Three Essays on Regulation and Governance in Financial Markets

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ABSTRACT

Three Essays on Regulation and Governance in Financial Markets

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This dissertation consists of three essays that address recent topics regarding regulation and governance in financial markets that concern for scholars, policymakers, and investors. The first paper looks at the relationship between default risk and corporate governance for financial firms in 28 countries outside of North America in the post-financial crisis period, where default risk is measured by both credit default swap (CDS) spreads and estimated by a Merton-type model. Reduced default risk helps the stock market rebound during the post-crisis period. Both internal governance variables, including institutional, insider ownership, board composition and CEO power, and external regulatory factors, are examined and they show significant effects on default risk. In addition, the impacts of various governance variables are continent-specific: they have a higher impact on default risk for Asian firms than for European firms. Regulatory factors are important moderators of the governance mechanisms for banks: higher Tier 1 capital ratios reduce both CDS spreads and fundamental default risk; recipients of secret emergency loans from the US Federal Reserve System (the Fed) exhibit lower CDS spreads in post-crisis but higher fundamental default probabilities.

In the second essay, we examine the cross-market correlation between options trading and both stock market return and stock price volatility. We document that contemporaneous call (put) option volume is positively (negatively) related to a stock's daily return. Both call and put options volumes amplify stock price volatility. Volatility transmission is stronger for larger firms

with more heavily traded options. Neither call nor put options open interest has significant impacts on the underlying stock volatility, consistent with the “day trader” hypothesis. A new market-level negative sentiment proxy conveys information that is directionally similar to that provided by put options volume. However, information transmission from the market-level negative sentiment variable to the stock market is subsumed by options trading effect for the most heavily traded contracts.

The last essay looks at the relationship between options trading activities and the return and volatility of its underlying asset, and the impact of regulated position limits on this relationship. We provide new evidence on the effect of position limits, based on options trading behavior in the period surrounding the suspension of trading limits for ETFs on the S&P 500 (SPY contracts) in the pilot program (amendment to CBOE Rule 4.11), whereby position limits were temporarily suspended. A trade-off between the informativeness of prices and return as well as volatility in the absence of trading limits is observed.

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CONTRIBUTION OF AUTHORS

Part of this thesis is published work with Lorne N. Switzer and Jun Wang.

Chapter 2:

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The manuscript has been reformatted and reorganized according to the requirements set out in the guideline of the School of Graduate Studies.

Table of Contents

List of Figures

Figure 3.1 Distribution of Firms by Industry (Full Sample)

This figure displays the distribution of firms by industry in the full sample. Among the 1834 firms, manufacturing industry occupies the largest percentage (41.78%), followed by service industry (15.45%). Finance, insurance, and real estate industry takes up 14.37%, while transportation, communication, electric, gas, and sanitary services industry shares 11.19%. All the other industries have percentages of less than 10%.

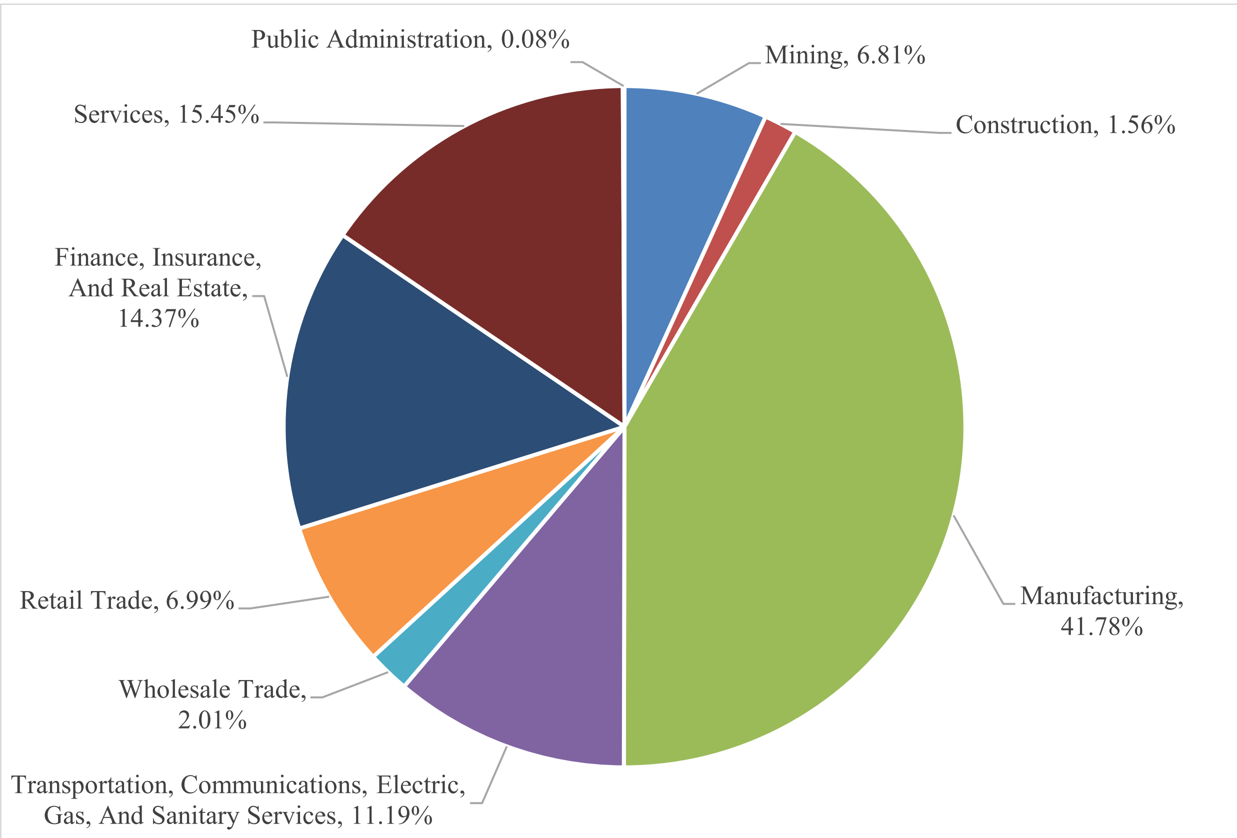
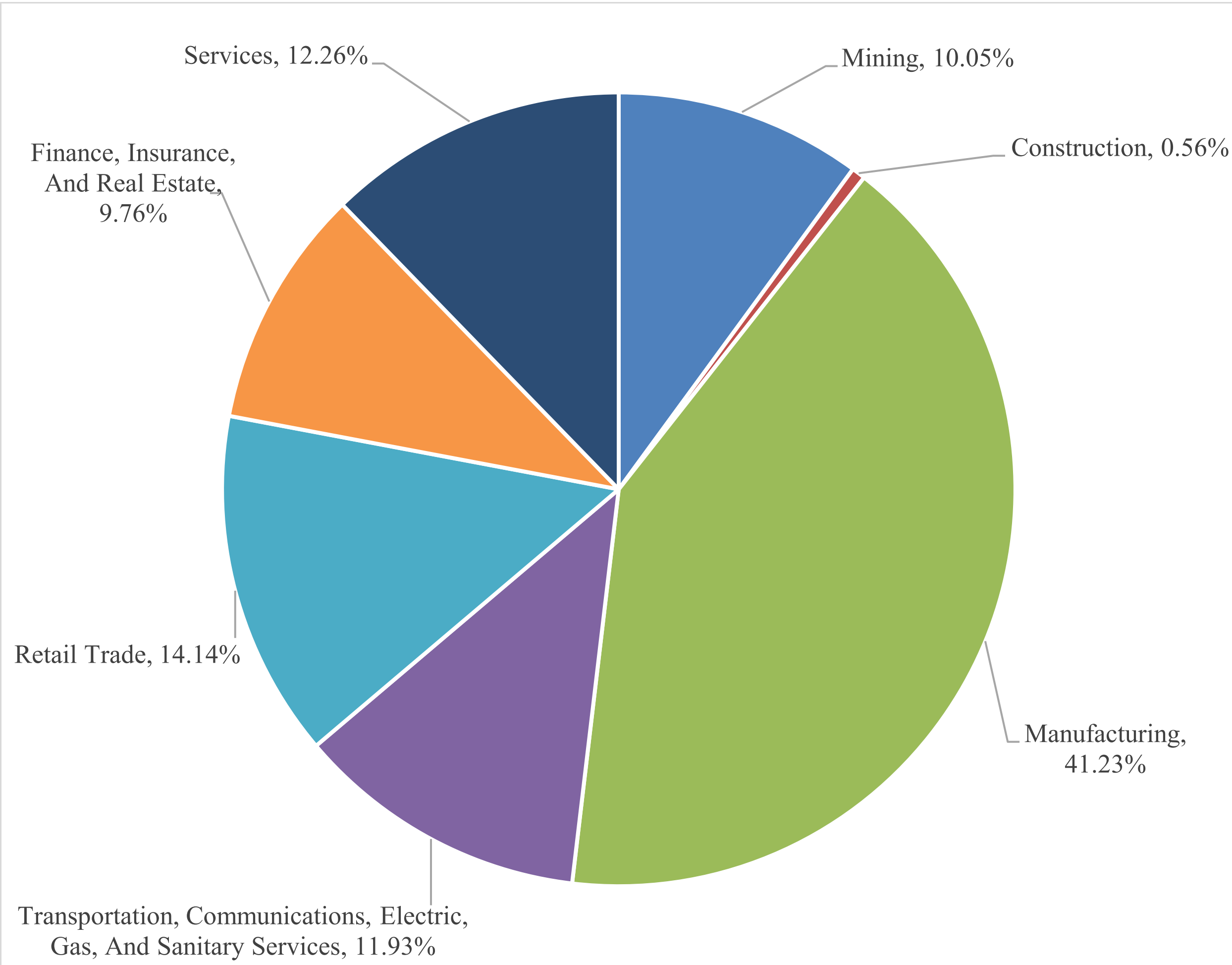


Figure 3.2 Distribution of Firms by Industry (Subsample)

This figure displays the distribution of firms by industry in the subsample. Among the 163 firms, manufacturing industry occupies the largest percentage (41.23%), followed by retail trade industry (14.14%). Service industry accounts for 12.26%, while transportation, communication, electric, gas, and sanitary services industry and mining industry represent 11.93% and 10.05% respectively. All the other industries have percentages of less than 10%.



List of Tables

Table 2.1 Sample description

Panel A: Sample selection

	Number of firms dropped	Remaining firms
Bloomberg financial firms (outside North America)		11140
Less		
Financial firms without traded CDS	10993	147
Financial firms without data on CDS spread	2	
Financial firms without data on corporate governance and fundamentals	28	
Final sample		117

Panel B: Sector distribution of final sample

Industry	Default probability sample		CDS spread sample	
	No.	%	No.	%
Banking	221	30.74	67	57.26
Financial services	190	26.43	17	14.53
Insurance	67	9.32	15	12.82
Real estate	241	33.52	18	15.38
Total	719	100	117	100

Panel C: Probit model (Obs. 1942)

Parameter	Estimate	Standard error	Wald chi-square	Pr > ChiSq
insti_holding	0.0528	0.1249	0.1787	0.6725
insid_holding	-4.6448	1.2229	14.4260	**0.0001**
board_indep	1.0429	0.1631	40.9013	**<.0001**
board_size	1.1760	0.1277	84.8257	**<.0001**
ceo_duality	0.3552	0.0979	13.1674	**0.0003**
total_assets	0.0006	0.0001	30.4504	**<.0001**
roa	-2.0428	0.8999	5.1532	**0.0232**
ltd	0.9855	0.2376	17.2035	**<.0001**
pb	-0.1532	0.0465	10.8408	**0.001**

Panel D: Heckman correction

Parameter	DF	Estimate	Standard error	t value	Approx Pr > |t|
_Rho	1	-0.189567	0.126041	-1.5	0.1326

_Rho: correlation between unobserved determinants of propensity to enter CDS market and unobserved determinants of CDS spread.

Table 2.2 Distribution of firms by country

Panel A: CDS spread sample				Panel B: Default probability sample			
Country	Number	% of subsample of continent	% of complete sample	Country	Number	% of subsample of continent	% of complete sample
		Australasia				**Australasia**	
Australia	9	100	7.69	Australia	52	100	7.23
		Europe				**Europe**	
Austria	1	1.92	0.85	Austria	5	2.54	0.70
Belgium	1	1.92	0.85	Belgium	9	4.57	1.25
Denmark	1	1.92	0.85	Denmark	3	1.52	0.42
Finland	1	1.92	0.85	Finland	6	3.05	0.83
France	10	19.2	8.55	France	17	8.63	2.36
Germany	2	3.85	1.71	Germany	4	2.03	0.56
Greece	3	5.77	2.56	Greece	5	2.54	0.70
Ireland	1	1.92	0.85	Ireland	5	2.54	0.70
Italy	4	7.69	3.42	Italy	16	8.12	2.23
Netherlands	1	1.92	0.85	Netherlands	4	2.03	0.56
Norway	1	1.92	0.85	Norway	7	3.55	0.97
Portugal	2	3.85	1.71	Portugal	3	1.52	0.42
Spain	4	7.69	3.42	Spain	9	4.57	1.25
Sweden	3	5.77	2.56	Sweden	18	9.14	2.50
Switzerland	4	7.69	3.42	Switzerland	12	6.09	1.67
Turkey	1	1.92	0.85	Turkey	12	6.09	1.67
United Kingdom	12	23.08	10.26	United Kingdom	62	31.47	8.62
		Asia				**Asia**	
China	4	7.41	3.42	China	112	24.78	15.58
Hong Kong	8	14.81	6.84	Hong Kong	36	7.96	5.01
India	7	12.96	5.98	India	86	19.03	11.96
Israel	1	1.85	0.85	Israel	5	1.11	0.70
Japan	25	46.30	21.37	Japan	165	36.50	22.95
Malaysia	2	3.70	1.71	Malaysia	16	3.54	2.23
Singapore	3	5.56	2.56	Singapore	21	4.65	2.92
Thailand	4	7.41	3.42	Thailand	11	2.43	1.53
		South America and others				**South America and others**	
Brazil	1	50	0.85	Brazil	15	83.33	2.09
Chile	1	50	0.85	Chile	3	16.67	0.42

Table 2.3 Pearson Correlation Test

	acds_trans	dp_trans	insti_holding	insid_holding	ceo_duality	board_indep	board_size	total_assets	roa	ltd	pb	T_one_ratio
acds_trans												
dp_trans	0.4091											
	(<.0001)											
insti_holding	-0.1258	-0.137										
	(0.0234)	(<.0001)										
insid_holding	0.0872	0.0313	-0.2006									
	(0.1165)	(0.1686)	(<.0001)									
ceo_duality	0.0669	0.1755	-0.1507	0.1208								
	(0.2291)	(<.0001)	(<.0001)	(<.0001)								
board_indep	-0.0354	-0.184	0.1245	-0.0078	-0.4408							
	(0.5254)	(<.0001)	(<.0001)	(0.7308)	(<.0001)							
board_size	0.0834	0.0576	0.1481	-0.2092	-0.1719	0.0009						
	(0.1337)	(0.0111)	(<.0001)	(<.0001)	(<.0001)	(0.9674)						
total_assets	-0.0237	0.0485	0.1108	-0.1104	-0.0996	0.1243	0.3174					
	(0.6705)	(0.0325)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)					
roa	-0.2634	-0.316	-0.0098	0.256	-0.0725	0.0792	-0.1718	-0.1331				
	(<.0001)	(<.0001)	(0.6664)	(<.0001)	(0.0014)	(0.0005)	(<.0001)	(<.0001)				
ltd	0.0931	0.1675	0.0729	0.0292	-0.1049	0.1604	-0.0766	-0.0748	-0.0397			
	(0.094)	(<.0001)	(0.0013)	(0.1987)	(<.0001)	(<.0001)	(0.0007)	(0.001)	(0.0804)			
pb	-0.2119	-0.2331	-0.0728	0.0824	-0.0503	0.0887	-0.1256	-0.0723	0.2543	-0.0458		
	(0.0001)	(<.0001)	(0.0013)	(0.0003)	(0.0267)	(<.0001)	(<.0001)	(0.0014)	(<.0001)	(0.0437)		
T_one_ratio	-0.3378	-0.3017	0.0881	0.0355	-0.1602	0.1431	-0.1969	0.086	0.2196	0.1877	0.1034	
	(<.0001)	(<.0001)	(0.0789)	(0.4797)	(0.0013)	(0.0042)	(<.0001)	(0.0863)	(<.0001)	(0.0002)	(0.0389)	
Emergen_loan	-0.1141	0.0862	0.1075	-0.0251	-0.1848	0.2279	0.239	0.4268	-0.0613	0.3182	-0.0792	0.2153
	(0.1242)	(0.0336)	(0.008)	(0.5364)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(0.1314)	(<.0001)	(0.0511)	(<.0001)

Table 2.4 Mean of Main Variables by Country

	Number of firms	Average CDS spread	Total assets ($B)	Institutional holdings	Insider holdings	Board independence	Board size	CEO duality	ROA	LTD	PB	Tier 1 ratio	Fed emergency loan ($M)
Australasia													
Australia	9	0.0194	67.3288	0.2030	0.0016	0.8788	2.2381	0	0.0130	0.1332	1.3803	0.0957	77.2767
Europe													
Austria	1	0.0272	113.0960	0.3220	0.0008	0.7745	2.8476	0	0.0010	0.1678	0.6971	0.1050	469.1000
Belgium	1	0.0168	173.2403	0.2969	0.0043	0.7515	2.3661	0	0.0014	0.0542	0.4758	0.1413	5922.3675
Denmark	1	0.0225	205.1022	0.1131	0.0002	0.6069	2.6126	0	0.0010	0.3067	0.7223	0.1657	488.5400
Finland	1	0.0247	13.1038	0.4362	0.0228	0.7546	2.1187	0	0.0397	0.0550	1.2761	0.1180	0
France	10	0.0245	575.1626	0.4229	0.0217	0.5394	2.6049	0.3214	0.0192	0.3137	0.9001	0.1149	2362.9362
Germany	2	0.0112	318.7935	0.4157	0	0.6042	2.7890	0	0.0047	0.0146	2.4402	N/A	N/A
Greece	3	0.1427	76.4945	0.0914	0.0002	0.3457	2.7259	0	-0.0438	0.0375	0.3859	0.0809	0
Ireland	1	0.1700	93.5951	0.9646	0.0009	0.6778	2.2499	0	-0.0402	0.1322	1.3036	0.1162	237.7500
Italy	4	0.0332	294.1465	0.3629	0	0.8592	3.0038	0.1	-0.0008	0.2720	0.4544	0.0954	601.9320
Netherlands	1	0.0234	168.4811	0.2856	0.0002	0.8956	2.2641	0	0.0042	0.0292	0.4213	N/A	N/A
Norway	1	0.0160	91.6258	0.7847	0.0011	0.6889	2.2675	0	0.0027	0.0183	0.8114	0.1101	0
Portugal	2	0.0745	96.9141	0.6243	0.0045	0.4839	3.2024	0	0.0016	0.2025	0.6838	0.1012	0
Spain	4	0.0523	378.7362	0.3228	0.0232	0.5809	2.7189	0.2727	0.0017	0.2130	0.6816	0.1009	274.6740
Sweden	3	0.0143	113.2552	0.4275	0.0017	0.5685	2.4646	0	0.0054	0.3919	1.1760	0.1594	198.1525
Switzerland	4	0.0140	305.3738	0.5793	0.0024	0.9231	2.5522	0.2727	0.0120	0.1047	0.9377	0.1836	2104.7826
Turkey	1	0.0308	42.5533	0.7099	0	0.3111	2.2675	0	0.0221	0.0451	1.6028	0.1476	0
U.K.	12	0.0182	185.6167	0.9213	0.0029	0.6390	2.4943	0	0.0132	0.1310	1.1046	0.1302	4915.4221
Asia													
China	4	0.0187	124.3566	0.7413	0	0.3619	2.7257	0	0.0121	0.0465	1.2970	0.0973	0
Hong Kong	8	0.0158	30.6576	0.4122	0.0142	0.4033	2.6740	0.5	0.0653	0.1059	1.0364	0.1098	0
India	7	0.0269	14.7671	0.6923	0.0010	0.4701	2.4382	0.5	0.0170	0.2836	1.9485	0.1015	0
Israel	1	0.0250	61.2280	0.2911	0.0003	0.4570	2.7296	0	0.0074	0.0911	0.8452	0.0865	49.7333
Japan	25	0.0390	80.1099	0.4597	0.0059	0.1611	2.2912	0.6081	0.0044	0.1888	0.7409	0.1162	63.3577
Malaysia	2	0.0130	35.5157	0.3735	0.0067	0.6306	2.2924	0	0.0137	0.0478	2.7016	0.1114	3.8381
Singapore	3	0.0169	43.8991	0.2927	0.0059	0.7505	2.4048	0	0.0556	0.1913	1.1108	0.1476	0
Thailand	4	0.0192	34.6003	0.5410	0.0017	0.4192	2.6314	0	0.0123	0.0797	1.6441	0.1037	0

Table 2.4 *(continued)*

South America and others													
Brazil	1	0.0166	35.6625	0.5438	0	0.3572	1.9459	0	0.0147	0.1221	1.3703	0.1076	0
Chile	1	0.0208	30.0073	0.9758	0.00002	0.7273	2.3979	0	0.0186	0.2691	3.5227	0.0879	0

Table 2.5 Full Sample Regressions

This table shows the regressions on the full sample from 2010 to 2012, which reports the results from OLS regressions of CDS spread (equations 1, 2, 3, and 4) and Default probability (equations 5, 6, 7, and 8) on a set of firms' corporate governance variables and control variables. Details of the variable definitions can be found in Appendix A. T_one_ratio represents the banking Tier 1 capital ratio. Emergen_loan is the log of the average daily balance of borrowing amount of federal emergency program. Equations 4 and 8 include only banking firms. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, where t-values are reported in parentheses.

	Dependent variable: CDS spread				Dependent variable: Bloomberg default probability			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
insti_holding		-0.3392**	-0.2611*	0.1104		-0.2874***	-0.3006***	0.0631
		(-2.08)	(-1.69)	(0.57)		(-5.09)	(-5.84)	(0.37)
insid_holding		1.852	2.2361	1.0443		0.0712	0.4462***	-0.3277
		(0.81)	(1.04)	(0.31)		(0.56)	(3.78)	(-0.35)
ceo_duality		0.1014	0.0504	-0.1202		0.2106***	0.1608***	-0.1037**
		(0.88)	(0.45)	(-0.85)		(4.87)	(4.09)	(-1.91)
board_indep		-0.0682	0.0924	0.0984		-0.3434***	-0.3638***	-0.1817**
		(-0.39)	(0.55)	(0.50)		(-4.67)	(-5.38)	(-2.42)
board_size		0.2362*	0.2774*	0.6994***		0.2111***	0.0878*	0.0766
		(1.67)	(1.94)	(4.28)		(4.3)	(1.87)	(1.14)

Table 2.5 *(continued)*

index_return	-0.5624**		-0.4598**	-0.3130	-0.7167***		-0.6402***	-0.1210
	(-2.47)		(-2)	(-1.39)	(-8.4)		(-7.77)	(-1.37)
total_assets	-0.0001		-0.0001	-0.0002**	0.00002		0.0001**	-0.00003
	(-1.22)		(-1.6)	(-2.22)	(0.51)		(2.31)	(-0.95)
Roa	-5.9957***		-6.4267***	-13.586***	-3.3981***		-3.3319***	-22.2532***
	(-4.58)		(-4.91)	(-4.25)	(-11.78)		(-11.51)	(-13.71)
Ltd	0.5385**		0.6055**	0.2193	0.7219***		0.9294***	0.2225
	(2)		(2.24)	(0.58)	(7.16)		(9.34)	(1.21)
Pb	-0.1779***		-0.1703**	-0.2407***	-0.0443***		-0.0421***	-0.1970***
	(-2.85)		(-2.58)	(-2.88)	(-7.19)		(-7.01)	(-5.69)
T_one_ratio				-0.0163				-0.0305***
				(-0.97)				(-4.77)
Emergen_loan				-0.0381**				0.0233***
				(-2.45)				(3.14)
Intercept	-3.6408	-4.2808	-4.2778	-5.0635	-3.9272	-4.2751	-3.9613	-3.4250
	(-37.32)	(-11.43)	(-11.26)	(-10.07)	(-148.55)	(-34.67)	(-33.16)	(-15.92)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	324	324	324	163	1939	1939	1939	399
R-Square	14.01%	3.17%	16.60%	48.07%	17.75%	6.47%	23.96%	60.19%

Table 2.6 European versus Asian firms

Table 2.6 shows the regressions on European firms and Asian firms. In Panel A, the equations (1), (2), (3), and (4) use CDS spread as dependent variable, while the equations (5), (6), (7), and (8) use Ln [Y / (1-Y)] as the measure of default probability as dependent variable. In Panel B, the first five equations regress on CDS spread and the remainder regress on default probability. T_one_ratio represents the banking Tier 1 capital ratio. Emergen_loan is the log of the average daily balance of borrowing amount of federal emergency program. Both equation 4 and equation 8 in Panel A (equations 5 and 10 in panel B) include only banking firms. The measures of other variables are the same as those shown in Table 2.4. ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t values are reported in parentheses.

Panel A: European firms

	Dependent Variable: CDS spread				Dependent Variable: Bloomberg default probability			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
insti_holding		-0.6488***	-0.3748*	-0.0539		-0.3778***	-0.2297***	0.0664
		(-3.09)	(-1.93)	(-0.21)		(-4.53)	(-2.95)	(0.41)
insid_holding		-1.5312	-0.0974	9.8926		-1.0008***	-0.1744	-1.7258
		(-0.6)	(-0.04)	(1.8)		(-3.94)	(-0.66)	(-0.90)
ceo_duality		-0.0438	-0.1622	-0.1728		-0.0779	-0.0647	0.0025
		(-0.22)	(-0.91)	(-0.86)		(-0.7)	(-0.63)	(0.01)
board_indep		-1.0244***	-0.8395***	-0.9379***		-0.0505	-0.0459	-0.3894**
		(-3.4)	(-3.06)	(-3.66)		(-0.36)	(-0.35)	(-2.33)
board_size		0.3904*	0.3967*	0.5203**		0.5028***	0.2845***	-0.0760
		(1.82)	(1.96)	(2.22)		(5.46)	(3.00)	(-0.46)
index_return	-0.8759***		-0.4401	0.4678	-0.8245***		-0.69***	0.2317
	(-2.96)		(-1.48)	(1.54)	(-5.5)		(-4.54)	(1.11)
total_assets	-0.0002***		-0.0003***	-0.0004***	0.0002***		0.0001*	-0.0001**
	(-2.69)		(-3.44)	(-5.14)	(3.26)		(1.93)	(-2.08)
roa	-8.135***		-6.3968***	-8.4650**	-3.6785***		-3.2326***	-17.8537***
	(-4.25)		(-3.36)	(-2.50)	(-6.65)		(-5.82)	(-6.77)
ltd	0.1527		-0.328	-2.5365***	0.1505		0.2616	-0.6946*
	(0.44)		(-0.92)	(-5.94)	(0.91)		(1.57)	(-1.93)
pb	-0.3025***		-0.3185***	-1.1804***	-0.0673***		-0.0554**	-0.5866***
	(-2.82)		(-3.03)	(-5.88)	(-3.02)		(-2.33)	(-4.52)
T_one_ratio				0.0491**				-0.0404***
				(2.11)				(-2.86)
Emergen_loan				-0.0396**				0.02126*
				(-2.62)				(1.62)
Intercept	-3.2837	-3.6889	-3.4201	-3.0373	-4.006	-4.9994	-4.5335	-2.1369
	(-21.78)	(-5.69)	(-5.63)	(-3.75)	(-70.39)	(-19.16)	(-17.01)	(-3.92)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	143	143	143	79	528	528	528	153
R-Square	32.26%	19.46%	41.54%	74.08%	26.07%	14.35%	29.03%	61.67%

Table 2.6 *(continued)* *Panel B: Asian firms*

	Dependent Variable: CDS spread				Dependent Variable: Bloomberg default probability			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
insti_holding		-0.0303	-0.4137	-0.2561		-0.1305	-0.2798***	-0.0677*
		(-0.1)	(-1.21)	(-1.27)		(-1.4)	(-3.28)	(-1.50)
insid_holding		2.2371	2.3825	0.7727		0.4882***	0.4955***	-0.7888
		(0.49)	(0.49)	(0.25)		(3.17)	(3.53)	(-1.36)
ceo_duality		0.3896**	0.3777**	0.1319		0.1065**	0.0762*	-0.0017
		(2.27)	(2.01)	(0.91)		(2.1)	(1.67)	(-0.06)
board_indep		0.3215	0.5181	-0.2262		-0.3784***	-0.2661***	-0.1317**
		(0.92)	(1.31)	(-0.68)		(-3.56)	(-2.7)	(-2.46)
board_size		-0.2651	-0.0123	0.2565		-0.075	-0.0946	-0.080*
		(-1.14)	(-0.05)	(1.12)		(-1.11)	(-1.52)	(-1.88)
index_return	0.1254		0.146	0.1956	-0.675***		-0.6135***	-0.1673***
	(0.33)		(0.39)	(1.01)	(-6.57)		(-6.08)	(-3.76)
total_assets	0.0001		0.0002	0.0001	-0.0001		0.0001	0.0001***
	(0.5)		(1.28)	(1.63)	(-0.81)		(0.77)	(2.99)
roa	-3.4331*		-4.5053**	21.528	-3.4374***		-3.5569***	-17.924***
	(-1.8)		(-2.07)	(1.24)	(-8.15)		(-8.33)	(-5.33)
ltd	1.0236**		0.9057*	4.639***	1.3801***		1.436***	0.282
	(2.36)		(1.85)	(6.27)	-10.42		(10.85)	(1.53)
pb	-0.1249		-0.1036	-0.1605*	-0.0498***		-0.0492***	-0.1083***
	(-1.39)		(-0.98)	(-1.89)	(-7.82)		(-7.62)	(-5.30)
T_one_ratio				-0.0841***				-0.0181***
				(-3.22)				(-3.63)
Emergen_loan				-0.0156				0.0054
				(-0.5)				(0.86)
Intercept	-3.9616	-3.6039	-4.0815	-3.9648	-3.8726	-3.6274	-3.5493	-3.56
	(-27.04)	(-6.2)	(-6.54)	(-5.26)	(-123.25)	(-21.89)	(-23)	(-23.44)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Obs.	154	154	154	63	1232	1232	1232	223
R-Square	6.57%	6.29%	11.67%	66.82%	19.84%	4.21%	23.84%	68.36%

Table 3.1 Descriptive Statistics of Variables

Panel A (Panel B) shows the descriptive statistics of variables in the full sample (subsample). Return is the daily return of common stock. G&K volatility is Garman-Klass volatility. PARK volatility is Parkinson volatility. R&S volatility is Rogers-Satchell volatility. The descriptions and formulae of all three volatility proxies are provided in this paper. Call (put) option volume is the daily trading volume of call (put) option. Δ COOI (Δ POOI) is the signed difference of call (put)option open interest between day t and day t-1. FEARS index represents market-level negative sentiment. S&P500 VIX is CBOE volatility index that reflects the market's expectations for the relative strength of near-term price changes of the S&P 500 index. S&P500 return is the daily return of S&P500 index. Firm size is the market capitalization with daily frequency. Call/put option volume, call/put option open interest, firm market size, and all volatility-measured variables are transformed into natural log values before the multivariate regressions.

Panel A Descriptive Statistics of Full Sample								
Variable	Obs.	Mean	Std. Dev.	Min	0.25	Median	0.75	Max
Return	1669469	0.00056	0.02899	-0.85351	-0.01015	0.00009	0.01079	3.93846
G&K Volatility	1669469	0.00067	0.00276	0	0.00010	0.00022	0.00054	0.63210
PARK Volatility	1669469	0.00180	0.00721	0	0.00025	0.00058	0.00144	1.17449
R&S Volatility	1669469	0.00070	0.00303	0	0.00009	0.00022	0.00055	0.61850
Call Option Volume	1669469	3.59260	3.08932	0	0	3.46574	5.98896	15.48678
Put Option Volume	1669469	3.04370	3.03545	0	0	2.63906	5.41165	13.92481
Δ COOI	1669469	0.00097	0.17245	-12	0	0.00053	0.01143	12.21785
Δ POOI	1669469	0.00093	0.18961	-13	0	0	0.00959	13.10991
FEARS Index	1669469	-0.00135	0.41282	-1.92886	-0.18276	-0.01961	0.14185	3.87195
S&P500 VIX	1669469	2.79880	0.18854	2.42657	2.66096	2.75874	2.90362	3.73146
S&P500 Return	1669469	0.00048	0.00809	-0.03941	-0.00352	0.00040	0.00490	0.03903
Firm Size	1669469	14.35479	1.86042	6.74640	13.09558	14.35966	15.57285	20.46798
Panel B Descriptive Statistics of Subsample								
Variable	Obs.	Mean	Std. Dev.	Min	0.25	Median	0.75	Max
Return	117363	0.00058	0.02593	-0.721	-0.00888	0.00037	0.00983	1.40122
G&K Volatility	117363	0.00044	0.00203	0	0.00007	0.00015	0.00036	0.3343
PARK Volatility	117363	0.0012	0.00569	0	0.00017	0.00039	0.00098	1.07675
R&S Volatility	117363	0.00044	0.00205	0	0.00007	0.00015	0.00036	0.35442
Call Option Volume	117363	9.10298	1.20969	0	8.33447	9.05975	9.81837	15.48678
Put Option Volume	117363	8.70002	1.25917	0	7.92985	8.69901	9.46506	13.92481
Δ COOI	117363	0.00037	0.09753	-12	0.00073	0.00834	0.02068	12.21785
Δ POOI	117363	0.00043	0.09914	-13	0.00097	0.00832	0.02032	13.10991
FEARS Index	117363	-0.00129	0.41197	-1.92886	-0.18276	-0.01961	0.14185	3.87195
S&P500 VIX	117363	2.79968	0.18867	2.42657	2.66096	2.75938	2.90471	3.73146
S&P500 Return	117363	0.00048	0.0081	-0.03941	-0.00352	0.0004	0.0049	0.03903
Firm Size	117363	17.20171	1.56543	9.73036	16.23603	17.48092	18.3438	20.46798

Table 3.2 Correlation Matrix of Variables

Panel A (Panel B) shows the Pearson correlation matrix of variables in the full sample (subsample). Return is the daily return of common stock. G&K is Garman-Klass volatility. PARK is Parkinson volatility. R&S is Rogers-Satchell volatility. The descriptions and formulae of all three volatility proxies are provided in this paper. Call (put) volume is the daily trading volume of call (put) option. Δ COOI (Δ POOI) is the signed difference of call (put)option open interest between day *t* and day *t-1*. FEARS index represents market-level negative sentiment. S&P500 VIX is CBOE volatility index that reflects the market's expectations for the relative strength of near-term price changes of the S&P 500 index. S&P500 return is the daily return of S&P500 index. Firm size is the market capitalization with daily frequency. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A Full Sample Correlation Matrix

	Return	G&K	PARK	R&S	Call Volume	Put Volume	Δ COOI	Δ POOI	S&P500 VIX	FEARS Index	S&P500 Return	Firm Size
Return	1.0000											
G&K	0.0568***	1.0000										
PARK	0.0607***	0.9542***	1.0000									
R&S	0.0466***	0.9699***	0.8711***	1.0000								
Call Volume	0.0401***	0.0010	0.0079***	-0.0059***	1.0000							
Put Volume	-0.0086***	-0.0123***	-0.0059***	-0.0180***	0.8421***	1.0000						
Δ COOI	0.0020***	0.0105***	0.0090***	0.0111***	0.0088***	0.0063***	1.0000					
Δ POOI	-0.0028***	0.0093***	0.0091***	0.0091***	0.0032***	0.0185***	0.4539***	1.0000				
S&P500 VIX	-0.0701***	0.0633***	0.0639***	0.0611***	-0.0023***	0.0238***	0.0011	0.0045***	1.0000			
FEARS Index	-0.0321***	0.0053***	0.0057***	0.0049***	0.0007	0.0038***	0.0112***	0.0129***	0.0212***	1.0000		
S&P500 Return	0.3165***	-0.0139***	-0.0151***	-0.0129***	0.0163***	-0.0134***	-0.0090***	-0.0080***	-0.2138***	-0.0896***	1.0000	
Firm Size	0.0161***	-0.2199***	-0.2222***	-0.2151***	0.5853***	0.6145***	-0.0028***	-0.0007	-0.0329***	0.0001	0.0021***	1.0000

Table 3.2*(Continued)*

Panel B Subsample Correlation Matrix

	Return	G&K	PARK	R&S	Call Volume	Put Volume	Δ COOI	Δ POOI	S&P500 VIX	FEARS Index	S&P500 Return	Firm Size
Return	1.0000											
G&K	-0.0507***	1.0000										
PARK	-0.0475***	0.9632***	1.0000									
R&S	-0.0465***	0.9623***	0.8656***	1.0000								
Call Volume	0.0678***	0.0597***	0.0666***	0.0545***	1.0000							
Put Volume	-0.0220***	0.0512***	0.0581***	0.0464***	0.7846***	1.0000						
Δ COOI	0.0223***	0.0126***	0.0127***	0.0120***	0.0285***	0.0265***	1.0000					
Δ POOI	-0.0046	0.0083***	0.0084***	0.0086***	0.0203***	0.0339***	0.8568***	1.0000				
S&P500 VIX	-0.0790***	0.0906***	0.0860***	0.0922***	0.0188***	0.0786***	-0.0041	-0.0035	1.0000			
FEARS Index	-0.0327***	0.0052	0.0041	0.0053	0.0085***	0.0135***	-0.0210***	-0.0220***	0.0218***	1.0000		
S&P500 Return	0.3720***	-0.0261***	-0.0239***	-0.0264***	0.0204***	-0.0432***	-0.0072*	-0.0079***	-0.2135***	-0.0894***	1.0000	
Firm Size	0.0153***	-0.2550***	-0.2517***	-0.2518***	0.2776***	0.3256***	-0.0057	-0.0057	-0.0271***	0.0003	0.0000	1.0000

* p<0.10, ** p<0.05, *** p<0.01

Table 3.3 Regressions of Stock Return on Option Trading Activities (Full Sample)

The dependent variable is daily return of underlying common stock. Models 1 & 2 are conducted without firm and year fixed effects, while Models 3 & 4 are with firm and year fixed effects. Call (put) volume is daily trading volume of call (put) option. Δ COOI (Δ POOI) captures the difference of call (put) option open interest between day t and day t-1. Fears is FEARS index. Lag return is one-day lag of stock return. S&P500 return is the daily return of S&P500 index. S&P500 VIX is CBOE volatility index at daily frequency. Firm size is the market capitalization of a firm. The t-statistics are reported in the parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00037*** (22.39)		0.00111*** (42.06)	
Put Volume		-0.00021*** (-14.25)		-0.00031*** (-13.28)
Δ COOI	0.00098*** (4.00)	0.00105*** (4.28)	0.00081*** (3.32)	0.00103*** (4.18)
Δ POOI	-0.00046** (-2.56)	-0.00040** (-2.25)	-0.00050*** (-2.86)	-0.00042** (-2.40)
FEARS	-0.00027*** (-5.47)	-0.00027*** (-5.29)	-0.00030*** (-6.06)	-0.00028*** (-5.57)
Lag Return	0.00183 (0.53)	0.00231 (0.68)	-0.00258 (-0.75)	-0.00022 (-0.06)
S&P500 Return	1.12891*** (120.85)	1.13132*** (120.99)	1.12284*** (121.01)	1.13038*** (121.01)
S&P500 VIX	-0.00041*** (-3.31)	-0.00014 (-1.08)	-0.00036** (-2.43)	0.00024 (-1.64)
Firm Size	-0.00012*** (-4.17)	0.00045*** (17.86)	0.00183*** (14.65)	0.00302*** (24.78)
constant	0.00157*** (2.73)	-0.00544*** (-10.07)	-0.02931*** (-15.54)	-0.04315*** (-23.48)
R-Square	10.10%	10.10%	10.70%	10.30%
Firm and Year Fixed Effects	No	No	Yes	Yes

* p<0.10, ** p<0.05, *** p<0.01

Table 3.4 Regressions of Stock Price Volatility on Option Trading Activities (Full Sample)

Panel A, B & C show, in turn, regressions using Garman-Klass (G&K) volatility, Parkinson (PARK) volatility, and Rogers-Satchell (R&S) volatility as the dependent variables. Models 1 & 2 are conducted without firm and year fixed effects, while Models 3 & 4 are with firm and year fixed effects. Call (put) volume is daily trading volume of call (put) option. Δ COOI (Δ POOI) captures the difference of call (put) option open interest between day t and day t-1. Fears is FEARS index. Lag G&K, lag PARK, and lag R&S are corresponding one-day lags of stock price volatility. S&P500 VIX is CBOE volatility index at daily frequency. Firm size is the market capitalization of a firm. Model is expressed below. The t-statistics are reported in the parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A Garman-Klass Volatility

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00013***		0.00015***	
	(27.02)		(25.48)	
Put Volume		0.00013***		0.00013***
		(26.08)		(25.45)
Δ COOI	-0.00002	0.00001	0	0.00003*
	(-1.11)	(0.36)	(0.21)	(1.85)
Δ POOI	0.00001	-0.00004**	0.00003*	-0.00001
	(0.37)	(-2.14)	(1.90)	(-0.76)
FEARS	0.00004***	0.00004***	0.00004***	0.00004***
	(7.71)	(7.30)	(6.87)	(6.49)
Lag G&K	0.28858***	0.28969***	0.23962***	0.24052***
	(21.45)	(21.60)	(18.49)	(18.56)
S&P500 VIX	0.00056***	0.00050***	0.00054***	0.00049***
	(23.09)	(21.50)	(23.37)	(21.51)
Firm Size	-0.00036***	-0.00036***	-0.00096***	-0.00093***
	(-27.07)	(-26.67)	(-18.65)	(-18.43)
constant	0.00360***	0.00389***	0.01232***	0.01208***
	(22.10)	(22.43)	(16.91)	(16.88)
R-Square	15.30%	15.20%	18.60%	18.50%
Firm and Year Fixed Effects	No	No	Yes	Yes

Table 3.4 *(Continued)*

Panel B Parkinson Volatility

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00036***		0.00042***	
	(28.40)		(26.70)	
Put Volume		0.00036***		0.00038***
		(27.21)		(26.34)
Δ COOI	-0.00019*	-0.00012	-0.00013	-0.00004
	(-1.67)	(-1.01)	(-1.10)	(-0.34)
Δ POOI	-0.00000	-0.00012**	0.00007	-0.00006
	(-0.04)	(-2.44)	(1.37)	(-1.27)
FEARS	0.00012***	0.00011***	0.00010***	0.00010***
	(8.10)	(7.66)	(7.31)	(6.88)
Lag PARK	0.31282***	0.31407***	0.26409***	0.26524***
	(26.40)	(26.68)	(22.22)	(22.36)
S&P500 VIX	0.00143***	0.00128***	0.00137***	0.00123***
	(23.55)	(21.70)	(22.70)	(20.64)
Firm Size	-0.00094***	-0.00095***	-0.00252***	-0.00242***
	(-29.13)	(-28.57)	(-19.37)	(-19.05)
constant	0.00939***	0.01019***	0.03215***	0.03148***
	(23.39)	(23.73)	(17.44)	(17.36)
R-Square	17.00%	16.90%	20.20%	20.00%
Firm and Year Fixed Effects	No	No	Yes	Yes

Panel C Rogers-Satchell Volatility

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00014***		0.00015***	
	(27.60)		(25.24)	
Put Volume		0.00014***		0.00013***
		(26.62)		(25.27)
Δ COOI	0.00002	0.00005***	0.00005***	0.00008***
	(1.34)	(3.09)	(3.02)	(4.88)
Δ POOI	0.00001	-0.00003*	0.00004**	-0.00001
	(0.70)	(-1.79)	(2.22)	(-0.29)
FEARS	0.00004***	0.00004***	0.00004***	0.00003***
	(7.22)	(6.83)	(6.40)	(6.04)
Lag R&S	0.25213***	0.25298***	0.20413***	0.20479***
	(19.28)	(19.42)	(15.64)	(15.70)
S&P500 VIX	0.00062***	0.00056***	0.00060***	0.00055***
	(22.44)	(20.92)	(22.73)	(21.06)
Firm Size	-0.00040***	-0.00040***	-0.00105***	-0.00102***
	(-27.41)	(-27.05)	(-19.08)	(-18.92)
constant	0.00397***	0.00429***	0.01344***	0.01321***
	(22.55)	(22.93)	(17.37)	(17.39)
R-Square	13.00%	12.90%	16.40%	16.30%
Firm and Year Fixed Effects	No	No	Yes	Yes

* p<0.10, ** p<0.05, *** p<0.01

Table 3.5 Regressions of Daily Stock Return on Option Trading Activities (Subsample)

The dependent variable is daily return of underlying common stock. Models 1 to 2 are all conducted with firm and year fixed effects. Call (put) volume is daily trading volume of call (put) option. Δ COOI (Δ POOI) captures the difference of call (put) option open interest between day t and day t-1. Fears is FEARS index. Lag return is one-day lag of stock return. S&P500 return is the daily return of S&P500 index. S&P500 VIX is CBOE volatility index at daily frequency. Firm size is the market capitalization of a firm. The t-statistics are reported in the parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00236***			
	(11.50)			
Δ COOI		0.00635		
		(1.19)		
Put Volume			-0.00041***	
			(-2.59)	
Δ POOI				-0.00069
				(-0.73)
FEARS	-0.00006	0.00005	0.00003	0.00001
	(-0.50)	(0.34)	(0.20)	(0.07)
Lag Return	0.02047***	0.02293***	0.02368***	0.02369***
	(2.58)	(3.09)	(2.96)	(2.98)
S&P500 Return	1.18243***	1.19261***	1.19012***	1.19176***
	(34.08)	(33.97)	(34.00)	(34.02)
S&P500 VIX	0.00042	0.00092**	0.00111**	0.00091**
	(0.98)	(2.19)	(2.48)	(2.18)
Firm Size	0.00189***	0.00249***	0.00259***	0.00249***
	(3.89)	(6.21)	(6.35)	(6.22)
constant	-0.05523***	-0.04540***	-0.04413***	-0.04538***
	(-6.40)	(-6.21)	(-6.31)	(-6.21)
R-Square	15.00%	14.40%	14.40%	14.40%
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes

* p<0.10, ** p<0.05, *** p<0.01

Table 3.6 Regressions of Stock Price Volatility on Option Trading Activities (Subsample)

Panel A, B & C show, in turn, regressions using Garman-Klass (G&K) volatility, Parkinson (PARK) volatility, and Rogers-Satchell (R&S) volatility as the dependent variables. Models 1 to 4 are all conducted with firm and year fixed effects. Call (put) volume is daily trading volume of call (put) option. Δ COOI (Δ POOI) captures the difference of call (put) option open interest between day t and day t-1. Fears is FEARS index. Lag G&K, lag PARK, and lag R&S are corresponding one-day lags of stock price volatility. S&P500 VIX is CBOE volatility index at daily frequency. Firm size is the market capitalization of a firm. Model is expressed below. The t-statistics are reported in the parentheses. *, **, *** denote statistical significance at 10%, 5%, and 1% level.

Panel A Garman-Klass Volatility

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00026***			
	(6.23)			
Δ COOI		0.00007		
		(0.87)		
Put Volume			0.00025***	
			(6.00)	
Δ POOI				0.00002
				(0.41)
FEARS	0.00002	0.00003***	0.00002	0.00003***
	(1.90)	(2.74)	(1.64)	(2.68)
Lag G&K	0.21390***	0.22559***	0.21448***	0.22573***
	(5.33)	(5.36)	(5.30)	(5.37)
S&P500 VIX	0.00057***	0.00060***	0.00048***	0.00060***
	(9.04)	(9.43)	(8.17)	(9.44)
Firm Size	-0.00093***	-0.00085***	-0.00092***	-0.00085***
	(-5.36)	(-4.98)	(-5.32)	(-4.98)
constant	0.01237***	0.01330***	0.01277***	0.01330***
	(4.60)	(4.57)	(4.69)	(4.57)
R-Square	19.00%	17.80%	19.00%	17.80%
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes

Table 3.6 *(Continued)*

Panel B Parkinson Volatility

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00077***			
	(6.51)			
Δ COOI		0.00013		
		(0.62)		
Put Volume			0.00072***	
			(6.44)	
Δ POOI				-0.00001
				(-0.09)
FEARS	0.00005**	0.00007***	0.00004	0.00007***
	(1.96)	(3.03)	(1.61)	(2.96)
Lag PARK	0.24373***	0.25897***	0.24436***	0.25913***
	(10.62)	(10.99)	(10.60)	(11.03)
S&P500 VIX	0.00140***	0.00149***	0.00114***	0.00149***
	(8.08)	(8.63)	(6.87)	(8.63)
Firm Size	-0.00254***	-0.00230***	-0.00252***	-0.00230***
	(-5.60)	(-5.16)	(-5.56)	(-5.16)
constant	0.03364***	0.03623***	0.03481***	0.03623***
	(4.80)	(4.75)	(4.89)	(4.75)
R-Square	19.20%	17.90%	19.10%	17.90%
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes

Panel C Rogers-Satchell Volatility

	Model 1	Model 2	Model 3	Model 4
Call Volume	0.00026***			
	(6.30)			
Δ COOI		0.00011		
		(1.36)		
Put Volume			0.00025***	
			(6.03)	
Δ POOI				0.00007
				(1.10)
FEARS	0.00002	0.00003**	0.00002	0.00003**
	(1.36)	(2.03)	(1.15)	(2.01)
Lag R&S	0.15580***	0.16421***	0.15618***	0.16432***
	(3.78)	(3.80)	(3.76)	(3.81)
S&P500 VIX	0.00065***	0.00068***	0.00056***	0.00068***
	(8.99)	(9.25)	(8.37)	(9.25)
Firm Size	-0.00098***	-0.00090***	-0.00097***	-0.00090***
	(-5.45)	(-5.09)	(-5.42)	(-5.09)
constant	0.01299***	0.01396***	0.01338***	0.01396***
	(4.66)	(4.64)	(4.75)	(4.64)
R-Square	17.30%	16.20%	17.30%	16.20%
Firm and Year Fixed Effects	Yes	Yes	Yes	Yes

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4.1 Descriptive Statistics and Correlation Matrix of Variables

Panel A describes the characteristics of variables of interest, while Panel B shows their correlations with each other. Return shock is the residual ARIMA process of SPY logarithmic return. Volatility shock is the residual of ARIMA model of squared SPY logarithmic return. Expected call (put) volume represents the predicted volume of ARIMA model, while call (put) volume shock represents the residual of that model. S&P 500 index return is directly downloaded from CRSP database. VIX defines the S&P 500 volatility index and is downloaded from Chicago Board Options Exchange (CBOE). t-statistics for Diff in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Panel A: Sample Descriptive Statistics

Variable	Observations	Mean	Standard Deviation	Min	Max	Median	Diff. (Nonpilot - Pilot)
Return Shock	2,580	-3.46E-07	0.0105207	-0.1049112	0.0666259	0.0004124	2.27e-06 (0.0054)
Volatility Shock	2,580	-1.67E-08	0.0003724	-0.0042935	0.0082722	-0.0000269	0.0000263 (1.7828) *
Expected Call Volume	2,581	13.77758	0.3121084	12.84643	14.77691	13.74978	0.1349052 (11.146) ***
Call Volume Shock	2,581	0.0011668	0.3435053	-1.165781	2.216755	-0.0108278	0.018976 (1.3919)
Expected Put Volume	2,581	14.23976	0.2724137	13.44287	15.2609	14.2008	0.1417146 (13.5620) ***
Put Volume Shock	2,581	0.0007158	0.2950263	-1.276849	1.123398	-0.0125209	0.0192464 (1.6440)
S&P 500 Index Return	2,581	0.0005215	0.0109159	-0.1198405	0.0938277	0.0006688	0.0000724 (0.1670)
VIX	2,581	17.57947	7.395186	9.14	82.69	15.5	6.684005 (25.4670) ***

Table 4.1 *(continued)*

Panel B：Sample Correlation Matrix

	Return Shock	Volatility Shock	Expected Call Volume	Call Volume Shock	Expected Put Volume	Put Volume Shock	S&P 500 Index Return	VIX
Return Shock	1							
Volatility Shock	-0.2655	1						
Expected Call Volume	-0.0149	0.043	1					
Call Volume Shock	-0.0781	0.1636	-0.0004	1				
Expected Put Volume	-0.0058	0.0555	0.875	0.0539	1			
Put Volume Shock	-0.2594	0.2023	0.0179	0.7332	0.0002	1		
S&P 500 Index Return	0.9633	-0.241	0.0077	-0.0698	0.0154	-0.2332	1	
VIX	-0.1717	0.1745	0.5441	0.1119	0.6452	0.1446	-0.1451	1

Table 4.2 SPY Return Shock Estimations

Dependent variable is SPY return shock measured by the residuals of ARIMA model. Panel A shows the regression results of call option, while Panel B shows those of put option. Expected call (put) volume is the one-day lagged predicted call (put) option volume from ARIMA model. Call (put) volume shock is the one-day lagged residual value from ARIMA model representing the portion unexplained by the lags. VIX defines the CBOE S&P 500 Volatility index. Pilot is a dummy variable that equals to one for SPY pilot program period, and zero otherwise. t-statistics are reported in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Panel A: Call Option			
	Model 1	Model 2	Model 3
Expected Call Volume (ECV)	0.0001753 (0.75)	0.0001979 (0.82)	0.0002035 (0.81)
ECV * Pilot			0.000022 (0.25)
Call Volume Shock (CVS)	-0.0008880*** (-5.50)	-0.0008766*** (-5.35)	-0.0014391*** (-4.90)
CVS * Pilot			0.0009371*** (2.74)
S&P 500 Index Return	0.9230327*** (50.39)	0.9220195*** (50.00)	0.9217459*** (50.07)
VIX	-0.0000459 (-1.30)	-0.0000557 (-1.37)	-0.0000549 (-1.36)
Pilot		-0.000301 (-1.57)	-0.0005999 (-0.51)
constant	-0.0020879 (-0.73)	-0.0020556 (-0.72)	-0.0021438 (-0.71)
R-square	0.93	0.93	0.93

Table 4.2 *(continued)* *Panel B: Put Option*

	Model 1	Model 2	Model 3
Expected Put Volume (EPV)	0.000549 (1.40)	0.0005828 (1.44)	0.0005709 (1.36)
EPV * Pilot			0.0000446 (0.56)
Put Volume Shock (PVS)	-0.0008048*** (-4.44)	-0.0007840*** (-4.21)	-0.0012331*** (-3.67)
PVS * Pilot			0.0007502* (1.91)
S&P 500 Index Return	0.9217029*** (49.67)	0.9206354*** (49.25)	0.9201914*** (49.11)
VIX	-0.0000549 (-1.39)	-0.0000652 (-1.45)	-0.0000643 (-1.43)
Pilot		-0.0003065 (-1.57)	-0.000937 (-0.85)
constant	-0.0073325 (-1.45)	-0.007458 (-1.47)	-0.0073022 (-1.39)
R-square	0.93	0.93	0.93

* p<0.10, ** p<0.05, *** p<0.01

Table 4.3 SPY Volatility Shock Estimations

Dependent variable is SPY volatility shock measured by the residuals of ARIMA model. Panel A shows the regression results of call option, while Panel B shows those of put option. Expected call (put) volume is the contemporaneous predicted call (put) option volume from ARIMA model. Call (put) volume shock is the contemporaneous residual value from ARIMA model representing the portion unexplained by the lags. VIX defines the CBOE S&P 500 Volatility index. Pilot is a dummy variable that equals to one for SPY pilot program period, and zero otherwise. T-statistics are reported in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Panel A: Call Option			
	Model 1	Model 2	Model 3
Expected Call Volume (ECV)	-0.0000435 (-1.28)	-0.0000456 (-1.27)	-0.0000608 (-1.42)
Call Volume Shock (CVS)	0.0001433*** (8.85)	0.0001425*** (8.70)	0.0002257*** (5.82)
S&P 500 Index Return	-0.0071596* (-1.78)	-0.0070749* (-1.77)	-0.0069546* (-1.75)
VIX	0.0000075 (1.28)	0.0000083 (1.23)	0.0000085 (1.26)
Pilot		0.0000255 (0.88)	-0.0003241 (-0.56)
ECV * Pilot			0.0000254 (0.61)
CVS * Pilot			-0.0001380*** (-3.13)
Constant	0.0004709 (1.21)	0.0004711 (1.21)	0.000677 (1.32)
R-square	0.097	0.098	0.102

Table 4.3 *(continued)* *Panel B: Put Option*

	Model 1	Model 2	Model 3
Expected Put Volume (EPV)	-0.0000565 (-0.89)	-0.0000598 (-0.90)	-0.0000713 (-0.90)
Put Volume Shock (PVS)	0.0001725*** (4.53)	0.0001714*** (4.45)	0.0002907*** (5.50)
S&P 500 Index Return	-0.0063495 (-1.51)	-0.0062642 (-1.50)	-0.0061209 (-1.48)
VIX	0.0000078 (1.17)	0.0000087 (1.14)	0.0000087 (1.14)
Pilot		0.000026 (0.86)	-0.0001741 (-0.21)
EPV * Pilot			0.0000141 (0.24)
PVS * Pilot			-0.0001975*** (-3.72)
Constant	0.000671 (0.84)	0.0006882 (0.84)	0.0008505 (0.84)
R-square	0.097	0.098	0.104

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4.4 SPY Expected Volatility Estimations

Dependent variable is SPY expected volatility measured by the predicted values of ARIMA model. Models 1 & 2 show the regression results of call option, while Models 3 & 4 show those of put option. Expected call (put) volume is the contemporaneous predicted call (put) option volume from ARIMA model. Call (put) volume shock is the contemporaneous residual value from ARIMA model representing the portion unexplained by the lags. VIX defines the CBOE S&P 500 Volatility index. Pilot is a dummy that equals to one for SPY pilot program period, and zero otherwise. T-statistics are reported in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

	Model 1	Model 2	Model 3	Model 4
Expected Call Volume (ECV)	-0.0000177 (-0.61)	0.0000148 (0.43)		
Call Volume Shock (CVS)	-0.0000202* (-1.89)	0.0000015 (0.08)		
ECV * Pilot		-0.0000686** (-2.51)		
CVS * Pilot		-0.0000368* (-1.70)		
S&P 500 Index Return	0.0033954 (1.37)	0.0033899 (1.37)	0.0033227 (1.29)	0.0033257 (1.29)
VIX	0.0000324*** (6.46)	0.0000319*** (6.38)	0.0000333*** (5.91)	0.0000326*** (5.73)
Pilot	0.0001112*** (5.00)	0.0010538*** (2.80)	0.0001122*** (4.93)	0.0013754** (2.55)
Expected Put Volume (EPV)			-0.0000505 (-0.94)	-0.0000054 (-0.08)
Put Volume Shock (PVS)			-0.0000351 (-1.56)	-0.0000046 (-0.16)
EPV * Pilot				-0.0000890** (-2.32)
PVS * Pilot				-0.0000505* (-1.93)
Constant	-0.0002713 (-0.86)	-0.0007125* (-1.75)	0.0001872 -0.28	-0.0004448 (-0.54)
R-square	0.447	0.448	0.448	0.45

* p<0.10, ** p<0.05, *** p<0.01

Table 4.5 SPY Return Shock Estimations (Pre-covid)

Dependent variable is SPY return shock measured by the residuals of ARIMA model. The sample after 2020-01-01 is excluded due to Covid-19. Models 1 & 2 show the regression results of call option, while Models 3 & 4 show those of put option. Expected call (put) volume is the one-day lagged predicted call (put) option volume from ARIMA model. Call (put) volume shock is the one-day lagged residual value from ARIMA model representing the portion unexplained by the lags. VIX defines the CBOE S&P 500 Volatility index. Pilot is a dummy that equals to one for SPY pilot program period, and zero otherwise. T-statistics are reported in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

	Model 1	Model 2	Model 3	Model 4
Expected Call Volume (ECV)	-0.0002738 (-1.62)	-0.0003417* (-1.93)		
Call Volume Shock (CVS)	-0.0007479*** (-5.11)	-0.0010986*** (-4.01)		
ECV * Pilot		0.00012* (1.92)		
CVS * Pilot		0.000554* (1.74)		
S&P 500 Index Return	0.9840665*** (135.39)	0.9837767*** (134.89)	0.9835198*** (135.32)	0.9833183*** (134.47)
VIX	-0.0000350** (-2.35)	-0.0000347** (-2.33)	-0.0000383** (-2.49)	-0.0000376** (-2.44)
Pilot	-0.0001297 (-1.38)	-0.0017698** (-2.10)	-0.0001447 (-1.53)	-0.0019208** (-2.17)
Expected Put Volume (EPV)			-0.0000455 (-0.21)	-0.0001215 (-0.55)
Put Volume Shock (PVS)			-0.0006992*** (-4.66)	-0.0008810*** (-2.85)
EPV * Pilot				0.0001256** (1.98)
PVS * Pilot				0.0002858 (0.81)
Constant	0.0039099* (1.70)	0.0048342** (2.01)	0.000863 (0.29)	0.0019279 (0.63)
R-square	0.952	0.952	0.952	0.952

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4.6 SPY Volatility Shock Estimations (Pre-covid)

Dependent variable is SPY volatility shock measured by the residuals of ARIMA model. The sample after 2020-01-01 is excluded due to Covid-19. Models 1 & 2 show the regression results of call option, while Models 3 & 4 show those of put option. Expected call (put) volume is the contemporaneous predicted call (put) option volume from ARIMA model. Call (put) volume shock is the contemporaneous residual value from ARIMA model representing the portion unexplained by the lags. VIX defines the CBOE S&P 500 Volatility index. Pilot is a dummy that equals to one for SPY pilot program period, and zero otherwise. T-statistics are reported in parentheses. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

	Model 1	Model 2	Model 3	Model 4
Expected Call Volume (ECV)	-0.0000252 (-1.62)	-0.0000331 (-0.93)		
Call Volume Shock (CVS)	0.0001284*** (10.30)	0.0001843*** (5.53)		
ECV * Pilot		0.0000116 (0.24)		
CVS * Pilot		-0.0000881** (-2.39)		
S&P 500 Index Return	-0.0031266** (-2.03)	-0.0030844** (-2.02)	-0.0018239 (-1.16)	-0.0017442 (-1.13)
VIX	0.0000052** (2.34)	0.0000053** (2.40)	0.0000053** (2.42)	0.0000053** (2.53)
Pilot	0.0000125 (1.37)	-0.0001463 (-0.22)	0.0000121 (1.33)	0.0001741 (0.19)
Expected Put Volume (EPV)			-0.0000306 (-1.39)	-0.0000266 (-0.52)
Put Volume Shock (PVS)			0.0001825*** (11.59)	0.0002725*** (6.98)
EPV * Pilot				-0.0000114 (-0.17)
PVS * Pilot				-0.0001392*** (-2.94)
Constant	0.0002473 (1.12)	0.0003554 (0.71)	0.0003358 (1.06)	0.0002774 (0.38)
R-square	0.107	0.113	0.126	0.137

* p<0.10, ** p<0.05, *** p<0.01

Table 4.7 Ordinary Least Squares Estimation

Dependent variable is SPY equity return. Pilot is a dummy that equals to one for SPY pilot program period, and zero otherwise. The model in Panel A examines whether SPY ETF perfectly tracks S&P 500 Index, and whether SPY pilot project improve the tracking ability of SPY ETF. Panel B performs Wald Test assesses the joint hypothesis that the constant term C(1) is 0 and the slope term for the S&P 500 C(2) equals 1. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Panel A: OLS Regression

Variable	Coefficient	Std. Error	t-Statistic	Probability
Constant	-0.0000951	0.0000273	-3.489486	0.0005***
S&P 500 Index Return	0.989537	0.001647	600.8067	0.0000***
Pilot	0.0000688	0.0000363	1.896786	0.0580*

Panel B: Wald Test

Test Statistic	Value	df	Probability
F-statistic	27.04805	(2, 2577)	0.0000
Chi-square	54.09609	2	0.0000

Null Hypothesis: C(1) = 0,C(2) = 1

Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	-0.0000951	0.0000273
-1 + C(2)	-0.010463	0.001647

Restrictions are linear in coefficients.

Table 4.8 EGARCH Model

Dependent variable is SPY equity return. Pilot is a dummy that equals to one for SPY pilot program period, and zero otherwise. This analysis examines whether SPY ETF perfectly tracks S&P 500 Index and whether SPY pilot project improve the tracking ability of SPY ETF, while accounting for time varying asymmetric volatility of SPY return using EGARCH model. *, **, and *** indicates significance at 10%, 5%, and 1% respectively.

Variable	Coefficient	Std. Error	z-Statistic	Probability
Constant	-0.0000548	0.0000227	-2.416187	0.0157**
S&P 500 Index Return	0.995679	0.000723	1376.472	0.0000***
Pilot	0.0000536	0.0000215	2.491224	0.0127**
		Variance Equation		
C(4)	-9.013459	0.415166	-21.71050	0.0000
C(5)	0.418977	0.024233	17.28952	0.0000
C(6)	0.056362	0.020560	2.741368	0.0061
C(7)	0.376187	0.029080	12.93632	0.0000

Appendix A: Definition of Variables

Variables	Definition	Sources
institutional holdings	Percentage of outstanding shares held by institutions. Based on holdings data collected by Bloomberg.	Bloomberg
insider holdings	Percentage of outstanding shares currently held by insiders. Based on holdings data collected by Bloomberg.	Bloomberg
board independence	Independent directors as a percentage of total board membership.	Bloomberg
board size	Number of full-time directors on the company's board, as reported by the company.	Bloomberg
ceo duality	Dummy variable indicating whether the company's Chief Executive Officer is also Board Chair, as reported by the company.	Bloomberg
total assets	The total of all short and long-term assets as reported on the Balance Sheet.	Bloomberg
roa	Indicator of how profitable a company is relative to its total assets, in percentage. We define return on assets as returns divided by total assets each year from 2010 to 2012.	Bloomberg
ltd	Measures the percentage of long-term debt to total assets. Unit: Actual. It is calculated as: (Long Term Borrowings / Total Assets) * 100	Bloomberg
pb	Ratio of the stock price to the book value per share. Calculated as: Price-to-Book Ratio = Last Price / Book Value Per Share	Bloomberg
cds spread	CDS premium containing information on the default probability associated with a reference entity, which is collected by Markit Inc.	Markit Group
T_one_ratio	Tier 1 capital ratio	Compustat
Emergen_loan	Emergency loans from the Federal Reserve	Bloomberg

Appendix B: Generalized Method of Moments (GMM) estimation of overidentification

Panel A: Results including the Japanese highest-CDS firm			
Variable	Coefficient	t-Statistic	Prob.
INSTI_HOLDING	-6.9992	-2.2115	0.0278
INDEX_RETURN	0.0418	0.0359	0.9714
INSID_HOLDING	-12.5475	-1.0127	0.3121
CEO_DUALITY	-2.4383	-1.6589	0.0982
BOARD_INDEP	-11.4371	-1.6667	0.0966
BOARD_SIZE	0.6188	0.6844	0.4943
TOTAL_ASSETS	0.3373	0.993	0.3216
ROA	-0.5393	-0.0658	0.9476
LTD	1.0387	0.7604	0.4476
PB	0.4181	0.9012	0.3682
J-statistic: 0.5086			
Prob. (J-statistic): 0.4758			
Panel B: Results excluding the Japanese highest-CDS firm			
Variable	Coefficient	t-Statistic	Prob.
INSTI_HOLDING	-0.2459	-0.7329	0.4642
INDEX_RETURN	-0.0931	-0.3815	0.7031
INSID_HOLDING	2.7587	1.5926	0.1123
CEO_DUALITY	0.0642	0.7571	0.4496
BOARD_INDEP	0.2852	1.9952	0.047
BOARD_SIZE	0.2838	2.1	0.0366
TOTAL_ASSETS	-0.0227	-0.8417	0.4006
ROA	-3.2829	-2.9385	0.0036
LTD	0.4359	1.845	0.0661
PB	-0.1394	-2.7229	0.0069
J-statistic: 1.5214			
Prob. (J-statistic): 0.2174			
Panel C: Generalized Method of Moments (GMM) estimation endogeneity tests			
		Value	Probability
Difference in J-stats		0.4633	0.4961
Restricted J-statistic: 2.9672			
Unrestricted J-statistic: 2.504			

Chapter 1: Introduction

This dissertation consists of three essays studying current issues on governance and regulations on financial markets, covering diverse topics. The first essay looks at the relationship between default risk and corporate governance for financial firms in 28 countries outside of North America in the post-financial crisis period. The second essay examines the cross-market correlation between options trading and both stock market return and stock price volatility. The last essay looks at the relationship between option trading activities and return and volatility of its underlying asset, and the impact of regulated position limits on this relationship. Each of the three essays are self-contained and presented from chapters 2 to 4. In this chapter, we highlight their motivations, primary results, and main contributions to literature.

The financial crisis of 2007–08 engendered huge losses to many firms worldwide, especially in financial sectors. The severity of the large-scale defaults in financial sectors and the wealth loss of stakeholders, especially stockholders and bondholders, and the associated impact on financial stability have attracted the attention of policymakers, scholars, and practitioners. How to control and reduce risk prior to and during a crisis period has been the subject of considerable research in the corporate governance literature for the past several years (e.g., Gupta, Krishnamurti, and Tourani-Rad, 2013; Caprio, Laeven, and Levin, 2007). However, crisis conditions in many international markets did not end with the recovery of the US market. By end of 2009, with Eurozone member states unable to bail out their over-indebted banks, the European Banking Crisis erupted, leading to widespread defaults and various stopgap banking system bailouts.[1] The IMF

[1]For example, the Allied Irish Bank and the Bank of Ireland received a €7 billion rescue package in 2009 and recapitalized their assets. Greece's four largest banks—National Bank of Greece SA, Piraeus Bank SA, Euro-bank Ergasias SA, and Alpha Bank AE—have been regular recipients of emergency loans from the European Central Bank. In addition to European banks, several financial firms in Asia have faced default during the post-financial crisis period. Aiful Corporation, one of the largest Japanese consumer finance companies, failed to honor maturing

has dubbed the post-crisis experience of different regions of the world as reflecting the "multispeed global economy."[2] There is no doubt that bondholders prefer default risk reduction. The question is whether the reduced default risk favored by bondholders really benefits stockholders so that stockholders also have an incentive to take actions that can reduce firms' risk, rather than focusing solely on increasing their investment return. The study shows that there is a positive relation between the lagged default risk and stock returns for the sample firms, both before and during the crisis period, which is consistent with Chava and Purnanandam's (2010) finding that stockholders expect higher returns for bearing default risk. However, during the post-crisis period there is a negative relationship between the lagged default probability and stock return, implying that the stock market rebound reflects the declining default risk.[3] Therefore, reduced default risk indeed benefits shareholders during the post-crisis period.

Now the question is how to reduce the default risk of the financial sector over the post-crisis period. There is a widespread view that the problems in many countries outside North America can be attributed to failures and/or weaknesses in corporate governance structures, both internal and external, that result in a lack of safeguarding against excessive risk-taking by financial services companies. Indeed, no countries outside the United States have introduced the sweeping Dodd Frank-type regulatory initiatives to improve the governance of the financial sector. Some studies have examined the interaction of governance mechanisms and the performance of firms during the 2007–08 crisis period (e.g., Aebi, Sabato, and Schmid, 2012; Beltratti and Stulz, 2012; Erkens,

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loans in December of 2009, which triggered a restructuring event and involved the payout of CDS insuring $1.3 billion of its debt. Neo-China Land Group, an investment holding company based in China, had its credit rating downgraded by Moody's by three notches, to "Ca," in 2009 due to missed coupon payments of $19.5 million on its outstanding $400 million 2014 bonds.

[2] World Economic Outlook Reports 2013. https://www.imf.org/external/ns/cs.aspx?id=29

[3] I perform a set of regressions of the stock return on the lagged default probability during three periods: before the crisis, during the crisis, post-crisis, using data collected from Bloomberg, and the whole sample period is from 2006 to 2013. The coefficients of default risk are 0.1376 (before), 0.2675 (during), -0.0271(post), and 0.1500 (whole period). Except for the coefficient estimated during the crisis period, all coefficients are significant at the 10% level.

Hung, and Matos, 2012; Liu, Uchida, and Yang, 2012). However, few papers look at the performance of non-US firms *in the aftermath* of the crisis. Hence, it is worthwhile to perform robustness tests for not just different sample periods, but also for different countries. Are there differential responses to internal and external governance mechanisms for countries outside the US? Do we observe convergence of governance structures around the world, as per Denis and McConnell (2003)? Such convergence is the goal of regulators in international financial markets. Basel III requires financial institutions to have higher Tier 1 (T1) capital ratios, but whether this requirement is well founded in terms of reducing firms' default calls for more evidence. In addition, during the crisis the US Federal Reserve System (the Fed) did provide foreign financial institutions with emergency loans, but did those foreign financial institutions become less risky after the Fed came to their rescue? We directly address these questions as well. To the best of our knowledge, there has been no research examining the impact of governance mechanisms on credit risk for financial firms in countries outside North America, considering the impact of the secret emergency loans that were provided by the Fed to foreign financial institutions over the period 2007 to 2009 on default risk.

The purpose of this study is to address these gaps. The research considers a sample of firms from 28 different countries and analyze the impacts of various governance variables on firm default risk, controlling for the differences in country development and general market conditions, in addition to a set of firm characteristics. We use two measures of firm default risk to explore the relationship between corporate governance and firm default risk during the post-crisis period. The first measure is the five-year credit default swap (CDS) spread. CDS spread has several advantages in capturing default probabilities. Unlike bonds, CDS are not in fixed supply and should be less sensitive than bonds to liquidity effects. In addition, as noted by Garcia and Yang (2009), compared to corporate bonds, CDS spreads are less susceptible to squeezes or to becoming "special" with repo rates below market rates for similar maturities and credit risks. However, a large number of firms do not have traded CDS information, so there could be sample selection bias. Therefore, we also address the possibility of selection bias for the CDS sample firms. The second measure is Merton-type five-year default probability to measure a firm's fundamental default risk.

The essay considers five key internal governance mechanisms: institutional ownership, insider ownership, board independence, board size, and CEO duality. These measures are widely used as factors directly linked to firms' corporate governance quality (e.g., Anderson and Fraser, 2000; Bhojraj and Sengupta, 2003; Erkens, Hung, and Matos, 2012; Liu, Uchida, and Yang, 2012; Switzer and Wang, 2013a, 2013b). We further examine two important external regulatory factors, including T1 capital ratio and whether the firms are recipients of secret emergency funding from the Fed, based on data availability. We use instrumental variable methods to address the potential endogeneity of institutional ownership and find that institutional ownership (board size) is negatively (positively) related to default risk using both measures across countries; board independence (insider holdings and CEO duality) lowers (increases) default probabilities but not CDS. Moreover, we find that the impacts of various governance variables on firm default risk are continent-specific: most governance variables are significantly related to default risk for Asian firms; for European firms, however, only board size and institutional holdings are significant. Regulatory factors are also important. Foreign financial institutions with higher T1 capital ratio have lower CDS and lower fundamental default risk; however, those that received secret emergency funding from the Fed in the period 2007 to 2009 have lower CDS spreads post-crisis but higher fundamental default probabilities.

The second essay looks at the impact of derivatives trading on underlying asset market, which has been a matter of great interest to academics, practitioners, and regulators for decades. The seminal study of Black (1975) highlights the leverage incentives for informed traders to transact in options market rather than equity market. Several studies have looked at the potential adverse effects of derivatives trading in terms of market manipulation and adverse market impacts of large trades. (e.g., Kyle (1984); Gastineau and Jarrow (1991); Gastineau (1992); Jarrow (1992, 1994); Dutt and Harris (2005); Sanders and Irwin (2015)). Most exchanges have in place position limits to restrain manipulation or potentially destabilizing trades. On October 15, 2020, Commodity Futures Trading Commission (CFTC) adopted new rules on position limits, which finally ended their long efforts to implementing position limit rules pursuant to Dodd-Frank Act that began with publication of proposed and final rules in 2011. The purpose of the new framework is to prevent unfettered trading activity from destabilizing the underlying markets. With the new rules, federal position limits have been established on 25 different futures contracts. By definition, a position limit is a preset level of ownership established by exchanges or regulators that limits the number of shares or derivative contracts that a trader, or any affiliated group of traders and investors, may hold. Its purpose is to preclude any entity from exerting undue control over a particular market.

In academia, supporters and opponents have long been discussing the necessity and effectiveness of position limits on derivative markets and both sides have their merits. One major challenge of studying the effect of position limits is the difficulty to obtain data. Specifically, an unpublished literature review of position limits[4], submitted by the CFTC's Office of the Chief Economist (OCE), indicates that the design of an economic study towards the effect of position limits is complicated by the fact that position limits or quantity limits have been an inherent feature

[4] https://agriculture.house.gov/uploadedfiles/position_limits_analysis.pdf, accessed on November 20, 2020.

of derivative contracts since their inception. Consequently, to conduct a counterfactual study looking at the impact of position limits using standard tests (such as Difference-in-Difference) is out of the question. As an alternative approach, in this essay we look at how derivative trading activities affect the behavior of the underlying asset markets. In particular, the study provides new evidence on the information transmission between options trading activities, and stock market return as well as stock price volatility. Does heavier trading induce greater volatility? This essay provides new evidence on this score. The results should be of interest to academics, practitioners and regulators in evaluating the costs and benefits of quantity restriction on derivatives contracts.

Cross-market studies between options and equity markets have shown mixed results. Those studies also ignore stock volatility.[5] Roll, Schwartz, and Subrahmanyam (2009) examine the contemporaneous relationship between options trading activity and firm valuation. Their results show that higher options trading activity is associated with greater values of Tobin's q, suggesting that options facilitate market completion and provide a venue for incorporating private information into prices. They do not look the cross-sectional impact of options trading on stock market volatility, nor do they consider potential differences between put vs. call options trading.[6] Indeed, the cross-sectional impact of options trading on stock market volatility, has been hitherto largely ignored by literature.

Our study focuses on the links between individual stock options trading and stock market return as well as stock price volatility. Bessembinder and Seguin (1992), examine the cross-market

[5] Early studies include Anthony (1988), Stephan and Whaley (1990) and Chan, Chung, and Johnson (1993), Chakravarty, Gulen, and Mayhew (2004) and Vanden (2004, 2006). More recently, Muravyev, Pearson, and Broussard (2013) find that stock markets lead the options markets. In contrast, An, Ang, Bali and Cakici (2014) show a bi-directional relationship between options prices and future stock returns. A few studies look at the impact of initial options listing on underlying stocks' volatilities, with mixed findings (e.g., Whiteside, Dukes, and Dunne (1983); Skinner (1989); Bollen, (1998)).

[6] There are a few early studies on the impact of initial options listing on underlying stocks' volatilities, with mixed findings (e.g., Whiteside, Dukes, and Dunne (1983); Skinner (1989); Bollen, (1998)).

relationship between index futures-trading activity and overall equity market volatility, measured by the S&P 500 index. Our study differs from theirs in several ways: we look at individual options contracts, both calls and puts. It is not limited to large-cap companies. In addition, previous studies do not explore market sentiment effects, as identified in Baker and Wurgler (2006), and Tetlock (2007). In this regard, Da, Engelberg, and Gao (2015) introduce their Financial and Economic Attitudes Revealed by Search (FEARS) index that is constructed based on daily internet search activity. They demonstrate that this index can reflect market-level pessimistic sentiment: it is negatively correlated with contemporaneous stock return and strongly related to the transitory component of daily volatility. As Da et al. (2015) mention, since the FEARS index is a search-based rather than a survey-based index, it is available at high frequency levels. Moreover, it covers a broader range of investors by avoiding non-response issues from alternative survey-based approaches. This essay offers new evidence looking at the extent to which this new market-level negative sentiment proxy conveys information that is distinct from that provided by options trading activity as it affects the risk and returns of individual stocks.[7]

The main results are as follows. We find that contemporaneous call (put) options volume is positively (negatively) related to a stock's daily return. Both call and put options volumes amplify stock price volatility. We also show that volatility transmission is stronger for larger firms with more heavily traded options. This suggests that position limits on options might be in position to constrain extreme market volatility events. However, neither call nor put options open interest has significant impact on the underlying stocks, consistent with the "day trader" hypothesis. This result is consistent with Bessembinder and Seguin's (1993) hypothesis that open interest positions are largely reflective of hedging activities. Speculators' activities that may be volatility enhancing are

[7] We are grateful to Professor Zhi Da for generously providing the data from their original study as well as for an updated sample.

more likely reflected in intraday trading activities that are closed out by the end of the trading day (the "day trader" hypothesis). We also find that the FEARS index conveys similar but distinct information as put options volume. However, the information conveyed by negative market sentiment in FEARS index is subsumed by trading activity effects for more heavily traded options.

The last essay examines whether options trading contains information about future stock return and volatility. In a simple Black and Scholes course, a simple default hypothesis is that the options market is redundant which can be replicated in continuous time by investments in stocks and bonds (Black and Scholes, 1973), In this case, options trading volume should not contain any information or any incremental information besides that in stock volume. However, if informed traders can profit from their private information by using options, this may impact the underlying asset's price movements and return distribution (Easley et al., 1998). In addition, Black (1975) suggests that the higher leverage available in option markets could potentially encourage informed traders to transact options rather than stocks. Thus, if the option market is more attractive to market participants, one should expect that the option trades induced by informed agents reflect information which has yet been incorporated into stock prices. Chakravarty et al. (2004) use Hasbrouck's (1995) "information share" approach to try to understand the level of price discovery between stock and options markets. They find that certain proportion of information revealed first in the options markets and the markets tend to be more informative when options trading volume is high and stock volume is low. Johnson and So (2012) propose that options trading can be associated with information transmission from agents with negative news, as a means to bypass high short-sale cost or any short-sale restriction, this would lead to a negative correlation between option order flow and future stock return. More recently, however, researchers have focused on refinements to Black's (1975) embedded leverage hypothesis to study informed trading clustering in options markets, to explain why options trading has predictive content for future stock returns (see e.g. Augustin et al., 2016; Kacperczyk and Pagnotta, 2016; and Ge et al., 2016).In this study, we extend the literature by showing how regulated position limits affect the relationships between options trading activity and underlying asset return as well as underlying asset volatility.

Position limits are pre-determined levels of ownership that are established by exchanges or regulators to limit the number of shares or derivative contracts that a trader, or any affiliated group of traders and investors, may hold. They have been used as a means to preclude any entity from exerting undue control over a particular market. However, whether they are effective in terms of their initial purpose, and whether they adversely impede the price discovery process for assets, are matters of debate (see e.g., Kyle, 1984; Gastineau and Jarrow, 1991; Jarrow, 1992 & 1994; Sanders and Irwin, 2015). Empirical studies on the effects of position limits have been hampered by the fact that position limits have been in place continuously, from the outset of trading for most derivative contracts. Thus, an experiment conducted to assess the effects of positions limits using a standard "treatment" procedure such as a Difference-in-Difference test, is not feasible.

SPDR S&P 500 ETF Trust (SPY hereafter) is an exchange-traded fund which is traded on the NYSE Arca and tracks the performance of the S&P 500 index. The Chicago Board Options Exchange (CBOE hereafter) began trading SPY options on January 10, 2005, on the CBOE Hybrid Trading System. These options were established with an initial position limit of 75,000 contracts. Over time, the position limit barrier was reset on several occasions. By September 26, 2012, the SPY options limit increased to 900,000 contracts. On September 14, 2012, CBOE proposed to amend its rule to completely eliminate position and exercise limits for physically settled options on the SPY pursuant to a pilot program being effective starting September 27, 2012[8]. After a number of extensions, this SPY pilot program was officially terminated by CBOE on July 12, 2018. Upon termination, a revised position limit for SPY options was set at 1,800,000 contracts. The SPY pilot program provides a unique opportunity to test the impact of position limits on the underlying assets. Similar to most exchange traded options, SPY based options were initially established with firm position limits in place. However, unlike other options contracts, unfettered trading was permitted for an extended period of time. Given this unique experience, we are able to compare the distinct effects on the informativeness of options trading on stock's performance under two position limit scenarios.

Focusing on the SPY which tracks the performance of S&P 500 index, we argue that our findings in this article can reconcile the short-sale constraint cost hypothesis versus the embedded leverage hypothesis. Tracking S&P 500 index, the SPY ETF equity in the stock market possesses ample liquidity. Thus, it would be costly to trade on negative information in the equity market and, at the same time, the option market certainly offers a safer shelter for informed agents in terms of leverage. Furthermore, we find that SPY call and put options volumes that cannot be predicted by historical volumes (i.e., unexpected trading volume) contain stock information that help alleviate the next-day unexpected return, contributing to the SPY pricing efficiency. During the SPY pilot program period (no position limit), the negative relationship between unexpected options volumes and unexpected returns is less strong, implying that the position limit rule plays a role of regulating investors' trading in support of the financial market. In addition, we do observe that unexpected options volumes enhance the return volatility not predicted by its lagged values, but this increase

[8] See Securities Exchange Act Release No. 67937 (September 27, 2012) 77 FR 60489 (October 3, 2012) (SR-CBOE-2012-091).

is slightly weakened during the pilot period, raising a concern that position limits increase market uncertainties. This dilemma coincides with CBOE's reaction which re-establishes the position limit for SPY but largely raises its level.

The essay contributes to the literature in two ways. First, we add to the studies of position limit by intuitively comparing the trading of derivative contracts in pre- and post-limit periods, which has yet been considered before. In addition, we provide unique evidence regarding the effects of derivative trading on the underlying asset and its pricing efficiency as they may be mediated by position limits.

Chapter 2 to 4 correspond to these three essays, and we conclude in Chapter 5.

Chapter 2: Corporate Governance and Default Risk in Financial Firms over the Post-financial Crisis Period: International Evidence

2.1 Literature Review

Due to information asymmetry and conflicts of interest associated with the separation of ownership from control, corporate managers (agents) may not act in the best interests of shareholders (principals) but take actions that benefit themselves, according to Jensen and Meckling (1976). Corporate governance mechanisms are designed to monitor managers and reduce such agency costs. Good governance practices can benefit bondholders in addition to shareholders, who are important stakeholders of a firm's assets. It is a shared benefit argument. Bhojraj and Sengupta (2003) note that governance mechanisms can reduce firms' default risk by mitigating agency costs, monitoring managerial performance, and reducing information asymmetry between a firm and its capital providers. However, a firm's risk-taking behavior can also be influenced by conflicts of interest between shareholders and bondholders (see, e.g., Myers, 1977; Jensen and Meckling, 1976; Demsetz, Saidenberg, and Strahan, 1997; Pathan, 2009; Liu and Jiraporn, 2010). This is known as *agency cost of debt*. Our study focuses on default risk and governance for financial institutions. In assessing the effects of governance mechanisms on risk, two major features differentiate the governance of financial firms from that of nonfinancial firms, as noted by Mehran, Morrison, and Shapiro (2011). Firstly, financial firms have many more stakeholders than nonfinancial firms. Secondly, the nature of the business of financial firms is "opaque and complex" and can change very quickly (see also Morgan, 2002). Several studies have examined the impacts of governance mechanisms on bank performance and on risk-taking (e.g., Saunders, Strock, and Travlos, 1990; Gorton and Rosen, 1992; Anderson and Fraser, 2000; Caprio, Laeven, and Levine, 2007; Laeven and Levine, 2009; Pathan, 2009; Fahlenbrach and Stulz, 2011;

Beltratti and Stulz, 2012). In the following review, we describe the relationship between corporate governance and firms' default risk relative to four important aspects of corporate governance: the firm's ownership structure, especially stock ownership by institutional investors and insiders; board size; board independence; and CEO power.

Institutional investors can play an important monitoring role in reducing managerial opportunistic behavior and agency costs, to the benefit of both stockholders and bondholders. Gains to bondholders would in turn be reflected in lower default risk and lower CDS spreads. As an important shareholder group, institutional investors may also be in a better position than individual investors to lobby government regulators in support of firms in which they have significant interests. Bhojraj and Sengupta (2003) find that firms with higher institutional holdings experience lower bond yields and higher ratings on their new bond issues during the period 1991 to 1996. Ashbaugh-Skaife, Collins, and LaFond (2006) find no significant impact of institutional ownership on firms' credit ratings by using cross-sectional data for the 2002 fiscal year. Erkens, Hung, and Matos (2012) find that institutional holdings are positively related to firms' risk taking during the period 2004 to 2006, just prior to the 2007–08 crisis period. Aebi, Sabato, and Schmid (2012) find that institutions do not provide effective monitoring with respect to the risks taken in the banks during the crisis period. These two latter papers imply that firms with higher institutional ownership were willing to take more risk right before the crisis (as argued by agency cost of debt) or were unable to control the risks effectively during the crisis period, resulting in higher risk during the crisis period. During the post-crisis period, financial institutions that have invested in firms that survived the crisis may be more cautious in controlling risk and may focus on helping firms to recover from possible loss during the crisis period and boost stock performance; financial institutions are unlikely to apply pressure on firms to engage in excessive risk-taking at this stage.

Thus, we hypothesize that institutional ownership negatively relates to firms' default risk during the post-crisis period, implying that effective monitoring by institutions reduces a firm's default risk:

H1: *Institutional ownership is negatively related to a firm's default risk.*

As another important group in a firm's ownership structure, its insiders, such as managers, play an important role in determining a firm's risk-taking. With the increase in insiders' stock holding, insiders' interests are more aligned with those of shareholders and therefore induce more risk-taking to increase the payoff to shareholders at the expense of bondholders—that is, increase agency cost of debt. Higher insider ownership may also give insiders more power, which increases the probability of managerial moral hazard problem. Anderson and Fraser (2000) find different results for the relationship between managerial stock holding and banks' risk-taking during different sample periods. Specifically, managerial holdings positively affect a firm's total risk and its specific risk in the late 1980s, when the banking industry was less regulated, and the entire industry was in a state of financial stress. However, following legislation of The Financial Institutions Reform, Recovery, and Enforcement Act of 1989 (FIRREA) and The Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA), a move designed to restrict risk-taking, managerial holdings were negatively related to the risk of those banks during the period 1992 to 1994. Saunders, Strock, and Travlos (1990) show that the managers of banks with high stock holdings prefer high-risk projects, as their interests are more aligned with those of shareholders. This relation is especially pronounced during the 1979-to-1982 period of relative deregulation. In addition, Gorton and Rosen (1992) point out that increased insider holdings tend to encourage managers to raise more risky loans than relatively safe loans in the 1980s, implying a higher default risk. Based on previous theoretical and empirical evidence, we hypothesize that insider ownership has a positive relationship with firms' default risk.

H2: *Insider ownership has a positive association with a firm's default risk.*

Independent boards are in a better position to provide independent monitoring and oversight role of management actions in order to reduce managers' moral hazard problem than dependent boards. From this perspective, the credit risk level would be lower with a more independent board. We use the fraction of outside directors on a board to measure board independence. Switzer and Wang (2013a) use CDS spreads as a risk measurement to show that board independence is significantly negatively related to the default risk of US commercial banks. Board independence can also be measured indirectly by CEO duality. Since the raison d'être of a corporate board is to oversee management on behalf of shareholders, it is debatable whether a CEO should sit on the board, being supervised and serving as an effective monitor. Imhoff (2003) shows that CEOs can affect the constituency of corporate boards. Ashbaugh-Skaife, Collins, and LaFond (2006) demonstrate that CEO power is negatively related to firms' credit ratings, implying an increased risk level. However, Pathan (2009) finds that CEO power, measured by CEO duality, negatively relates to the risk of a bank, implying that a CEO prefers lower risk when s/he is board chair, in order to protect the bank's undiversified assets and his/her fixed salary. A number of recent studies show no significant effects of CEO power on a firm's risk (see, e.g., Liu, Uchida, and Yang, 2012; Aebi, Sabato, and Schmid, 2012). These recent findings lead to the third hypothesis:

H3: *Board independence is negatively associated with a firm's default risk, but the influence of CEO power on a firm's default risk is not clear.*

A second factor perceived to affect the board's ability to function effectively is the size of the board. A board should provide two important functions: monitoring and oversight of corporate insiders' actions on behalf of shareholders and providing resources to the firm by using directors' human capital and relational capital, according to resource dependency theory (Pfeffer and Salancik, 1978). From this perspective, a large board is preferable. A relatively large board may be more difficult for insiders to control, allowing for better monitoring and oversight of insider behavior. From this perspective, a large board is beneficial to bondholders in reducing risk. On the other hand, Lipton and Lorsch (1992) and Jensen (1993) argue that larger boards may be less effective than smaller ones because of coordination problems and director free riding. Yermack (1996) and Eisenberg, Sundgren, and Wells (1998) provide evidence in support of this view. In sum, there is no conclusive evidence on the relationship between board size and default risk. We argue that a larger board may benefit firms more than a smaller one during a crisis period, because, in an emergency, directors' human and relational capital have high value to control and reduce firms' default risk, as survival is a major concern during the crisis. However, during the post-crisis period, a small, efficient board is preferable, to reduce default risk. This leads to our next hypothesis.

H4: *Board size is positively associated with a firm's default risk.*

Official government accounts of the crisis also connect the excessive risk exhibited in the financial sector during the crisis to regulation failures. Policymakers have reacted with new regulations that cover consumer protection, executive pay, risk measurement, and more stringent capital requirements for financial institutions. For example, with regard to more stringent capital requirements, Basel III seeks to replace VaR with a measure of expected shortfall, which is defined as the average of all losses that are greater than or equal to VaR and calls for higher T1 capital cushions. Higher T1 should enable firms to better withstand shocks and should be associated with lower fundamental default risk and lower CDS spreads. This suggests the following hypothesis:

H5: *Tier 1 capital ratios lower CDS spreads and lowers fundamental default risk.*

One of the important crisis management tools under the Federal Reserve emergency program were loans targeting both US and several international financial institutions, over the period 2007 to 2009. The data reflect lending from the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility, the Commercial Paper Funding Facility, the Primary Dealer Credit Facility, the Term Auction Facility, the Term Securities Lending Facility, the discount window, and single-tranche open market operations, or ST OMO. The data, which were not released to Congress but were obtained by Bloomberg through the Freedom of Information Act, reflect what has been deemed one of history's largest financial bailouts. We have matched the daily transactions contained in the Bloomberg database with the foreign institutions in the sample. Our expectation was that the emergency loans would enhance the liquidity of these institutions, which would in turn lower their CDS spreads, the market measure of risk. On the other hand, one could argue that firms which obtained such loans might be induced to take on more risk, recognizing that the Fed could in the future again serve as a lender of last resort. This is analogous to the argument against deposit insurance to prevent excessive risk-taking or moral hazard. To the extent that such excessive risk-taking is observed, firm fundamental default risk should be positively associated with Fed emergency loans.[9]

H6: *Fed emergency loans lower CDS, but with moral hazard, fundamental default risk will*

[9]http://www.bloomberg.com/news/articles/2011-12-23/fed-s-once-secret-data-compiled-by-bloomberg-released-to-public.

increase for recipient firms.

2.2 Data and Sample Construction

2.2.1 Sample Construction

Since this research focuses on the post-crisis period, we choose the sample firms from the period 2010 to 2012. Except for CDS spreads, all of the data are obtained from the Bloomberg database. Years 2007 and 2008 have been regarded as a period of subprime mortgage crisis (Ryan, 2008; Erkens, Hung, and Matos, 2012). However, to clarify the boundary of the financial crisis without overlapping with the post-financial crisis, we still select year 2010 instead of 2009, leaving a one-year gap between the two periods to reduce the possibility of confounding effects.

The sample comprises 117 financial firms located outside North America based on the following selection criteria. First, we obtain all non-North American financial firms from Bloomberg. Then we add the firms' CDS spread data to the data set without deleting any observations—that is, firms with missing CDS data are not deleted but are coded "n.a." Finally, we delete firms from the Bloomberg database that have missing data on corporate governance and fundamentals. The final sample consists of 117 financial firms with complete CDS spreads, governance, and fundamental variables and 719 firms using the Merton default probability measures. Panel A of Table 2.1 shows the details of our sample-selection procedure.[10] Panel B of Table 2.1 presents the distribution of the sample firms based on their legal type, using both CDS spread and default probability as measures of firm default risk. The four financial sectors are Banking, Financial Services, Insurance, and Real Estate. Specifically, in the CDS sample, banks account for more than half of the sample, with 67 firms (57.26%), while the other three sectors

[10]In the selection process, we do not impose other restrictions (e.g., control for firms' size) on the sample.

take up nearly the same percentage of firms in the sample: Financial Services, 14.53%; Insurance, 12.82%; Real Estate, 15.38%. Table 2.2 shows the detailed distribution of our CDS sample firms and Bloomberg default probability sample firms by country. Not surprisingly, for both the CDS sample and the Default probability sample, European and Asian firms form the largest percentage.

We notice that the CDS sample is smaller than the Bloomberg default probability sample, so we perform two tests before proceeding with the main regressions. The study first employs a Probit regression to test the propensity of sample firms launching the CDS market, by incorporating other financial firms without traded CDS. The results reported in Panel C of Table 2.1 show that firms with lower insider holdings and profit, stronger board independence, larger board size, more assets, and higher leverage ratios are more likely to enter the CDS market. In addition, if the CEO of a company is also board chair, the company is more likely to have traded CDS. Furthermore, in order to test whether the sample has potential selection bias because the CDS sample is constructed purely of financial firms with traded CDS from Markit, we perform Heckman selection tests. As shown in Panel D of Table 2.1,[11] the estimate of ρ (_Rho), the correlation between unobserved determinants of propensity to enter the CDS market and unobserved determinants of the CDS spread, is insignificant, indicating that selection bias is not a concern in the study. Thus, we continue the regressions using the initial sample.

{Please Insert Tables 2.1 and 2.2 about here}

[11]Due to space restrictions, we do not include the complete Heckman regression result. However, it is available on request.

2.2.2 Description of Variables

a. Default Risk Measurements

Previous research has used several variables to measure firms' default risk—for example, z-score (Roy, 1952; Laeven and Levine, 2009), the standard deviation of stock returns (Demsetz, Saidenberg, and Strahan, 1997), credit ratings (Ashbaugh-Skaife, Collins, and LaFond, 2006; Liu and Jiraporn, 2010), cumulative default probabilities (Switzer and Wang, 2013a), and five-year CDS spread (Carlson and Lazrak, 2010; Switzer and Wang, 2013b). In this study, we use two measurements of firms' default risk. The first is the average five-year CDS spread. A CDS is a contract that provides insurance against the default of a particular company and is often used to measure companies' default risk. The higher the CDS spread, the higher the firm's default risk. There are two parties to the contract: the buyer of credit protection makes periodic payments to the seller of the credit protection until either the contract matures or there is a default event in the underlying company. In exchange for the periodic payments made by the buyer, the seller agrees to pay the buyer the difference between the face value and the market value of the reference obligation if a credit event occurs. There is a payment to compensate for default losses only in the case of a default event. The premium that determines the annuity payments is the rate that equates the expected streams of cash flow made by the buyer and the seller. The CDS premium therefore contains information on the default probability associated with a reference entity and reflects the perception of risk level of the reference entity by the market participants. Furthermore, CDS is less sensitive, although not completely so, to liquidity effects, since other securities may be in fixed supply, while the supply of CDS can be arbitrarily large. Therefore, CDS provides a good measure of default risk. The CDS information was obtained from the Markit database, which has been used in prior studies.

Another measure of firms' default risk is the five-year default probability provided by the Bloomberg database. According to Bloomberg, the default likelihood model used to calculate the five-year default probability is based on the Merton-type distance-to-default (DD) model (Merton, 1974), along with additional economically and statistically relevant factors. The smaller the DD, the closer the firm is to default—that is, the higher the default risk. The DD function is shown below (Bharath and Shumway, 2008):

$$DD = \frac{\ln\left(\frac{V_0}{D}\right) + \left(\mu - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

where V_0 is the total assets value of the firm at time 0; σ is the asset volatility; μ is the asset drift; D is the debt liabilities of the firm; T is the time to maturity; and DD is the distance to default. The key insight of the Merton framework is that the equity of the firm can be viewed as a call option on the total assets of the firm where the strike price is equal to its liabilities. However, the limitation in the original Merton framework is that it assumes that a firm can default only upon the maturity of firms' liabilities, which are assumed to be zero coupon bonds. In reality, the defaults can occur at any time. The Bloomberg default likelihood model overcomes this limitation by treating equity as a barrier call option to calculate the DD, explicitly incorporating the possibility that a firm could default before the maturity of the debt. Bloomberg uses the improved DD as one of the key parameters in its model, plus a mapping between DD and actual default rates, to build a nonlinear function of DD over default probability, which is expressed as follows: Default probability = *f (distance-to-default)*, where *f* is a nonlinear function. Bharath and Shumway (2008) show that while DD is a significant predictor of default, it is not a sufficient statistic; they successfully construct a reduced-form model with better predictive properties from the Merton-type model. In light of Bharath and Shumway's results, Bloomberg improves its default probability model by including additional information regarding different sectors in different industries. In the study, we use the Bloomberg estimated five-year default probability as the second measure of firms' default risk, to compare with the CDS spread, considering the potential endogenous problem between institutional ownership and CDS spread. CDS spread and default probability are transformed to the nature logarithm—that is, $Ln[Y / (1\text{-}Y)]$, where Y represents CDS spread or Bloomberg default probability.

b. Corporate Governance and Firm Characteristics

The article uses institutional stock holdings (*insti_holding*) as representative of institutional ownership, defined as the percentage of a firm's total outstanding shares held by its institutions. Insider ownership (*insid_holding*) is defined as the percentage of outstanding shares held by corporate insiders. For measures of boards and CEO power, we use board independence (*board_indep*) as one measure of board characteristics, which is the number of independent outside directors divided by board size, where board size (*board_size*) is the total number of directors on the company's board. Board independence is one of the most extensively studied board characteristics (Weisbach, 1988). Our second measure of board characteristics is CEO duality (*ceo_duality*), a dummy variable indicating whether a company's CEO is also chair of the board. We use it to measure the CEO's power in the company.

In addition, based on the literature, we control for firm size (*total_assets*), return on assets (*roa*), leverage (*ltd*), and price-to-book ratio (*pb*) (e.g., Bhojraj and Sengupta, 2003; Ashbaugh-Skaife, Collins, and LaFond, 2006; Aebi, Sabato, and Schmid, 2012; Erkens, Hung, and Matos, 2012). All the data are annual frequency. Detailed definitions of variables and data sources are shown in Appendix A.

Tables 2.3 and 2.4 present the Pearson correlation matrix of the variables, as well as the mean of the key variables.

{Please Insert Tables 2.3 and 2.4 about here}

As shown in Table 2.3, CDS spreads have high positive correlations with default probabilities, as expected. Emergency loans from the Fed and T1 capital are also positively correlated, indicating that aid from the Fed was not necessarily linked to bank capitalization. Emergency loans are positively correlated with institutional ownership, suggesting that institutions may have aided in the lobbying process for regulatory support for firms in which they were heavily invested. Board independence and CEO duality are highly negatively correlated, indicating that independent boards tend to avoid powerful CEOs. Most of the pairwise correlations between the explanatory variables are low, indicating that multicollinearity is not a serious problem in the sample.

In Table 2.4, we notice that Greece and Ireland have a considerably higher average five-year CDS spread than other countries and/or regions. Board size is on average quite high in Italy, Portugal, and Austria, and low in Brazil, Australia, and Finland. Financial institutions in Brazil, China, Japan, and Turkey have low board independence scores. CEO duality is a more frequent phenomenon in France, Hong Kong, India, Japan, and Spain. Table 2.4 also shows that substantial Fed emergency funding was provided to financial institutions in Belgium, France, Switzerland, the United Kingdom, and Italy. T1 capital ratios are quite high in Switzerland and below the 10% target of Basel III for financial institutions in Australia, Greece, Italy, China, Israel, and Chile.

2.3 Methodology and Empirical Results

2.3.1 Endogeneity Tests

The study assumes in our equation that institutional ownership can affect CDS spread by playing a monitoring role in the company. However, institutional holdings might be a potential endogenous variable with respect to CDS spread in that institutional investors might choose low-risk firms to form their portfolios. Therefore, CDS spread may affect the investment behavior of institutions. We introduce two instrumental variables to address the potential endogeneity issue. The first instrument is membership in the MSCI-country index, which is a dummy variable equal to one if the firm is a member in the firm list of MSCI-country index of the country and zero otherwise. The use of this instrument is inspired by Aggarwal et al. (2011), who similarly use membership in the MSCI-world index as an instrumental variable for total and foreign institutional ownership. Ferreira and Matos (2008) find that MSCI membership helps a firm attract foreign capital. Thus, MSCI-country index membership is correlated with the ownership measurement but not directly correlated with an individual firm's default risk. The second instrument is one-year lag of a firm's country-adjusted return on assets—that is, return on assets minus MSCI-country index return, while MSCI-country index return is used as a market benchmark. Employment of the second instrumental variable is inspired by Cornett et al. (2007); it is the lagged market-adjusted return of a firm (i.e., annual firm return minus the return on the S&P 500 index). A positive market-adjusted return might encourage institutions to increase the investment in the company during the following year.

We proceed with endogeneity tests by running the test of over-identifying constraints using Generalized Method of Moments (GMM) estimation, as shown in Panel A of Appendix B. Considering the potential influence of the extremely high default risk of Japanese firms, we have two separate results for the same test, with and without the Japanese firms included in our sample. According to the over-identifying tests, regardless of whether the possible outlier firms are included, the J-statistics are insignificant, with a probability of 0.4758 and 0.2174, respectively. Thus, we cannot reject the null hypothesis of the over-identifying constraints of the two instrumental variables, which supports the validity of the instruments. We then perform the GMM endogeneity test to see whether those instrumental variables can help address the potential endogenous problem—in other words, to see whether there is any endogeneity problem between institutional holdings and CDS spread in our research. The results of the endogeneity tests are shown in Panel B of Table 2.4. The results of GMM estimation indicate that the differences in J-statistics are completely insignificant, whether or not we include the Japanese firms with high CDS.[12] That is to say, the endogeneity test cannot reject the null hypothesis of no endogeneity. In summary, using these two instruments, the GMM over-identifying test and the endogeneity tests prove that endogeneity is not an issue and that the least squares method is a valid approach for this paper.

2.3.2 Full Sample Regressions

We first run regressions with the full sample, with institutional variables and a set of control variables as mentioned previously, also controlling for industry and country fixed effects. Table 2.5 presents the regression results of using both the average five-year CDS spread (equations 1, 2, 3, and 4) and five-year default probability estimated by Bloomberg (equations 5, 6, 7, and 8) as measures of a firm's default risk.

{Please Insert Table 2.5 about here}

[7] The probabilities of difference are 0.4961 when the Japanese firms are included and 0.4737 when they are not.

Models 1 and 5 show the regression results with only control variables included. As expected, firms with higher MSCI-country index return, higher return on asset, lower leverage, and higher price-to-book ratio are associated with lower default risk, as measured by both CDS spread and Bloomberg default probability. When we employ Bloomberg default probability as the dependent variable, models 5 to 7 suggest that almost all the corporate governance variables are significant at the 1% level, with expected signs. Specifically, higher institutional holdings, lower insider holdings, and higher board independence can lead to lower default probability. For the economic significance of key governance variables, such as institutional holing in Model 2, one percentage point increase (decrease) of institutional holdings would lead to 0.3392 percentage point decrease (increase) of *acds_trans* which is equivalent to 0.5840 percentage point decrease (increase) in CDS spread. Furthermore, if a firm has a large board and a CEO who is also chair of the board, its default risk is higher. These findings are consistent with those of Crutchley et al. (1999) and Bhojraj and Sengupta (2003). The results of insider holding are consistent with Jensen and Meckling's (1976) finding that corporate insiders may find it personally beneficial to enhance a firm's risk-taking, implying a positive relationship between insider ownership and default probability. In addition, the results for board independence and CEO power are consistent with the findings of Pathan (2009) and Ashbaugh-Skaife, Collins, and LaFond (2006). Models 1 through 3 in Table 2.5 show the results with CDS spreads as the dependent variable. The significant results for board size and institutional holdings remain when we use CDS spread as the dependent variable. While the significant impacts of insider holdings, CEO duality, and board size on default risk are found mostly with firms having available Bloomberg default probability, and while the results for CDS-based regression are insignificant, we cannot claim that there is no relationship between corporate governance and firms' default risk, because the bias may be due to the small size of our sample of CDS firms. In addition, the sample includes some "special" firms, such as those from Greece and Ireland and the Japanese firms with extremely high CDS during the sample period, which could also affect the results generated using the CDS sample.[13]

The regulatory variables do change some of the inferences. Better capitalized banks, based on their T1 capital, are shown to have lower fundamental default risk—that is, Bloomberg default probability—although the CDS benefits are less apparent (the coefficient of CDS is negative but not significant). This latter result may be due to the smaller sample size, or due to the fact that CDS holders do not view counterparty risk as troublesome, as the risk of default rises to a higher level.

Furthermore, Table 2.5 indicates that Fed emergency loans encouraged those foreign banks with access to Fed funding to take on more fundamental risk, as shown in model 8, consistent with the moral hazard explanation. On the other hand, the price of insurance against default risk, as measured by CDS spread, appears to have fallen—perhaps due to the pressures of institutional owners (since the coefficient of institutional ownership is no longer significant) combined with the expectation that the Fed stands ready to provide implicit default insurance to not just domestic financial institutions but to their foreign counterparts as well.

2.3.3 Continental Comparison Results

Compared with its counterparts in North America and Europe, the CDS market in Asia is relatively small and illiquid, perhaps due to the comparatively small bond markets, illiquid bond trading, and political climate (e.g., Shim and Zhu, 2014). In Table 2.6, we compare a subsample

[13] We have also excluded these special cases as outliers, and observe similar results, which are available on request.

with only European firms and a subsample with only Asian firms in the regressions to test the different impacts of corporate governance on default risk.

{Please Insert Table 2.6 about here}

Panels A and B in Table 2.6 show the results for European firms and Asian firms, respectively. Governance variables have a higher influence on default risk for Asian firms compared with European firms. For European firms, board size and institutional holdings are significantly related to both CDS spread and Bloomberg default probabilities. In terms of economic significance, for example, as shown in Panel A, Model 2, one percentage point increase (decrease) of institutional holdings would lead to 0.6488 percentage point decrease (increase) of *acds_trans*, equivalent to a 0.6567 percentage point decrease (increase) in CDS spread. For Asian firms, as shown in Panel B, CEO duality is still significant and positive when both risk measurements are used. Institutional holdings, insider holdings, and board independency still show significance in the regressions of Bloomberg default probability, with signs consistent with our hypothesis, while the results are not robust when CDS spreads are used as the dependent variable.

Do cultural factors play a role in explaining these differences? Fahlenbrach, Prilmeir, and Stultz (2012) propose that that risk culture can explain differential performance of US banks. This conclusion is based on the basic observation that banks that performed poorly in the US during the financial crisis of 1998 also performed poorly in the recent crisis; the firm's financing and investment structures are used as proxies for risk culture. Our study provides an alternative way of addressing cultural issues that might have a country or regional dimension. The results include country fixed effects,[14] which might capture some cultural differences across countries. However, country fixed effects might capture other factors, such as cross-country industry differences and differential macro-economic exposures. In a recent paper, Eun, Wang, and Xiao (2015) look at two dimensions of culture to explain differences in market riskiness across countries: the Gelfand et al. (2011) cultural tightness measure and the Hofstede (2001) individualism measure. They find that greater cultural tightness is associated with lower market and firm-specific variations in returns. On the other hand, countries with more individualistic cultures have higher firm-specific variations of returns. As a crude test, we have computed these measures for the sample, and find that the cultural tightness measures are higher for the countries represented by the Asian firms in the sample than for those represented by the European firms (Gelfand et al., 2011, score of 7.72 vs. 6.31). Furthermore, countries represented by the Asian firms are considerably less individualistic than those represented by the European firms (Hofstede, 2001, score of 36.25 vs. 61.25). The greater importance of governance mechanisms in Asian companies may reflect cultural proclivities to control not just stock return risk but default risk as well. More in-depth exploration of these issues is a matter for future research.

[14] Results excluding country-fixed effects are quantitatively and qualitatively similar.

Chapter 3: Cross-Market Information Transmission from Options Trading to Equity Markets

3.1 Data and Description of Variables

Our sample is based on common stock return, volatility, as well as underlying equity options over the period January 2012 to December 2016. Daily stock market data are obtained from Center for Research in Security Prices (CRSP). The options data are obtained from OptionMetrics. To have an accurate match of observations between CRSP and OptionMetrics, We rely on the Linking Suite provided by Wharton Research Data Services (WRDS) which links each security ID (SECID) from OptionMetrics to corresponding security permanent number (PERMNO) from CRSP, with a score (from 1 to 6) assigned to each link. Since there exists a situation where one PERMNO maps to multiple SECID, the selection criteria are defined as that the start date of a link should be earlier than January 1, 2012 and the end date should be later than December 31, 2016. In addition, we adopt the WRDS procedure that chooses the link with the lowest score. Thus, all mappings in the sample have the score equal to one and the mapping becomes unique. To further ensure the accuracy of this mapping, we delete all firms whose SIC codes in CRSP differ from those in OptionMetrics.

The S&P 500 volatility index (VIX) is obtained from Chicago Board Options Exchange (CBOE). General investor sentiment is proxied by Financial and Economic Attitudes Revealed by Search (FEARS) index. Da, Engelberg, and Gao (2015) initially construct this index for windows between 2004 and 2011. The index of the new period (2012-2016) is calculated by the authors. Merging all data together generates the full sample consisting of roughly 1800 firms and 1.7 million observations.

To measure a stock's volatility, we employ three alternative proxies. First, Garman-Klass (G&K) volatility (Garman and Klass (1980)). After horse-racing range-based estimators, Molnár (2012) shows that Garman-Klass volatility is the most efficient one. It is almost eight times more efficient than the close-to-close based volatility. Following Daigler and Wiley (1999), we use the reduced-form G&K estimator, which removes the open/high/low/close cross-terms but still have a high correlation (up to 95%) with the original one. Second, Parkinson (PARK) volatility (Parkinson (1980)). Compared to the regular volatility using close-to-close price, PARK estimator incorporates the information happening during the day and uses intraday high and low prices of the day to estimate the volatility, which is more precise if there is a big price movement in a day. Third, Rogers-Satchell (R&S) volatility (Rogers and Satchell (1991)). R&S estimator incorporates a drift term (i.e., mean return not equal to zero). Thus, it provides a better volatility estimate when the underlying is trending.

To account for the potential biases associated with infrequent trading of options contracts, we also generate a subsample of stocks with heavily traded options for separate analyses. This subsample consists of the top 100 stocks each year based their average total options transaction volumes, thereby results in a separate sample of approximately 120 thousand observations. The industry distributions for the full sample and the subsample are provided in Figures 3.1 and 3.2 respectively. For both sample groups, manufacturing firms are dominant, represent about 40% of the observations. Retail trade represents a larger share of the sample of heavily traded option firms (14% vs. about 7%).

{Please insert Figures 3.1 and 3.2 about here}

Table 3.1 provides descriptive statistics for the full sample (Panel A) and the subsample (Panel B). As indicated therein, firms with greater options trading volume also have larger market capitalization. They are less volatile, measured by three volatility proxies. Call/put options volume, call/put options open interest, firm market size, and all volatility-measured variables are transformed into natural log values before the multivariate regressions. The changes in call/put options open interest (ΔCOOI / ΔPOOI) are calculated as the difference between day *t* and day *t-1*. Note that the average daily trading volume is markedly higher for the most heavily traded 100 stocks (approximately 9000 contracts per day vs. 40 contracts per day).

{Please insert Tables 3.1 & 3.2 about here}

Table 3.2 shows the correlation matrix of the variables for both full and sub-samples. As shown, the three alternative volatilities are highly correlated with each other (coefficients ranging from 86.56% to 96.99%), and negatively correlated with firm size. Call options trading volumes have a high correlation with put options trading volumes of 84.21% (78.46) in the full sample (subsample). Call and put options trading volumes are also highly correlated with firm size.

3.2 Empirical Results

3.2.1 Full Sample

The basic regression models for the return and volatility measures are as follows. Equation (1) uses the stock's daily return as the dependent variable. Equation (2) uses the volatility measures as dependent variables. These analyses are performed with and without year and firm fixed effects. Standard errors of all models are clustered by firm.

$$Stock's\ return = \alpha_0 * Call\ (or\ Put)\ Option\ Volume + \alpha_1 * \Delta COOI + \alpha_2 * \Delta POOI + \alpha_3 * FEARS\ Index + Controls + Firm\ \&\ Year\ FE + \epsilon \quad (1)$$

$$Stock's\ Volatility = \beta_0 * Call\ (or\ Put)\ Option\ Volume + \beta_1 * \Delta COOI + \beta_2 * \Delta POOI + \beta_3 \delta * FEARS\ Index + Controls + Firm\ \&\ Year\ FE + \epsilon \quad (2)$$

where, $\Delta COOI$ ($\Delta POOI$) represents the daily changes of call (put) options open interest; the control variables in (1) include one-day lag of stock return, S&P 500 index return, S&P 500 volatility index, and the firm size; the control variables in (2) consist of one-day lag of stock volatility, S&P 500 volatility index, and the firm size. Coefficient estimates for equations (1) and (2) are provided in Tables 3.3 and 3.4 respectively.

{Please insert Table 3.3 about here}

As shown in Table 3.3, higher options trading does not necessarily lead to higher stock market returns, as suggested in Roll, Schwartz, and Subrahmanyam (2009). We do find that higher call options volume is significantly and positively related to the underlying stock's daily return. However, increased put options volume has a significantly negative association with stock returns. For the economic significance of these results, using Model 3 & 4 of Table 3.3 as examples, one percent increase in the call (put) option contracts is correlated with 0.0000111 increase (0.0000031 decrease) in the stock return. The average call (put) option volume from Table 3.1 is 36 (21) contracts. If an institutional investor trades 10000 call (put) option contracts that correlates with

27678% (47519%) increase in the number of contracts, the stock return could theoretically increase (decrease) by 0.00624 (0.00191). In addition, the daily changes of call options open interest ($\Delta COOI$) are positively related with stock return. Conversely, changes in put options open interest ($\Delta POOI$), are negatively associated with stock return. Consistent with Da, Engelberg and Gao (2015), the FEARS index has a negative impact on stock return. Market-level volatility (VIX) negatively affects stock's return but is not significant. Table 3.4 presents the results of the volatility regressions (Equation 2).

{Please insert Table 3.4 about here}

Estimates are provided for the three alternative measurements of volatility, as discussed above. Panel A shows the results for the G&K measure. Panel B presents the results using the Parkinson Measure. Panel C shows the estimates using the R&S volatility measure. As is evident, most of these measures provide qualitatively similar results. Increased call and put options volumes are volatility enhancing (significant at 1% level). Taking Model 3.3 & 3.4 using Garman-Klass volatility for examples, 10000 call (put) option contracts transaction is correlated with 0.0844% (0.0802%) increase in the stock volatility. Changes in call and put options open interest are generally insignificant for the three volatility measures, consistent with the "day trader" hypothesis of Bessembinder and Seguin (1993) for futures markets.

Consistent with Da et al. (2015), for the firms in the full sample, the FEARS index of market pessimism is positively associated with stock volatility and is highly significant (at the 1% level for all the models). Finally, as might be expected, firm size is negatively related to stock price volatility.

3.2.2 Subsample (Top 100 Firms)

How are the results affected if we focus on large firms to control for possible thin trading biases for options? The estimation results are shown in Tables 3.5 & 3.6 with firm and year fixed effects. Standard errors of all models are clustered by firm.

{Please insert Table 3.5 about here}

Similar to the findings in our full sample, the call options volume is significantly positively related to stock returns. Put options trading volume has a significantly negative relationship with stock return. Daily changes of call and put options open interest, however, are not significant although their coefficients have the consistent directions as those in the full-sample regressions. In addition, FEARS index is not significant at all among the four models, which indicates that market-level pessimism or noise traders do not have a separate and distinct impact on stock return that is over and above the signal transmitted by options trading.

{Please insert Table 3.6 about here}

Table 3.6 provides the corresponding regression estimates for the volatility equation (2). Call and put options volumes consistently show significant and positive correlations with three alternative volatilities, which are always at 1% significance level. Daily changes of call and put options open interest ($\Delta COOI$ and $\Delta POOI$) are not significantly related to the volatilities, again consistent with the "day trader" hypothesis. In contrast to the full sample, however, as with the stock return regressions in which FEARS effect is muted for stocks with the most heavily traded options, FEARS index holds a positive relation with the volatilities but much less significant than that in the full-sample regressions. Besides, the control variables still hold a strong correlation with all three volatilities.

The results of sub-sample estimations confirm our interpretation towards the full-sample estimations, which again implies the possibility that speculators camouflage themselves within intraday transactions and erase their traces at the close of trading day. They incline to use intraday trading to affect the stocks' prices and returns and also amplify the volatilities. On the contrary, the hedging activities, proxied by options open interests, do not cause fluctuation in the stock markets.

Chapter 4: The Impact of Position Limits on the Relationship between Option Trading and Stock Performance: Evidence from the SPY pilot program

4.1 Literature Review

4.1.1 Option Trading Volume and Stock Returns

The informational content of options trading activity on stock return has been studied extensively in the literature. (See e.g., Stephan and Whaley, 1990; Vijh, 1990; Chan et al., 1993; Easley et al., 1998; Pan and Poteshman, 2006; Ni et al., 2008; Roll et al., 2010; Johnson and So, 2012; Hu, 2014; Ge et al., 2016; Bernile et al., 2019; Zhou, 2022, etc.). Researchers have found both positive and negative correlations for options trading with future stock return.

Easley et al. (1998) develop a multimarket sequential trade model incorporating both options and stocks, and explicitly identify the options trades with "positive news" and those with "negative news". Theoretically, they determine the conditions under which informed traders choose to trade stocks, options, or a mixture of these two assets. In addition, their model predicts a pooling equilibrium in which buying a call or selling a put carries positive information about future stock prices, and in which selling a call or buying a put carries negative information. Empirically, they investigate the predictability of their model and find that, when aggregating options trades in terms of positive or negative news, the options volume responds to stock price changes with lags of between twenty and thirty minutes.

Pan and Poteshman (2006) construct options put-call ratios from buyer-initiated new open positions and argue that this ratio is a manifestation of informed trading in the options market, which positively correlates to stock's future price movements. Since the data used to construct the put-call ratio are not publicly observable, the predictability of put-call ratio can be interpreted as the stock prices adjusting slowly to the private component of information carried in the options trading.

Roll et al. (2010) is the first paper introducing the concept of relative trading activity in options and stock. They develop a simple empirical construct, the options/stock total trading volume ratio (O/S), to observe its reaction surrounding earnings announcements and the driving forces behind this volatile ratio. In general, the rising activity of options traders (i.e., an increasing O/S ratio) in the period culminating in an earnings announcement reveals that some of the traders are informed or at least they believe they are. Furthermore, the positive (negative) correlation found between pre-announcement O/S ratio and stock's cumulative abnormal returns (CARs) before (after) the announcement indicates that the relative options trading volumes affect stock prices. Johnson and So (2012) extend Roll et al. (2010) by examining the relation between O/S ratio and future stock return. They empirically document a negative relationship in which low O/S firms outperform high O/S firms, especially when the short-sale costs are high. Following the long-short strategy sorting on O/S ratio, a portfolio can achieve the weekly average risk-adjusted return of 0.34% (annually 19.3%).

Hu (2014) assumes the predictive power of options trading arises from market makers' delta hedging need which transfers the options order imbalance in the stock exposure to the stock order imbalance by trading on the underlying stocks. To understand this interaction between options market and stock market, the author decomposes the overall imbalance in stock transactions into the component induced by option transactions and the remaining induced by stock market transactions unrelated to options trading. The result indicates that the predictability is driven by the options-induced order imbalance, and it positively predicts the next-day stock returns controlling for microstructure variables including the past stock and options returns. This return predictability does not reverse direction in longer horizons, suggesting the hypothesis that option trading carries stock information.

Similar to Hu (2014) who attributes the predictability of options trading to market makers' delta hedging, Ni et al. (2021) suggest that re-hedging options positions (i.e., rebalancing delta hedging) by options market makers cause stock price movements and affect stock return volatility. To rebalance their negative gamma options positions, dynamic delta hedgers buy after stock price increases and sell after stock price decreases, which drives the stock price temporarily away from the level implied by fundamentals. In addition, Ni et al. (2021) also provide evidence of a significant negative relation between stock return volatility and the net gamma of the options positions of likely delta hedgers which is robust to options expiration week and the liquidity of underlying stocks. It's worth noting that the special net gamma constructed in this article reflects purely hedge rebalancing demand and contains no historical information.

Bernile et al. (2019) examine the predictability of the options volume distribution to future stock return using a volume-weighted average strike-spot price ratio (VWKS) to characterize the central location of the distribution of trading volume along the moneyness. As a result, they document that VWKS ratio embeds valuable fundamental information about the underlying stock and positively correlates with subsequent underlying returns. This relation becomes even stronger with the arrival of new value-relevant information.

In contrast to the aforementioned studies which document a positive relationship between options trading volume and future stock return, Johnson and So (2012) find the reverse: a negative relationship. To reconcile this inconsistency, Ge et al. (2016) disaggregate the options trades to different categories: synthetic long vs. synthetic short positions and open vs. close positions. They re-calculate the O/S ratio for these categories. They find that, while volume that opens synthetic long positions positively predicts returns, volume that opens synthetic short positions or unwinds bought call positions negatively predicts returns. The negative correlation observed in Johnson and So (2012) can be explained by volume clustering for synthetic shorts initiations or unwound calls. In addition, Ge et al. (2016) also find that opening trades contain more information than closing trades which is consistent with the results of Pan and Poteshman (2006) using data on buyer-initiated new open positions.

Zhou (2022) conducts a cross-sectional study linking nondirectional options trading volume with future stock returns and shows a significantly negative correlation between options trading volume and firms' future stock returns controlling for stock characteristics. This negative relation is robust to options classification (i.e., by call and put, moneyness, or maturity) and different scenarios (e.g., variable measures, market states, asset-pricing anomalies, etc.).

4.1.2 Options trading volume and stock volatility

The spillover from options trading volume to stock market volatility has received only limited attention, to the best of our knowledge. Ni et al. (2008) consider the effect of informed trading of individual equity options on future equity volatility. Traders with directional return information can choose either the stock or derivatives markets to execute their informed transactions. However, as Ni et al. (2008) note, traders with volatility information about the underlying assets, can only use nonlinear securities such as options. Indeed, they find that the daily non-market maker net demand for volatility constructed from open options volume significantly and positively predicts the future realized volatility of underlying stocks for at least one week into the future. When the options volume could have been part of straddle trade which is the leading strategy for trading on volatility, this predictability is stronger.

4.1.3 Position limits

One of the constraints to trading in options and other derivative products is the existence of position limits for traders. In a seminal article, Kyle (1984) demonstrates the potential benefits of position limits in restricting market manipulation in futures contracts with physical settlement. In contrast, Gastineau and Jarrow (1991) advocate the elimination of position limits in favor of a more comprehensive margin system to prevent market manipulation and improve market efficiency.

Actual empirical work on the effects of position limits in derivatives is scant. Dutt and Harris (2005) present a simple model to determine optimal position limit levels (i.e., prudent position limit) for cash-settled index derivative contracts. They suggest that existing position limits of futures and options contracts are not consistent with the levels suggested by their model. Using daily position data for a specific long-only index fund, Sanders and Irwin (2016) analyze the impact of changes in positions on market returns in thirteen agricultural futures markets but find no causal relationship, opposing the necessity of setting new position limits in those markets. Based on this result, they conclude that existing position limits of the exchanges are satisfactory. However, they do not look at changes in position limits per se.

Chang et al. (2013) study the effectiveness of position limits in foreign exchange futures markets by distinguishing the different roles in price discovery process between hedging transaction and speculative transaction. While hedging activities are less likely to be information motivated and delay the price discovery, speculative activities are found to improve the process. This finding on speculators is helpful for policy makers in designing position limit rules and it helps refute the arguments which simply attribute the market inefficiency and instability to speculators' trading behaviors, consistent with Gastineau and Jarrow (1991).

In sum, there is no clear theoretical consensus on the effects of position limits on derivative contracts and on the performance and efficiency of underlying markets. The empirical evidence is also limited and indirect. None of the extant studies looks at how the existence or non-existence of position limits affects the return and volatility of the underlying assets. This paper is the first that provides evidence on this score, based on options trading behavior in the period surrounding the suspension of trading limits for ETFs on the S&P 500 (SPY contracts) in the pilot program.

4.2 Data and Methodology

The entire SPY sample period spans from October 1, 2010 to December 31, 2020. The SPY pilot program was in effect from September 27, 2012 to July 12, 2018. The daily SPY stock data are obtained from Center for Research in Security Prices (CRSP). Daily options data are collected from OptionMetrics. The daily return of the SPY is calculated taking the log of daily closing price divided by its one-day lag. SPY volatility is defined as the squared daily return. The call and put options volumes of SPY are the logs of the contract volumes. S&P 500 Volatility Index (VIX) data are obtained from CBOE.

Bessembinder and Seguin (1992, 1993) link futures-trading activity (i.e., volume and open interest) with stock price and futures price volatility. Specifically, they use the univariate Box-Jenkins methods (e.g., ARIMA models) to assess whether volume-volatility relation differs for expected and unexpected (i.e., surprise) components of volume as well as open interest from derivatives markets. Given the autocorrelation characteristics of time-series data, Bessembinder and Seguin (1992, 1993) employ ARIMA process to decompose the futures volume into expected and unexpected components. Following this methodology, we divide the SPY call and put options trading volumes into expected and unexpected parts. In addition, we apply ARIMA process to SPY equity return and volatility to extract the shocks that cannot be predicted by the performance in previous days.

To start the analyses of the time-series data, we check the stationarity using augmented Dickey-Fuller tests for SPY return. Based on Mackinnon approximate p-values, we reject the null hypothesis of random walk across all investigated variables. To determine the optimal lag of SPY daily return, volatility, and call/put options trading volume, we rely on their autocorrelation and partial autocorrelation plots, Akaike's information criterion (AIC), as well as Schwarz's Bayesian information criterion (SBIC). For example, the above selection criteria suggest AR(9) process for SPY logarithmic return. Estimating the return with its 9 lagged values, the residuals from the AR(9) model are defined as the return shocks while the estimated values are the expected component. Similar ARIMA processes are conducted on SPY volatility, SPY call options volume, and SPY put options volume[15].

{Please insert Table 4.1 and about here}

Panel A of Table 4.1 describes the characteristics of some variables employed in the analyses. In total, we have 2581 observations from 2010 to 2020. Since the SPY equity partially reflects the market condition (i.e., it tracks the S&P 500 index performance) and is highly liquid, its return shock (volatility shock) fluctuates between -10.49% (-0.43%) and 6.66% (0.83%), with a median at 0.04% (-0.0027%). Both expected call options volume (ECV hereafter) and expected put options

[15] Besides the SPY equity return which follows AR(9) process, the SPY equity volatility follows AR(20) process, and the call (put) option trading volume follows AR(19) process. Estimating details are provided upon request.

volume (EPV hereafter) display a relatively stable pattern with logged values at between 12 and 15. Regarding options volume shock, the average of call options volume shock (CVS hereafter) is higher than that of put options volume shock (PVS hereafter). Correspondingly, the PVS contains more negative observations than CVS, comparing their median values (-1.25% and -1.08%). S&P 500 index return ranges from -11.98% to 9.38%, in which the extreme negative value occurs during the market turmoil surrounding COVID-19 on March 16, 2020. The maximum value of the VIX (82.69) occurs on the same day. Interestingly, this extreme negative event is also captured two days earlier by the SPY return shock with its minimum value as low as -10.49%, indicating a potential predictive power of SPY equity on S&P 500 index. To avoid the possibility that our empirical results are driven by extreme values, we create a subsample excluding Covid-19 period in the robustness tests. The last column of Panel A compares the variables of interest between SPY pilot program period and non-pilot period, which gives the mean difference of each variable with its t-statistics in the parenthesis. All the variables display insignificant differences with t-statistics below 1.96 for the pilot and non-pilot periods except the ECV, EPV and S&P 500 volatility index. However, both call and put options volumes produce positive mean differences, showing that the options trading volumes on average decrease in the SPY pilot period versus non-pilot period.

Panel B of Table 4.1 shows us the Pearson correlation between the variables. The SPY equity return shock is highly correlated with S&P 500 index return, which is normal since the SPY tracks S&P 500 index performance. ECV displays a high correlation (87.5%) with EPV, demonstrating that investors are active in both call and put sides of SPY options trading. Furthermore, the strong correlation between VIX and ECV (EPV) at 54.41% (64.52%) enhances the possibility that investors tend to trade on SPY options contracts in response to the market panic, or investors' trading of SPY options affects the market volatility to some extent. In addition to the above findings, we notice that CVS is highly correlated with PVS at 73.32%. Since the options volume data are nondirectional and represent the aggregate volume for both call and put options, the high correlation between CVS and PVS can be interpreted in different ways: the investors holding positive news about the market are equally active to the investors holding negative news, or the investors having positive (negative) news long (short) the call options and short (long) the put options contracts, or a mixture of these two. Due to the focus of our study and the limitation of used data, we do not identify the types of transaction (e.g., Lee and Ready, 1991) but investigate the overall effects of SPY options shock on its stock market performance.

Below are the two main regression models for the SPY return shock and volatility shock measures. Equation (1) uses the SPY equity daily return shock as the dependent variable, while Equation (2) uses the SPY equity daily volatility shock as the dependent variable.

$$Return\ Shock = \alpha_0 * ECV(EPV) + \alpha_1 * CVS(PVS) + \alpha_2 * Pilot + Controls + \varepsilon \quad (1)$$

$$Volatility\ Shock = \theta_0 * ECV(EPV) + \theta_1 * CVS(PVS) + \theta_2 * Pilot + Controls + \varepsilon \quad (2)$$

where, ECV, EPV, CVS, PVS are defined in the above. Pilot is a dummy variable that equals to one if the data is within the time period of SPY pilot program, and zero otherwise. The control variables include the S&P 500 index return and S&P 500 volatility index. The regression results are reported in the next section.

4.3 Empirical Results

4.3.1 SPY return shock

We first investigate the impact of options trading volume on SPY returns. Table 4.2 provides the results regressing SPY equity return shock on call (put) options trading volumes while controlling for the market overall performance, heteroskedasticity is corrected using robust variance estimates. The goodness of fit improvement from model 1 to the other three models is caused by the inclusion of S&P 500 index return, which the SPY is designed to track, in the estimation. In Panel A, while the ECV is insignificant at all, the CVS negatively predicts the future SPY return shock which is significant across all the estimation models. This evidence is consistent with the hypothesis that informed traders efficiently transmit price-related information from the options market to equity markets. More specifically, investors holding private information trade on the call options contracts, which has a direct impact on the price of underlying asset (i.e., SPY equity). In terms of the economic significance of our empirical results, taking Model 3 of Panel A for example, the coefficient on CVS is -0.0014391, showing that one percent increase in the call volume shock predicts a decrease in SPY return shock by 0.0014391%. From Table 4.1, the sample mean of CVS is 0.0011668 which is approximately equal to one call option contract. Thus, if an informed trader transacts one hundred SPY call option contracts that is not predicted by the market, there will be a 10000% increase in the CVS. This will lead to a decrease in the next-day SPY return shock of 0.6649%. The VIX does not display a significant relationship with the return shock.

The main interest in this article is the impact of position limits on the relationship between options trading and stock performance examined based on SPY pilot program. Pilot is a dummy that equals to one if the options trading volume occurs during SPY pilot program period (no position limit), and zero otherwise. We follow Bessembinder and Seguin (1992, 1993) and develop the interaction term between ECV (CVS) and Pilot which specifies any additional effect of options volume on return shock during the pilot period. Only the interacted term between CVS and Pilot has a significantly positive coefficient, meaning that the call options volume shock has a reduced impact on SPY return shock in the pilot period relative to the non-pilot period where position limits are in effect. The pilot dummy is negatively related with the return shock but is not significant.

{Please insert Table 4.2 and about here}

Panel B of Table 4.2, which looks at put options, displays similar results to those in Panel A, which focuses on call options. The PVS negatively and significantly predicts future return shock across all models (Model 1, 2, and 4), while EPV has no significant relationship in any estimation. With regard to the economic significance of the results for PVS, based on the estimates in Panel B, if an informed trader transacts one hundred SPY put option contracts that is not predicted by the market, one can expect a decrease in the next-day SPY equity return shock by 0.5695%. The interaction term of PVS and pilot is positively significant at 10% level in the last column. For the reduced effect of volume shocks on returns shocks during SPY pilot period as reflected in the interaction, it could also be due to the decrease in the return shocks in the pilot period relative to non-pilot period. In the last column of Panel A of Table 4.1, the difference between mean return shocks for nonpilot versus pilot periods is positive, though not significant.

We argue that the results from Table 4.2 are in line with the actions taken by CBOE on SPY pilot program. After a number of extensions for SPY pilot program since its launch in 2012, CBOE decided to terminate this program on July 12, 2018 and re-established the position limit of SPY option to 1,800,000 contracts increasing from 900,000 contracts prior to the pilot program. On June 25, 2020, COBE proposed again to raise the SPY position limit from 1,800,000 to 3,600,000 contracts[16]. For both pilot and non-pilot periods, the trading volume shocks occurred in call and put options significantly reduce next-day SPY return shocks then improve the price efficiency, although such improvement from options volume shock (CVS and PVS) is weaken during the pilot period. Thus, the implementation of position limit does contribute to regulating the effects of option trading on SPY stocks to certain extent. Thus, it might be sensible for CBOE to re-establish the position limit of SPY but increase it in order to offer more space for informed options trading. Our findings of negative relationship between options trading volume and stock return are similar to those found by Johnson and So (2012) and Zhou (2022), though they use the original return rather than the return shock used here.

4.3.2 SPY volatility shock

Table 4.3 shows the regression results regressing SPY volatility shock on contemporaneous options trading volume, controlling for market overall performance, and correcting for heteroskedasticity with robust variance estimates. The SPY volatility shock is measured by the residual value of the autoregression model of SPY squared return, which represents the component that cannot be predicted by SPY historical volatility. Schwert (1990) summarises several stylized facts about stock return volatility, including: i. it is persistent, meaning that an increase in current volatility lasts for many periods; ii. it is related to macroeconomic volatility, recessions, and banking crises. However, Schwert's (1990) article does not investigate the different components of volatility, which is what this essay tries to elaborate.

[16] See Securities and Exchange Commission (Release No. 34-89151; File No. SR-NASDAQ-2020-033).

{Please insert Table 4.3 and about here}

In both Panel A (call option) and Panel B (put option) of Table 4.3, we find that the volatility shock cannot be explained by any factors except the options volume shock (i.e., CVS and PVS). CVS and PVS are positively correlated with SPY volatility shock at 1% significance level across all six models, indicating that the unanticipated portion of options trading volume enhances the SPY return volatility that is captured neither by its lagged values nor by market volatility. In terms of the economic significance of these results, if informed traders transact one hundred call (put) option contracts in CVS (PVS), the SPY volatility is enhanced by 0.104% (0.134%) that is not predicted by the market. Relying on the put-call parity of VIX options, Chung et al. (2011) find that the information recovered from VIX options significantly improves the prediction of future dynamics of S&P 500 index, and the information content is similar but not identical to that extracted from S&P 500 options. In the essay, although we use the original VIX instead of its related options and use the SPY tracking S&P 500 index instead of the index per se, we do not expect to see the insignificant coefficients on VIX across all estimations in Table 4.3. One possible explanation is that we use the volatility shock whose fluctuation is irrelevant to the contemporaneous market performance but investors' trading activities. Our study then estimates the following Table 4.4 which further supports the hypothesis. The interacted term between CVS (PVS) and pilot identifies any difference in the correlation between options volume shock and volatility shock for the pilot versus non-pilot period. The corresponding coefficients in both panels of Table 4.3 demonstrate that the correlation is attenuated in the pilot period relative to non-pilot period, especially for the correlation between PVS and SPY volatility shock. Again, this attenuation could link to the improvement in SPY volatility shock during the pilot period. As indicated in Panel A of Table 4.1, the averaged volatility shock in nonpilot period is greater than pilot period.

{Please insert Table 4.4 and about here}

The estimations in Table 4.4 are similar to Models 2 & 3 in Table 4.3 but using the expected volatility of SPY as the dependent variable. Specifically, the volume shock. VIX is significantly and positively correlated with the expected volatility for both call and put options models, similar to the findings of Chung et al. (2011) about future dynamics of S&P 500 index and consistent to Schwert's (1990) summary that stock volatility is related to macroeconomic volatility. This supports the above hypothesis that the anticipated portion of volatility is related to the overall market performance while the unanticipated portion (i.e., volatility shock) is related to investors' informed trading (i.e., CVS and PVS). In addition, the significant coefficients on Pilot dummy indicate that the expected volatility during pilot period is higher than non-pilot period. ECV, EPV, CVS, and PVS do not display any significant correlation with the expected volatility.

4.4 Robustness

4.4.1 Covid-19 concern

The sample used in this article embraces the period October 2010 to December 2020 and includes the market turmoil surrounding the COVID-19 collapse in March 2020, followed by the dramatic recovery in the months thereafter. To ensure that our analyses are not distorted by the market-wide impact of Covid-19, we construct a sub-sample by removing data starting January 1, 2020 and re-estimate my main regressions. Table 4.5 and 4.6 display the sub-sample results with return shock and volatility shock as dependent variables, respectively. The predictability of CVS and PVS to SPY return shock are qualitatively unchanged in Table 4.5 relative to Table 4.3, with larger unanticipated options volume reducing the future return shock. Comparing the full sample estimations, we do not find any significant difference of volume predictability for pilot versus non-pilot periods in this pre-covid sample. The individual pilot dummy negatively correlates with return shock at 5% significance level, demonstrating a decrease in unexpected SPY returns during the SPY pilot program time period. S&P 500 index return remains a strong correlation with the return shock, while VIX displays a weak correlation at 5% significance level.

{Please insert Table 4.5 and about here}

{Please insert Table 4.6 and about here}

Table 4.6 repeats the findings in Table 4.3 to a large extent. Both CVS and PVS significantly enhance the unanticipated SPY volatility. Similar to return shock estimations, when the full sample is truncated, the difference between pilot and non-pilot periods is nuanced as reflected by the insignificant coefficients of interacted terms (i.e., CVS*Pilot and PVS*Pilot). VIX shows a weak effect at 5% significance level relative to that in Table 4.3. So far, both robustness tables confirm the main results in Table 4.2 and 4.3 and suggest the effects of unexpected options trading volumes on the unexpected return and volatility of SPY equity.

4.4.2 S&P 500 index or pilot effect

In this subsection of robustness, we discuss the economic impact of the position limit pilot project on SPY equity return. One might question that the significant correlations documented in the above tables are largely driven by S&P 500 index return and are irrelevant to the pilot project. Bertone et al. (2015) document significant intraday deviations from the law of one price (LOP) for a portfolio of Dow Jones Industrial Average index constituents (DJIA) and the index ETF (DIA). They find that the deviation from LOP, measured by tracking errors between DIA and DJIA returns, is negatively correlated with DIA trading volume. Furthermore, a significant decline of such deviation is identified to be related to regulated events such as the repeal of the uptick rule where short selling activities are less constrained. Similar results are also found by Bertone et al. (2015) when analyzing the relationship between S&P 500 and SPDR, which is similar to the topic of interest. Overall, their findings indicate an improvement in operational market efficiency. To compare the tracking error, calculated by Bertone et al.'s methodology but using daily observations, with the SPY daily return shock, we calculate the correlation between these two variables and obtain the percentage value 12.53%, indicating a low correlation between them. The significant relationships documented in this essay cannot be subsumed into the explanation of ETF tracking error.

{Please insert Table 4.7 and about here}

Given the concern that S&P 500 index return might dominate the above regressions and impair the correlation between pilot dummy and the SPY return shock, we conduct the least squares regression by regressing SPY daily return on S&P 500 index return and pilot dummy which is provided in Panel A of Table 4.7. The coefficient of S&P 500 index return is close to but less than one which indicates that the SPY ETF does not completely track the S&P 500 index. Constant term is negative and significant, indicating that the tracking is imperfect, and there is a downward bias in the SPY stock return. During the pilot period, this downward bias is mitigated with a positive coefficient on pilot dummy, indicating an improved tracking efficiency of SPY ETF when the trading limits are suspended. To further confirm the effect of pilot period, we run the Wald Test as shown in Panel B. The null hypothesis is that the constant term C(1) and the slope term for the S&P 500 index (C2) equals one. With a significant Chi-square statistic, the Wald test of coefficients rejects the null hypothesis and confirms that SPY ETF does not completely track S&P 500 index, and pilot period does show a difference on SPY equity return versus the non-pilot period.

{Please insert Table 4.8 and about here}

To account for time varying asymmetric volatility of SPY return, the study also performs the analyses using the EGARCH model. The EGARCH results shown in Table 4.8 are consistent with those of OLS regression from Table 4.7. The pilot dummy coefficient reaches a higher significance level (i.e., from 10% to 5%) when accounting for time varying asymmetric volatility by EGARCH. In terms of the downward bias reflected in the negative constant term, non-constrained SPY options trading nearly offset such bias, in which the aggregation of coefficient of pilot and constant is close to one. Overall, the findings from Table 4.7 & 4.8 support our empirical results that the pilot period when no position limits are in effect, SPY options trading affects SPY equity return.

Chapter 5: Concluding Remarks

In this thesis, we study governance and regulations in the financial markets. The first essay investigates the relationship between important corporate governance variables and firm default risk during the post-2007–08 financial crisis period, using CDS spread and Merton type default probability as two measurements of firm default risk. This research contributes to the literature in several ways. First, while most research focuses on the crisis in the two critical years (2007 and 2008), we provide new evidence on the role of corporate governance in the post-financial crisis period. Second, we focus on the markets outside of North America, in many of which crisis conditions persist and sweeping regulatory changes affecting the governance of firms have not taken place. Higher institutional ownership and greater board independence are shown to reduce firms' default probabilities. On the other hand, insider ownership, CEO duality, and board size are positively related to default probabilities. When CDS spread is used as a measure of default risk, the impacts of institutional holdings and board size on default risk remain and are robust. Regulatory factors are also crucial. Foreign financial institutions with higher T1 capital ratio have lower CDS spread and lower fundamental default risk; however, those that received secret emergency funding from the Fed during the period 2007 and 2009 have lower CDS spreads post-crisis, but higher fundamental default probabilities, consistent with moral hazard hypothesis. Finally, when we split the full sample into European and Asian subsamples, the governance variable effects are not homogeneous. Governance variables have a greater impact on Asian firms than on European firms. This result may reflect norms that closely tie governance to cultural tightness (conformance with norms) and cultural aversion to individualism. Further exploration of the links between culture and the choice of governance mechanisms to control default risk is a topic for future research.

The second essay examines the cross-market effect of options trading on stock return and volatility. Using a large sample of US exchange-traded equity options, we find significant cross-market information transmission from options trading to underlying equity markets. The results show the importance of distinguishing between call vs. put options trading as they affect stock returns. Options trading per se does not necessarily increase returns, as suggested by Roll, Schwartz, and Subrahmanyam (2009). we find that call options trading is positively associated with stock returns. Put options trading on the other hand reflects bearishness in the stock markets on a given trading day. Both call and put options trading are associated with increased volatility. On the other hand, the changes in options open interest do not impart any significant volatility effect, consistent with the view that most speculators as day traders close out their positions by the end of the trading day.

Our results are in part, consistent with Da et al. (2015), showing that market-wide negative sentiment, as proxied by the FEARS index, also affects stock return and volatility for firms. However, FEARS index appears to be of no significant consequence for the most heavily traded options. Whether distinctions between trader types (speculators vs. hedgers vs. liquidity traders) may also explain the lack of a FEARS factor for the heavily traded options group remains a topic for future research.

Taking advantage of SPY pilot program, the last essay examines the relationship between options trading volume and stock's performance, and the impact of position limit on this relationship. It finds that SPY call and put options volume shocks reduce future return shocks, though this effect is alleviated during the pilot period without the position limit, suggesting a regulatory role of position limit on options investors' trading. However, the volume shocks do enhance the SPY return volatility shocks which increase market uncertainties, but this effect is eased when position limits are removed. The dilemma between return shock and volatility shock suggests that it is more a question of how instead of why we establish the position limits in derivatives markets. We suggest that further research could focus on how the market should establish an appropriate position limit and what are the appropriate levels. For example, Dutt and Harris (2005) and Zhang (2022).

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