0.274

Control variables are the same as in Table 3. Robust standard errors are in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

significantly negative for all models in both the high-tech subsample (Panel A) and the manufacturing subsample (Panel B). Overall, Table 9 indicates that our PSM-DID results are not likely spuriously driven by the contemporaneous dot-com crash, which could influence both stock liquidity and corporate cash holdings.

5. Conclusion

This study is the first attempt to show the relation between stock liquidity and corporate cash holdings. We find firms with liquid stocks hold less cash after controlling several firm characteristics. To mitigate endogenous concerns, we employ decimalization as a quasi-natural experiment and find firms experiencing largest increase in liquidity will significantly reduce cash holdings.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2018.06.018.

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