Stock Liquidity and Default Risk*

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Internet Appendix

A1. Cox Proportional Hazard Model

As a robustness test, we examine actual bankruptcies instead of the risk of default. We estimate a Cox proportional hazard rate model as in Bharath and Shumway (2008). We have shown a relation between liquidity and default risk. But as default risk is only a proxy for actual bankruptcy cases the result may not carry through. However, analysis on bankruptcy cases is difficult given how infrequently they occur.

The Cox proportional hazard rate model uses a dynamic logit specification to model the expected time to failure. It assumes the probability of default at any time is conditioned on survival until that time. It allows the expected time to default to vary across firms. This approach requires actual bankruptcy data, and employs both accounting and market predictor variables. Driven by its ability to incorporate timely information contained in market-driven variables the model has superior forecasting performance compared to other static bankruptcy prediction models such as Altman (1968) and Zmijewski (1984).

Chava and Jarrow (2004), building on Shumway (2001), explore industry effects by grouping firms into four industry groups based on different regulatory environments and different asset/product structures: (i) finance, insurance and real estate, (ii) transportation, communications and utilities, (iii) manufacturing and mineral, and (iv) miscellaneous industries. They find that industry effects are important in forecasting bankruptcy probability. We estimate the hazard rate model with Bharath and Shumway (2008)'s variables and industry dummies. Year fixed effects are also included. We extend the model by adding a liquidity measure to examine whether there is a link between stock liquidity and bankruptcies.

The bankruptcy dataset is the same as the one used in Chava and Jarrow (2004), Chava, Stefanescu, and Turnbull (2011), and Alanis and Chava (2012).[1] The comprehensive dataset includes the Chapter 7 and Chapter 11 bankruptcy cases between January 1993 and July 2008

[1] We thank Sudheer Chava for providing the bankruptcy dataset.

filed by US public firms listed on the NYSE, AMEX and NASDAQ. The database consolidates cases from four sources: the Wall Street Journal Index, SEC Filings, the SDC Database, and the CCH Capital Changes Reporter. After merging the bankruptcy dataset with CRSP and Compustat 38,129 firm-year observations are left between 1993 and 2007, with 482 bankruptcy cases.

Table A1 contains the likelihood estimates for the Cox proportional hazard model.

Insert Table A1 About Here

We use five specifications. Column (1) contains no liquidity measure. Columns (2) to (5) add *Effective Spread*, *Quoted Spread*, *Amihud*, and *Zeros*, respectively. The table shows that the coefficients for the four liquidity measures are all positive and statistically significant at the 1% level. Specifically, the hazard ratio of *Effective Spread* (*Quoted Spread*, *Amihud*, and *Zeros*) is 1.2952 (1.6834, 1.0599, and 1.1096), indicating that one-unit increase in *Effective Spread* (*Quoted Spread*, *Amihud*, and *Zeros*) can lead to 29.52% (68.34%, 5.99%, and 10.96%) increase in the likelihood of bankruptcy. [2]

The results for other control variables are similar to Bharath and Shumway (2008)'s findings. Firms with higher equity value, less debt, lower stock return volatility, higher excess return, and greater net income to asset ratio are less likely to go bankrupt.

To test whether stock liquidity is a statistically significant predictor of bankruptcy risk we apply a likelihood ratio rest. In Table A1 we report -2 of the logarithm of the likelihood of model which is used to conduct a likelihood ratio test. The Column (1) specification, excluding a liquidity variable, is the constrained model. Columns (2) – (5), with varying measures of

[2] The Hazard Ratio of the coefficient β is computed as e^{β}, indicating the effect of one-unit change in the independent variable on the bankruptcy probability.

liquidity, are the unconstrained models. The Chi-statistic, which equals 2 times the difference between the logarithms of the likelihoods of the constrained and unconstrained models, is asymptotically distributed according to the Chi-square distribution. The Chi-square statistics for the four models in Columns (2) – (5) are all statistically significant, implying that stock liquidity is an important factor in the bankruptcy prediction model.

A2. Robustness

The main analysis is performed around the 2001 decimalization. However, we exploit two other liquidity shocks to test to test the robustness of the findings. The first alternative identification method uses the 2000 decimalization pilot program. The second alternative identification method uses the 1997 tick size reduction from 8ths to 16ths. In both alternative settings we continue to find that an improvement in liquidity decreases default risk.

A2.1. The Pilot Program of Decimalization

A limitation of the construction of treatment and control groups in the decimalization analysis is that both groups are exposed to the regulatory change. The analysis relies on the cross-sectional varying impact of the rule change. In this section, we rely on the pilot program of decimalization (the Pilot program) in 2000 to address this concern. Unlike the main analysis the pilot program had a staggered introduction and so there is a natural control group that is not subject to the tick size change.

The conversion from fractional to decimal pricing was implemented through a phase-in approach to reduce the risk to the issuers, investing public, participants, clearing and depository organizations, and related firms.[3] The phase-in implementation consists of four phases. 7 NYSE-listed stocks were chosen for a decimal pricing test on August 28, 2000. In the second phase, 57

[3] See more information at http://www.sec.gov/rules/other/decimalp.htm.

additional NYSE stocks were added to the pilot program on September 25, 2000.[4] NYSE expanded the pilot program on December 4, 2000, adding 94 securities in the third phase.[5] By the end of January, 2001, NYSE extended the decimal pricing to all their remaining stocks. Nasdaq decimalized all of its stocks between March 12, 2001 and April 9, 2001. According to the NYSE the pilot stocks were chosen either for ease of implementation (Phase 1) or to have divergent levels of daily trading activity and trading locations (Phase 2).[6] It is unlikely that the criteria used to choose the pilot stocks are related to factors affecting corporate default risk. Thus, the pilot program of decimalization creates a natural setting to analyze the effect of stock liquidity on firms' default risk.

To conduct the DiD analysis based on the pilot program of decimalization we focus on NYSE-listed firms and restrict the sample period to the first quarter of 2000 and the fourth quarter of 2000, using quarterly data for all variables. The pilot program includes the 158 NYSE-listed stocks (the pilot stocks) in the first three phases. We merge the list of pilot stocks with CRSP/Compustat database, giving us a final sample of 121 stocks. The pilot stocks are the treatment group, while the remaining NYSE-listed stocks make up the control group. Both the treatment and control stocks were priced in 1/16ths in the first quarter of 2000. By the fourth quarter of 2000 only the pilot stocks were priced in decimals.

We perform the following DiD regression:

$$\mathrm{EDF}_{i.t+1} = \alpha + \beta_1 Pilot_i * After_t + \beta_2 Pilot_i + \beta_3 After_t + \gamma Controls_{i,t} + Error_{i,t}, \qquad (6)$$

where *Pilot* is a dummy variable equal to one if a firm is included in the pilot program, and zero otherwise; *After* is a dummy variable equals one for Q4 of 2000 and zero for Q1 of 2000;

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[4] See more information at http://www1.nyse.com/pdfs/decimal081600.pdf.
[5] See more information at http://online.wsj.com/articles/SB97354943912849232.
[6] See more information at http://www1.nyse.com/pdfs/decimal081600.pdf.

*Pilot*After* is the interaction term between *Pilot* and *After*. *Controls* capture the same set of control variables as in Equation (4). Table A2 presents the results.

Insert Table A2 About Here

Columns (1) and (2) only include NYSE-listed firms. For Columns (3) and (4) we expand the control group to include Nasdaq firms. Columns (2) and (4) include industry fixed effects for the Fama-French 12 industries. Standard errors are clustered by firm. The coefficient on *Pilot*After* is stable across the specifications, ranging from -0.0157 to -0.0163, and is always statistically significant at the 10% level. The results show that the shock to liquidity decreased the default risk of pilot stocks by about 1.6%. While the magnitude of the coefficient is smaller than those found in Table 5, Panel F, the sign and interpretation remains consistent: increasing stock liquidity can decrease default risk.

A2.2. The 1997 tick size reduction

One concern with regard to the use of decimalization as a shock to stock liquidity is that decimalization coincides with the bust of the dot-com bubble, which might affect the treatment and control firms in a different fashion. In untabluated results we re-conduct the difference-in-difference analysis in Section 4 excluding high-tech firms and the results still hold, which partially addresses the concern. We next re-estimate the model using the 1997 tick size reduction as another shock to liquidity. In June, 1997, stock exchanges in U.S. including NYSE, Amex, and NASDAQ reduced the minimum tick size from 1/8 of a dollar to 1/16 of a dollar.

We employ the same approach in Section 4 for the analysis of the 1997 tick size reduction event. We first divide the firm into three groups based on the change of *Effective Spread* from 1996 to 1998, and retain the first and the last group. The propensity score matching procedure leaves us with 493 treatment-control pairs. We next run the DiD regression from Equation (5) for the matched sample. The coefficient of the interaction term *Treatment*After* in Table A3 is -0.06, which is quite similar to that in Panel F of Table 5, indicating that the treatment firms experience a larger drop of 6.0% in *EDF* after the 1997 tick size reduction than the control group.

Insert Table A3 About Here

References

Alanis, E., Chava, S., 2012. Shareholder bargaining power and debt overhang. Unpublished working paper. Georgia Institute of Technology.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. Journal of Finance 23, 589-609.

Bharath, S.T., Shumway, T., 2008. Forecasting default with the Merton distance to default model. Review of Financial Studies 21, 1339-1369.

Chava, S., Jarrow, R.A., 2004. Bankruptcy prediction with industry effects. Review of Finance 8, 537-569.

Chava, S., Stefanescu, C., Turnbull, S., 2011. Modeling the loss distribution. Management Science 57, 1267-1287.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard model. Journal of Business 74, 101-124.

Zmijewski, M.E., 1984. Methodological issues related to the estimation of financial distress prediction models. Journal of Accounting Research 22, 59-82.

Table A1. Cox Proportional Hazard Rate Model

The table reports several Cox proportional hazard rate models. There are totally 38,129 firm-year observations between 1993 and 2007 with 482 bankruptcy cases. Model (1) is the Bharath and Shumway (2008) model. Model (2) to (5) extend the Bharath and Shumway (2008) model by adding one of the four liquidity measures, *Effective Spread*, *Quoted Spread*, *Amihud*, and *Zeros,* respectively. . Other control variables are *Ln(Equity), Ln(Debt),* $1/\sigma_E$ *, Excess Return, and Income/Assets*. We add Fama-French 12 industry dummies. See Table 1 for definitions of all variables. Standard errors are clustered at the firm level and are presented in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)
Effective Spread $_{t-1}$		0.2587***			
		(0.0201)			
Quoted Spread $_{t-1}$			0.5208***		
			(0.0365)		
Amihud $_{t-1}$				0.0582**	
				(0.0274)	
Zeros $_{t-1}$					0.1040***
					(0.0055)
Ln(Equity) $_{t-1}$	-0.4035***	-0.3026***	-0.1134**	-0.3791***	-0.2356***
	(0.0500)	(0.0507)	(0.0521)	(0.0514)	(0.0504)
Ln(Debt) $_{t-1}$	0.3615***	0.3740***	0.4229***	0.3665***	0.3879***
	(0.0300)	(0.0299)	(0.0322)	(0.0301)	(0.0308)
$1/\sigma_{E\ t-1}$	-0.9527***	-0.8140***	-0.7255***	-0.9393***	-0.9284***
	(0.0903)	(0.0859)	(0.0812)	(0.0898)	(0.0872)
Excess Return $_{t-1}$	-2.6248***	-2.6955***	-2.5615***	-2.6413***	-2.3790***
	(0.2225)	(0.2338)	(0.2231)	(0.2236)	(0.2087)
Income/Assets $_{t-1}$	-2.7476***	-2.8887***	-2.9726***	-2.7904***	-3.2457***
	(0.5664)	(0.5736)	(0.6005)	(0.5668)	(0.5707)
Industry Dummy	Yes	Yes	Yes	Yes	Yes
N	38129	38129	38129	38129	38129
Log Likelihood	-3954.8771	-3908.8996	-3865.2163	-3953.0319	-3830.5569
-2 Log Likelihood	7909.754	7817.799	7730.433	7906.064	7661.114
-2 Log Lik. Difference		91.955	179.3216	3.6904	248.6404
#of Bankruptcies	482	482	482	482	482
Prob. of Bankruptcy	1.26%	1.26%	1.26%	1.26%	1.26%
Hazard Ratio for Liquidity	N/A	1.2952	1.6834	1.0599	1.1096

Table A2. Difference-in-Difference Analysis around the Pilot Decimalization Program

The table presents OLS regressions with EDF as the dependent variable using the decimalization pilot program. *Pilot* is a dummy variable equal to one if a stock is in the decimalization pilot program and zero otherwise. *After* is a dummy variable equal to one for Q4, 2000 and zero for Q1, 2000. *Pilot*After* is the interaction term between these two variables. The sample includes 121 NYSE-listed pilot firms as treatment firms and 2,019 NYSE non-pilot firms (and 2,665 Nasdaq firms) as control firms. Standard errors are clustered by stock and shown in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1%, respectively.

	Dependent Variable: EDF_{t+1}			
	(1)	(2)	(3)	(4)
Pilot*After	-0.0161*	-0.0162*	-0.0157*	-0.0163*
	(0.0088)	(0.0087)	(0.0088)	(0.0088)
Pilot	0.0107	0.0097	0.0062	0.0092
	(0.0085)	(0.0084)	(0.0086)	(0.0086)
After	-0.0006	-0.0009	-0.0019	-0.0015
	(0.0020)	(0.0020)	(0.0014)	(0.0014)
$Ln(Equity)_t$	0.0047***	0.0060***	0.0040***	0.0045***
	(0.0008)	(0.0010)	(0.0004)	(0.0005)
$Ln(Debt)_t$	-0.0001	-0.0001	-0.0004***	-0.0003**
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
$1/\sigma_{E\,t}$	-0.0115***	-0.0097**	-0.0076***	-0.0061***
	(0.0041)	(0.0041)	(0.0021)	(0.0020)
Excess $Return_t$	-0.2372***	-0.2300***	-0.0971***	-0.0753***
	(0.0677)	(0.0690)	(0.0135)	(0.0130)
$Income/Assets_t$	-0.0009	-0.0006	-0.0006**	-0.0005*
	(0.0012)	(0.0012)	(0.0003)	(0.0003)
ΔTobin's Q*After	-0.0059***	-0.0070***	-0.0046***	-0.0056***
	(0.0011)	(0.0012)	(0.0005)	(0.0006)
Intercept	0.0284***	0.0290***	0.0279***	0.0314***
	(0.0049)	(0.0049)	(0.0032)	(0.0033)
Industry Dummy	No	Yes	No	Yes
Include Nasdaq Firms	No	No	Yes	Yes
N	2140	2140	4805	4805
Adjusted R^2	0.0728	0.0799	0.0476	0.0479

Table A3. Difference-in-Difference Analysis Using 1997 tick size reduction (from 8th to 16th)

The table presents a difference-in-difference analysis using 1997 tick size reduction from 8th to 16th. We repeat the propensity score matching and the DiD approach used in Table 5 and the resulting sample contains 493 treatment-control pairs. This table reports the results for the difference-in-difference regression based on the matched sample. *Treatment* is a dummy variable equal to one if a stock is in treatment group and zero if in control group. *After* is a dummy variable equal to one for 1998 (post-1997 year) and zero for 1996. *Treatment*After* is the interaction between these two variables. Standard errors are clustered by stock and shown in parentheses. *, **, *** indicates statistical significance at the 10%, 5%, and 1%, respectively.

	Dependent Variable: EDF_t	
	(1)	(2)
Treatment*After	-0.0566***	-0.0566***
	(0.0169)	(0.0168)
Treatment	-0.0187*	-0.0197*
	(0.0110)	(0.0118)
After	0.0376**	0.0377**
	(0.0162)	(0.0161)
$Ln(Equity)_t$	-0.0248***	-0.0244***
	(0.0049)	(0.0044)
$Ln(Debt)_t$	0.0204***	0.0196***
	(0.0042)	(0.0040)
$1/\sigma_{E\,t}$	-0.0174***	-0.0174***
	(0.0039)	(0.0045)
Excess $Return_t$	-0.0199***	-0.0208***
	(0.0074)	(0.0080)
$Income/Assets_t$	-0.2358	-0.2349
	(0.1839)	(0.1936)
ΔTobin's Q*After	-0.0118	-0.0116
	(0.0099)	(0.0093)
Intercept	0.1678***	0.1688***
	(0.0310)	(0.0306)
Industry Fixed Effects	No	Yes
N	1962	1962
Adjusted R^2	0.2079	0.2026