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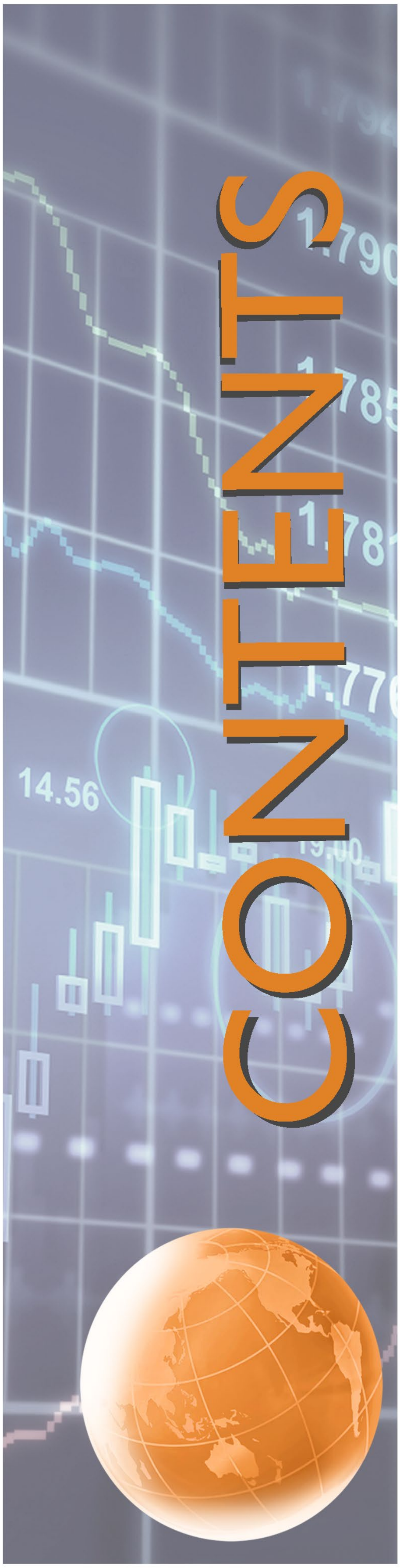

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DOES HERDING EXIST IN LOTTERY STOCKS? EVIDENCE FROM THE INDIAN STOCK MARKET

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Abstract:

In this paper, we investigate the presence of herd behaviour among lottery stocks using Max, skewness and idiosyncratic volatility in the Indian stock market during the period January 2000 to December 2018. We demonstrate that the herd behaviour is non-existent across proxies of lottery-stocks MAX and skewness and find that the herd behaviour is present among highly idiosyncratic stocks. This sheds light on why herding is not detected in the prior studies as it may be concentrated among stocks with certain characteristics. Further, it provides evidence of adverse herding.

Keywords: Herd behaviour, lottery-stocks, emerging markets

JEL classification: G15

1. Introduction

The word herd is described in the Cambridge dictionary as "to make animals move together as a group." In the financial market, investors and fund managers also move together in groups, to take a decision regarding buying and selling assets in the market. When investors are influenced by other's action and imitates their behaviour ignoring their own information, it is termed as herd behaviour in the financial lexicon (Devenow and Welch, 1999). The herd behaviour of investors may lead to excess volatility and fragility to the financial market, etc. (Bikhchandani and Sharma, 2000).

There are voluminous studies examining herd behaviour in the developed and emerging markets (Christie and Huang 1995; Chang et al., 2000; Hwang et al., 2004; Demirer and Kutan 2006; Tan et al., 2008; Chiang and Zheng 2010; Economou et al. 2011; Kapusuzoglu 2011; Clements, Hurn & Shi., 2017). These studies capture herding behaviour based on different market states. Existing studies in the Indian equity market reported absence of herding behaviour for normal stocks (non-lottery types) under different market conditions (extreme upper tail and lower tail, up and down markets) (Lakshman et al., 2011; Lao and Singh, 2011; Saumitra and Sidharth, 2012; Patro and Kanagaraj, 2012; Prosad et al., 2012; Garg and Gulati, 2013; Poshakwale and Mandal, 2014). One of the probable reasons why these studies didn't detect the herding behaviour is that it may be confined in a particular sub-set of the stocks instead of the overall market (Fama and French, 2008; Aziz and Ansari, 2017). Especially, stocks which attract retail and individual investors like lottery stocks (Kumar, 2009) may be the ideal candidate to be examined for the presence of herding behaviour (Rahman et al. 2015).

Following the same intuition, Gong and Dai (2018), examine the presence of herd behaviour in the lottery-type stocks in the Chinese market and find that investors exhibit stronger herding behaviour in such stocks. The novelty and recentness of the reported empirical phenomenon motivate us to probe the herd behaviour in lottery-type stocks in Indian stock market.

Kumar (2009) argues that investors perceive low-priced stocks with high idiosyncratic volatility and idiosyncratic skewness as lotteries. In addition, Bali, Cakici, and Whitelaw (2011) proposed extreme positive returns as a proxy for lottery-type stocks. Following Kumar (2009) and Bali et al. (2011), we take idiosyncratic volatility, skewness, and extreme positive returns as empirical proxies for lottery-type stocks and examine the investor herd behaviour in such stocks.

The results suggest that the herd behaviour is non-existent in lottery-type stocks as proxied by, Max, and skewness. However, some evidence of herding was found during up market condition for high idiosyncratic stocks in the Indian equity market. This finding is consistent with the prior studies in the Indian context for normal stocks. This study fills the empirical void for the presence of herd behaviour in lottery stocks for the Indian stocks market. Rest of the paper is organized as follows: Section 2 discusses the data and methods employed; Section 3 presents the main results and Section 4 contains concluding remarks.

2. Data and Methods

Daily closing prices have been obtained for the constituent companies of S&P BSE500 index from ProwessIQ, a database maintained by Centre for Monitoring Indian Economy (CMIE) for the period January 2000 to December 2018. Each month from January 2000 to December 2018 stocks are segregated into three groups based on a proxy of lottery stocks i.e. MAX, Skewness, and idiosyncratic volatility. Herding is tested separately for each group to check the pervasiveness of the herding behaviour across lottery and non-lottery stocks. MAX is computed as follows:

$$Max_{i,t} = Max\left(R_{i,d}\right), d = 1, \ldots D_t \quad (1)$$

where, $R_{i,d}$ is the daily return of stock *i* on day *d*, and D is the number of days in month *t*. Three versions of Max are computed following Bali et al. (2011) i.e. Max(1), Max(2), and Max(3), where Max(2) is the average of two maximum daily returns in a month and Max(3) is the average of three largest returns in a month. Skewness of a stock is calculated as:

$$Skew_{i,t} = \frac{1}{D_t} \sum_{d=1}^{Dt} \left(\frac{r_{i,d} - \mu_i}{\sigma_i}\right)^3 \quad (2)$$

Skewness of each stock is computed over a window of one (Skew(1)) and three months (Skew(3)). Idiosyncratic volatility is computed relative to the Carhart's (1997) model:

$$R_{i,d} - Rf_d = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \varepsilon_t. \quad (3)$$

Idiosyncratic volatility is defined as the standard deviation of the error term in eq 3:

$$IVOL_{i,t} = \sqrt{var(\varepsilon_{i,d})} \quad (4)$$

The factors were obtained from the data library of Agrwalla, Jacob and Varma (2014). IVOL is computed over a window of one (IVOL(1)) and three months (IVOL(3)). After computing the lottery proxies and segregating the sample each month into three groups based on it, we followed Christie and Huang (1995) and Chang, Cheng, and Khornan (2000) to test for the presence of the herd behaviour across these groups.

Following Christie and Huang (1995), we examine the extreme tails of the market return to capture herding behaviour using cross-sectional standard deviation (CSSD):

$$CSSD_t = \frac{\sqrt{\sum_{i=1}^{N} (R_{it} - R_{mt})^2}}{N-1} \quad (5)$$

where R_{it} is the return of stock *i* at time *t* and R_{mt} is the cross-sectional mean of the N returns in the sample. Taking $CSSD_t$ as the dependent variable, a regression equation is formed below to detect herding behaviour.

$$CSSD_t = \alpha + \beta^L D^L{}_t + \beta^U D^U{}_t + \varepsilon_t \quad (6)$$

The negative coefficient of β^L and β^U signifies the presence of herding behaviour in the extreme lower and extreme upper tail of return distribution. The extremes are defined at 10, 5, and 1 percentiles.

Chang, Cheng, and Khorana's (2000) model uses cross-sectional absolute deviation (CSAD) to measure herding behaviour in up and down market condition:

$$CSAD_t = \frac{1}{N} \sum_{i=0}^{n} |R_{i,t} - R_{m,t}| \quad (7)$$

where R_{it} is the return of a particular stock at time *t* and R_{mt} is the average market return at time *t*. CSAD is regressed on absolute values of market return and its square to detect the herd behaviour:

$$CSAD_t = \alpha + \beta_1 |R_{m,t}| + \beta_2 |R_{m,t}^2| + \varepsilon_t \quad (8)$$

In normal market condition, the coefficient β_2 is expected to be positive and statistically significant as per rational asset pricing model. However, during extreme market conditions, a significant negative coefficient of R^2_{mt} would constitute as evidence of investors' herd behaviour. To account for the possible asymmetric effects of herding behaviour during up and down market conditions, the following empirical model is used:

$$CSAD_t = \alpha + \beta_1 (1-D)\left|R_{m,t}\right| + \beta_2 (D)\left|R_{m,t}\right| + \beta_3 (1-D)R^2_{m,t} + \beta_4 (D)R^2_{m,t} + \varepsilon_t \quad (9)$$

where, D = 1 if R_{mt}<0, and D = 0 if Rm_t>0. In other words, the model is estimated separately for the down and upmarket conditions. A negative and significant coefficient β_3 in the model is considered as an evidence of herding in the upmarket and negative β_4 signifies herding in the down market.

3. Results

Table 1 reports the results based on Christie and Huang's (1995) methodology of cross-sectional standard deviation (CSSD) described in equation 6 for 10, 5, and 1 percent criteria. The sample is sorted into three groups based on Max, skewness, and idiosyncratic volatility. Panel A of Table 1 shows that coefficients of βU (upper tail) and βL (lower tail) are significantly positive for all definitions of tails i.e. 10, 5, and 1 percent, for Max (1), Max (2), and Max (3), which suggests the absence of herding behaviour. This suggests an increase in equity return dispersion with respect to market return during the extreme low and up markets. Furthermore, the results of skewness (Panel B) also don't show any evidence of herding behaviour, as the coefficient of βU and βL are positive and significant for all the three definitions of up and down markets. In the case of idiosyncratic volatility, we find a negative and significant coefficient of βU (at 1 and 5% significance level) and βL (at 5 and 10% significance level) for high idiosyncratic volatility stocks (IVOL(3)) at 10 and 5 percent criteria. The phenomenon is however absent when IVOL is computed using one-month data. Overall, the results show the presence of herding behaviour in highly idiosyncratic stocks.

Table 2 and 3 provide the results based on Chang, Cheng and Khorana's (2000) method of cross-sectional absolute deviation (CSAD) explained in equation 8 and 9. In table 2, the coefficients β_2 for max, skewness, and idiosyncratic volatility based groups are positive and significant at the 1 percent level, indicating the absence of herding. On the contrary, it suggests presence of adverse herding (Gebka and Wohar, 2013). Table 3 reports a similar result based on equation 9 under different market conditions for all max, skewness, and idiosyncratic volatility-based groups of stocks. The coefficients of β_3 (upmarket condition) and β_4 (down market) are positive and significant at the 1 percent level indicating an increase in return dispersion in relation to market return during the extreme market conditions. Overall, the results suggest the absence of herding behaviour across stocks with low and high values of max and skewness using both major methods of testing the herd behaviour. For idiosyncratic volatility, the results show the presence of herding in highly idiosyncratic stocks.

Table 1: Regression results of the daily CSSD for stocks sorted on max, skewness and idiosyncratic volatility

					10%		5%		1%	
		α_0	β_U	β_L	α_0	β_U	β_L	α_0	β_U	β_L
Panel A: Max										
Max (1)	**Low**	0.0228	0.0031	0.0030	0.0229	0.0056	0.0048	0.0231	0.0123	0.0123
		(89.06)[a]	(4.97)[a]	(4.41)[a]	(91.83)[a]	(6.00)[a]	(4.71)[a]	(92.33)[a]	(5.30)[a]	(4.73)[a]
	Med	0.0265	0.0050	0.0037	0.0269	0.0034	0.0061	0.0271	0.0088	0.0174
		(44.51)[a]	(1.61)	(3.71)[a]	(41.75)[a]	(3.47)[a]	(4.18)[a]	(44.97)[a]	(4.53)[a]	(4.90)[a]
	High	0.0311	0.0025	0.0027	0.0313	0.0032	0.0047	0.0314	0.0082	0.0142
		(67.12)[a]	(3.46)[a]	(2.92)[a]	(70.36)[a]	(3.39)[a]	(3.57)[a]	(73.05)[a]	(3.96)[a]	(4.29)[a]
Max (2)	**Low**	0.0226	0.0030	0.0030	0.0227	0.0052	0.0051	0.0230	0.0123	0.0135
		(91.12)[a]	(4.99)[a]	(4.19)[a]	(93.03)[a]	(5.86)[a]	(4.58)[a]	(94.23)[a]	(5.34)[a]	(4.11)[a]
	Med	0.0260	0.0024	0.0039	0.0261	0.0042	0.0065	0.0264	0.0093	0.0168
		(43.79)[a]	(3.00)[a]	(4.08)[a]	(48.20)[a]	(4.35)[a]	(4.85)[a]	(51.74)[a]	(5.05)[a]	(5.56)[a]
	High	0.0316	0.0051	0.0024	0.0321	0.0026	0.0041	0.0322	0.0076	0.0136
		(67.43)[a]	(1.66)[c]	(2.56)[b]	(56.47)[a]	(2.69)[a]	(3.03)[a]	(59.42)[a]	(3.49)[a]	(4.17)[a]
Max (3)	**Low**	0.0226	0.0029	0.0030	0.0227	0.0049	0.0051	0.0229	0.0123	0.0139
		(91.02)[a]	(4.94)[a]	(4.15)[a]	(93.47)[a]	(5.74)[a]	(4.58)[a]	(94.74)[a]	(5.39)[a]	(4.26)[a]
	Med	0.0259	0.0024	0.0040	0.0260	0.0045	0.0066	0.0263	0.0097	0.0177
		(43.79)[a]	(3.04)[a]	(4.03)[a]	(48.09)[a]	(4.51)[a]	(4.72)[a]	(51.57)[a]	(5.01)[a]	(5.60)[a]
	High	0.0317	0.0051	0.0023	0.0321	0.0025	0.0040	0.0323	0.0072	0.0125
		(67.77)[a]	(1.65)	(2.60)[a]	(56.67)[a]	(2.63)[a]	(3.01)[a]	(56.70)[a]	(3.39)[a]	(3.94)[a]
Panel B: Skewness										
Skew (1)	**Low**	0.0271	0.0022	0.0029	0.0271	0.0042	0.0054	0.0273	0.0100	0.0167
		(44.81)[a]	(2.63)[b]	(2.98)[a]	(48.93)[a]	(3.91)[a]	(3.86)[a]	(52.46)[a]	(4.40)[a]	(4.23)[a]
	Med	0.0267	0.0056	0.0035	0.0272	0.0040	0.0055	0.0274	0.0104	0.0149
		(82.47)[a]	(1.86)[c]	(4.35)[a]	(57.93)[a]	(4.53)[a]	(4.35)[a]	(61.14)[a]	(4.91)[a]	(4.80)[a]
	High	0.0277	0.0024	0.0028	0.0278	0.0035	0.0047	0.0280	0.0084	0.0126
		(76.07)[a]	(3.99)[a]	(3.35)[a]	(79.51)[a]	(4.29)[a]	(4.08)[a]	(81.98)[a]	(4.41)[a]	(4.79)[a]
Skew (3)	**Low**	0.0264	3.52E-06	-2.75E-05	0.0263	0.0002	-0.0001	0.0263	0.0030	0.0040
		(75.30)[a]	(0.00)	-(0.04)	(76.45)[a]	(0.28)	-(0.11)	(78.15)[a]	(2.00)[b]	(2.03)[b]
	Med	0.0277	-0.0008	-0.0004	0.0277	-0.0008	-0.0007	0.0275	0.0014	0.0024
		(54.55)[a]	-(1.30)	-(0.53)	(57.69)[a]	-(1.06)	-(0.78)	(60.86)[a]	(0.88)	(1.12)
	High	0.0290	-(0.0003	-0.0008	0.0289	-0.0007	-0.0004	0.0289	9.55E-05	0.0020
		(46.16)[a]	-(0.35)	-(0.99)	(50.54)[a]	-(0.75)	-(0.41)	(53.85)[a]	(0.06)	(0.88)
Panel C: Idiosyncratic volatility										
IVOL (1)	**Low**	0.0222	0.0027	0.0031	0.0223	0.0049	0.0053	0.0225	0.0110	0.0127
		(87.22)[a]	(4.64)[a]	(4.26)[a]	(89.77)[a]	(5.81)[a]	(4.90)[a]	(90.98)[a]	(4.83)[a]	(4.82)[a]
	Med	0.0253	0.0060	0.0040	0.0258	0.0045	0.0061	0.0260	0.0105	0.0167
		(91.33)[a]	(1.98)[c]	(4.90)[a]	(58.34)[a]	(4.80)[a]	(4.64)[a]	(61.71)[a]	(5.93)[a]	(4.91)[a]
	High	0.0325	0.0017	0.0021	0.0326	0.0025	0.0042	0.0327	0.0073	0.0145
		(46.41)[a]	(1.92)[c]	(1.97)[b]	(50.44)[a]	(2.41)[b]	(2.94)[a]	(53.72)[a]	(3.26)[a]	(3.91)[a]
IVOL (3)	**Low**	0.0216	0.0009	0.0012	0.0217	0.0010	0.0014	0.0217	0.0026	0.0050
		(84.55)[a]	(1.68)[c]	(1.98)[b]	(83.64)[a]	(1.39)	(1.67)[c]	(85.26)[a]	(2.64)[b]	(2.48)[b]
	Med	0.0260	0.0003	-0.0004	0.0261	0.0003	-0.0004	0.0260	0.0030	0.0030
		(55.78)[a]	(0.56)	-(0.54)	(57.64)[a]	(0.36)	-(0.58)	(60.88)[a]	(1.76)[c]	(1.69)[c]
	High	0.0337	-0.0022	-0.0018	0.0335	-0.0023	-0.0018	0.0332	-0.0005	0.0010
		(47.30)[a]	-(2.69)[a]	-(1.98)[c]	(51.09)[a]	-(2.49)[b]	-(1.63)[c]	(53.93)[a]	-(0.30)	(0.41)

This table reports the results of the model (6) for three groups of stocks formed on the basis of a proxy of lottery-likeliness. Figures in parentheses are t-statistics based on Newey-West (1987) consistent standard errors. Subscripts (a), (b), and (c) represent statistical significance at 1, 5, and 10 percent levels, respectively.

Table 2: Regression results of the daily *CSAD* for portfolios sorted on max, skewness and idiosyncratic volatility

		α_0	β_1	β_2
Panel A: Max				
Max (1)	**Low**	0.0129 (62.56)[a]	0.4418 (11.30)[a]	6.5133 (5.25)[a]
	Med	0.0151 (53.82)[a]	0.5331 (10.33)[a]	9.38 (5.82)[a]
	High	0.0182 (56.23)[a]	0.6085 (12.11)[a]	8.5982 (5.97)[a]
Max(2)	**Low**	0.0127 (61.48)[a]	0.4303 (10.62)[a]	6.8034 (5.20)[a]
	Med	0.0149 (58.11)[a]	0.5321 (11.58)[a]	8.9597 (6.35)[a]
	High	0.0185 (53.70)[a]	0.6258 (11.48)[a]	8.6648 (5.41)[a]
Max (3)	**Low**	0.0126 (59.71)[a]	0.4195 (9.89)[a]	7.2075 (5.14)[a]
	Med	0.0148 (58.13)[a]	0.5482 (11.84)[a]	8.4042 (6.05)[a]
	High	0.0187 (53.83)[a]	0.6226 (11.73)[a]	8.8075 (5.74)[a]
Panel B: Skewness				
Skew(1)	**Low**	0.0150 (56.34)[a]	0.5158 (11.00)[a]	8.9171 (5.89)[a]
	Med	0.0155 (56.36)[a]	0.5417 (11.46)[a]	7.9834 (5.66)[a]
	High	0.0157 (62.73)[a]	0.5361 (11.47)[a]	7.4446 (5.26)[a]
Skew (3)	**Low**	0.0145 (59.13)[a]	0.5403 (11.51)[a]	7.5032 (4.78)[a]
	Med	0.0155 (59.85)[a]	0.5133 (11.89)[a]	8.3864 (6.37)[a]
	High	0.0156 (56.38)[a]	0.5234 (9.15)[a]	8.6060 (4.92)[a]
Panel C: Idiosyncratic risk				
IVOL (1)	**Low**	0.0125 (63.25)[a]	0.3756 (9.62)[a]	6.9588 (5.51)[a]
	Med	0.0148 (59.84)[a]	0.5532 (12.07)[a]	8.4382 (6.04)[a]
	High	0.0188 (53.32)[a]	0.6584 (12.15)[a]	9.0367 (5.70)[a]
IVOL (3)	**Low**	0.0120 (66.77)[a]	0.3351 (9.01)[a]	7.521 (6.20)[a]
	Med	0.0146 (59.02)[a]	0.5430 (10.99)[a]	8.7072 (5.46)[a]
	High	0.0189 (54.73)[a]	0.6947 (12.82)[a]	8.3082 (5.26)[a]

This table reports the estimates of model 8. Figures in parentheses are t-statistics based on Newey-West (1987) consistent standard error. Subscripts [a], [b], and [c] represent statistical significance at 1, 5, and 10 percent levels, respectively

Table 3: **Regression results of the daily *CSAD* for portfolios sorted on max, skewness and idiosyncratic volatility under up and down markets.**

		α_0	β_1	β_2	β_3	β_4
Panel A: Max						
Max (1)	**Low**	0.0129	0.3965	0.4804	7.5409	5.6569
		(60.75)[a]	(7.79)[a]	(10.93)[a]	(3.66)[a]	(4.07)[a]
	Med	0.0152	0.4632	0.5799	12.71	7.4202
		((45.51)[a]	(4.69)[a]	(10.89)[a]	(2.88)[a]	(4.75)[a]
	High	0.0183	0.5415	0.6698	9.5598	7.5380
		(55.29)[a]	(7.84)[a]	(12.76)[a]	(3.54)[a]	(5.33)[a]
Max (2)	**Low**	0.0128	0.3931	0.4623	7.6103	6.1135
		(58.77)[a]	(7.00)[a]	(10.56)[a]	(3.22)[a]	(4.42)[a]
	Med	0.0150	0.4591	0.5858	11.7932	7.1427
		(52.48)[a]	(6.08)[a]	(11.65)[a]	(3.63)[a]	(4.70)[a]
	High	0.0186	0.5557	0.6852	10.3157	7.3162
		(50.96)[a]	(6.49)[a]	(12.65)[a]	(2.86)[a]	(5.14)[a]
Max (3)	**Low**	0.0127	0.3887	0.4466	7.7930	6.6665
		(56.87)[a]	(6.51)[a]	(9.94)[a]	(3.03)[a]	(4.61)[a]
	Med	0.0149	0.4773	0.6007	11.0945	6.6621
		(52.90)[a]	(6.41)[a]	(12.13)[a]	(3.46)[a]	(4.67)[a]
	High	0.0188	0.5462	0.6860	10.7853	7.2719
		(51.14)[a]	(6.57)[a]	(12.76)[a]	(3.14)[a]	(5.11)[a]
Panel B: Skewness						
Skew (1)	**Low**	0.0151	0.4298	0.5791	12.2609	6.7735
		(52.01)[a]	(5.69)[a]	(11.64)[a]	(3.70)[a]	(4.33)[a]
	Med	0.0155	0.4768	0.5939	9.9020	6.5899
		(51.73)[a]	(6.14)[a]	(12.39)[a]	(3.00)[a]	(4.95)[a]
	High	0.0157	0.5068	0.5665	7.39	7.1552
		(62.05)[a]	(8.18)[a]	(12.17)[a]	(2.92)[a]	(5.66)[a]
Skew (3)	**Low**	0.0146	0.4589	0.6048	10.0487	5.7003
		(58.61)[a]	(7.74)[a]	(11.04)[a]	(4.18)[a]	(3.02)[a]
	Med	0.0155	0.4595	0.5521	10.5889	7.0028
		(55.68)[a]	(6.63)[a]	(11.83)[a]	(3.56)[a]	(4.92)[a]
	High	0.0156	0.5090	0.5376	8.6837	8.4242
		(53.02)[a]	(5.87)[a]	(10.92)[a]	(2.34)[b]	(6.43)[a]
Panel C: Idiosyncratic volatility						
IVOL(1)	**Low**	0.0125	0.3446	0.4029	7.2886	6.5294
		(62.29)[a]	(7.14)[a]	(9.28)[a]	(3.71)[a]	(4.63)[a]
	Med	0.0148	0.4920	0.5990	10.6987	6.9576
		(53.50)[a]	(6.35)[a]	(12.51)[a]	(3.22)[a]	(5.04)[a]
	High	0.0189	0.5697	0.7292	11.7087	7.1141
		(49.70)[a]	(6.29)[a]	(13.41)[a]	(3.05)[a]	(5.00)[a]
IVOL (3)	**Low**	0.0121	0.3147	0.3504	8.2655	7.0310
		(65.09)[a]	(6.67)[a]	(8.11)[a]	(4.45)[a]	(4.78)[a]
	Med	0.0147	0.4905	0.5812	10.8075	7.3752
		(53.99)[a]	(6.39)[a]	(10.97)[a]	(3.31)[a]	(4.29)[a]
	High	0.0190	0.6141	0.7615	10.4506	6.6623
		(50.85)[a]	(6.63)[a]	(14.84)[a]	(2.61)[b]	(5.39)[a]

This table reports the regression results for the model (9). Figures in parentheses are t-statistics based on Newey-West (1987) consistent standard error. Subscripts [a], [b], and [c] represent statistical significance at 1, 5, and 10 percent levels, respectively

4. Conclusion

This article explored the presence of herd behaviour in lottery stocks in the Indian stock market. Lottery stocks are proxied by max, skewness, and idiosyncratic volatility. Employing the methods of both Christie and Huang (1995) and Chang, Cheng, and Khorana (2000), we find that the herding behaviour is non-existent across stocks with low and high values of max and skewness. As for the idiosyncratic volatility, the results show the presence of herd behaviour in highly idiosyncratic stocks. However, in general, the results show the evidence of adverse herding or high return dispersion during extreme market conditions for all types of stocks. It may be induced by the presence of novice traders acting on non-fundamental factors or may be driven by overconfidence of investors (Gebka and Wohar, 2013).

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THE EFFECT OF OIL PRICE CHANGES ON CORPORATE INVESTMENT IN THE US: THE ROLE OF ASYMMETRIES

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Abstract:
This paper investigates the influence of oil price changes on corporate investment in the US using a large sample of 15,411 companies from 1984 to 2017. It adds to the literature by showing an asymmetric response of capital investments to oil price changes for non-oil companies. Particularly, positive oil price changes have a larger adverse impact on investments than the positive impact created by negative oil price changes. These results are important in assessing the impact of energy price fluctuations on the long-term investment decisions of US companies.

Keywords: Oil price; Corporate investment; U.S. firm; Asymmetry

JEL classification: G3, G32, Q4, Q41

1. Introduction

Oil-related products (e.g. gasoline) represent an important input that firms use for their operation. In fact, the profitability of oil-producing companies is more influenced by oil price changes than to oil-consuming company, since the latter is impacted by a range of other factors including oil price changes (Phan et al., 2015). Therefore, changes in oil prices may disrupt the critical decisions made by the company including the investment decisions because most investment expenditures are at least partly irreversible, that is, there is a cost of reducing capital if there is an unfavorable change in oil price. As a result, oil price changes carry serious implications on capital profitability and thus on investment decisions. [1] In addition, capital investment determines the growth prospects of the aggregate economy through capital accumulation. In the US market, which constitutes the sample of our study, the gross private domestic investment, including investment in plants, machinery, and equipment, accounted for around 18.1% of GDP in 2018 (Economic Report of the President, 2019, Table B-4).

[1] Changes in oil price can affect the demand for company output. For example, the household disposable income decreases with higher cost for energy consumption. This in turn may reduce the sales and thus the profitability of the company. Edelstein and Kilian, 2007; Hamilton, 2009 and Kilian, 2009 noted that energy price shocks are associated with lower consumer spending.

Oil price fluctuations may not only affect investments directly through their effect on company profitability but also may introduce uncertainty regarding future oil prices, causing firms to postpone growth plans and expansion decisions (Bernanke, 1983; Pindyck, 1991; Pindyck and Rotemberg, 1983). Other studies conclude that the influence on investment is negative and investment is less responsive to sales growth when oil price uncertainty is high (Elder and Serletis, 2010; Henriques and Sadorsky, 2011; Mohn and Misund, 2009; Ratti et al., 2011; Sadath and Acharya, 2015; Sadorsky, 2011; Uri, 1980; Wang et al., 2017; Yoon and Ratti, 2011).

Kellogg (2014) finds that drilling activity slows down during periods of high oil price volatility. Empirical proof of the positive influence of uncertainty is also provided by Henriques and Sadorsky (2011), who find a U-shaped relationship between oil company investments and oil price uncertainty. Recently, Phan et al. (2019) and Maghyereh and Abdoh (2020) show that crude oil price uncertainty negatively influences corporate investment. Sadath and Acharya (2015) document a negative relationship between energy prices and corporate investment in the Indian manufacturing sector, while Wang et al. (2017) find that oil price uncertainty has a negative impact on corporate investment expenditure in China, especially for non-state-owned listed companies. Loria (2017) finds that, while a small oil price increase leads to a decline in U.S. nonresidential fixed investment, the effect of a large oil price increase is ambiguous. However, Çakır Melek et al. (2017), Çakır Melek (2018), and Bjørnland and Zhulanova (2019) show that the response of U.S. investment to oil price shocks has changed following the shale boom in mid-2016. Specifically, they find that U.S. investment has become more responsive to demand shocks and less responsive to oil supply shocks. They argue that higher oil prices make oil businesses more profitable, which allows them to increase both production and investment. Similarly, Gilje et al. (2016), Feyrer et al. (2017), and Allcott and Keniston (2018) examine the local implications of the shale boom and find strong positive spillovers for employment and wages.

In all these studies, the influence of oil on investment is assumed to be symmetric and corporate capital expenditure sensitivity does not differentiate between the impact of positive and negative oil price changes. However, this distinction is important, as the differentiation allows for more accurate predictions and modeling of the reaction of corporate investment to oil price changes and uncertainty. In the literature, the analysis of asymmetry focuses on aggregate macroeconomic and stock markets, with no evidence on whether company investments respond differently to oil price increases and decreases. For example, Mork (1989) identifies asymmetry in the response of output to oil price shocks. An increase in oil price influences economic growth by a higher degree than a decrease in the oil price. Similar findings have been reported by Cologni and Manera (2009), Hamilton (2003), Lardic and Mignon (2008), Zhang (2008), and Awartani et al. (2020). The reaction of stock returns to oil prices is also found to be symmetric by Maghyereh and Al-Kandari (2006), Bachmeier (2008), Nandha and Faff (2008), and Maghyereh and Awartani (2016). Therefore, the main contribution of this paper lies in identifying the potential asymmetry in the response of the investments of US corporations to oil price changes. To the best of our knowledge, this analysis has not been yet conducted in the related empirical literature.

The nature of the influence of oil price changes on investment differs across firms in different industries. Oil-producing firms are expected to benefit from oil price hikes and therefore invest more following the increase in oil prices. The investment decisions of oil companies under oil price uncertainty has been modeled and studied by many researchers. Hurn and Wright (1994); Favero et al. (1994) note that expected oil prices and their uncertainty are important determinants along with geological factors of the development decision of oil corporations.[2] Berntsen et al. (2018) indicate that the price of oil can only influence the investment and development of oil wells in Norway. Baqaee and Farhi (2017) and Çakır Melek (2018) find that negative oil shocks can have larger effects on the fixed investments of oil and gas companies than those of non-oil and gas companies. As the influence of oil price changes is different for oil companies, we use a sample of only oil and gas companies and another sample for all other companies.

Our empirical results show significant asymmetry in the investment reaction of non-oil and gas companies to oil price changes. Particularly, the decrease in investments following oil price increase is higher than the increase in investments following oil price decrease. This indicates that positive changes in oil prices have a more determinantal impact on investments. This asymmetric investment response to oil price changes provides a further explanation for the asymmetry in the response of output to oil price shocks documented by Mork (1989) and others.[3] On the other hand, oil and gas companies' investments respond symmetrically to oil price changes where capital spending has the same sensitivity to positive and negative oil price shocks. Perhaps, the long-term nature, persistency, and irreversibility of these companies' investments make them less sensitive to the annual changes in oil prices.

The rest of the paper is organized as follows. In section 2, we describe the dataset and the model. The analysis of the empirical results is presented in Section 3. Finally, Section 4 draws concluding remarks.

2. Data and Methodology

The sample includes all companies listed on three US exchanges: the NYSE, AMEX, and NASDAQ. The annual financial data of all companies are collected o from 1984 to 2017 from the Compustat database. From the original dataset, we excluded finance, insurance, real estate, not-for-profit organizations, and governmental companies due to the specific nature of their activity.[4] All firms with missing data, with less than five years of data, or that belong to an industry not classified are also excluded from the sample. To alleviate the impact of outliers, we winsorized all firm-level variables at the 1st and 99th percentiles. The final sample consists of 15,411 firms, which sum up to 135,353 firm-year observations.

The daily West Texas Intermediate (WTI) closing crude oil price is used and retrieved from the US Energy Information Agency. Finally, annual real GDP growth data of the US is obtained from the Federal Reserve Bank of St. Louis.

[2] Investment in oil companies includes three stages: exploration, development, and extraction. There is always the option not to develop and postpone investment. Note that development investments are irreversible and are carried over a period that may extend to 10 years.

[3] In the literature, the asymmetry in the response of output is explained by reallocation, uncertainty and unemployment uncertainty, and monetary policy effects. See Hamilton (1988), Bernanke (1983), and Bernanke et al. (1997) for more in-depth analyses.

[4] The SIC codes for finance and real estate companies are 6000 and 6999 and those for not-for-profit and governmental ones are 9100 and 9727, respectively.

Corporate investments are computed as the proportion of capital expenditure to total assets in the previous year and denoted as INV_t. The percentage change in real oil price is computed and used as the main independent variable. Following the literature on the determinants of corporate investment, we control for leverage, cash flow, Tobin's Q, profitability, and size.[5] US economic growth is the main determinant of corporate investment and is controlled for by including real GDP growth. To accommodate for any possible structural changes in the variables during the US financial crisis, a dummy that equals 1 in 2007, 2008, and 2009 is added to the model. Table 1 lists the variables and their definitions and sources.

Table 1: Variable definitions and sources

Variable	Definition	Source
INV_t	Corporate investment; calculated as capital expenditure scaled by total assets in the previous year	Compustat
ΔO_t	Percentage change in real oil prices.	US Energy Information Agency
$\dot{o}_{t-1}^{+}$	Positive real crude oil price change	Authors' calculations
$\dot{o}_{t-1}^{-}$	Negative real crude oil price change	Authors' calculations
Lev_t	Firm leverage ratio; calculated as total debt (including loans, securities and other current liabilities) scaled by total assets	Compustat
CF_t	Cash flow; calculated as earnings before interest and taxes minus taxes and interest expense plus depreciation and amortization, scaled by total assets	Compustat
$Tobin\ Q_t$	Tobin's Q; calculated as the ratio of market value of equity plus preferred stock plus total debt to total assets	Compustat
$Prof_t$	Profitability; calculated as the ratio of earnings before interest, taxes, depreciation and amortizations (EBITDA) to total assets	Compustat
$Size_t$	Firm size; calculated as the natural logarithm of total assets	Compustat
GDP_t	Real GDP growth	Federal Reserve Bank of St. Louis
$Crisis_t$	Crisis dummy; equals 1 if the year is in the global financial crisis (2007–2009), and 0 otherwise	

Note: This table describes the variables used in the paper.

Empirical literature typically studies corporate investment behavior using a dynamic panel model (see, e.g., Blundell et al., 1999; Bond and Meghir, 1994; Gulen and Ion, 2015). Therefore, we estimate the following baseline dynamic panel model:

[5] See, for instance, Henriques and Sadorsky (2011), Andreou et al. (2017), Phan et al. (2019), Maghyereh and Abdoh (2020), among others.

$$INV_{i,t} = \beta_0 + \beta_1 INV_{i,t-1} + \beta_{oil}\Delta O_{t-1} + \sum_{k=1}^{k} \beta_k X_{i,t-1}^{k} + \beta_g GGDP_{t-1} + \beta_c Crisis_t + \tau_i + \delta_t + \varepsilon_{it}, \quad (1)$$

where i and t stand for the firm and the year, respectively. $INV_{i,t}$ is the dependent variable, representing investment expenditures as a percentage of the total assets of firm i at time t. The lagged value of corporate investment is added as an explanatory variable to control for persistence and possible autocorrelation in company investment spending.

The main independent variable is denoted as ΔO_{t-1}, representing the percentage change in real oil price. $X_{i.t}^{k}$ is the vector of firm-level control variables—leverage, cash flows, profitability, Tobin's Q, and firm size. $GGDP_{t-1}$ is the US real GDP growth rate, which is used to control the general economic conditions that influence capital spending in all firms. All control variables are lagged by one year to avoid potential endogeneity and simultaneity bias in the estimates. $Crisis_t$ is a crisis dummy variable that takes 1 in crisis years, and 0 otherwise. The firm-specific effects that control for firm heterogeneity are captured by τ_i, which is a firm variant but time-invariant. Time heterogeneity is captured by δ_t, which does not change across companies and only changes from year to year. ε_{it} is the error term, assumed to be normally distributed, $\varepsilon_{it} \sim iid\ N(0, \sigma^2)$.

As Equation (1) is linear in real oil returns, it is unable to capture any potential asymmetry in the response of corporate investment to oil price changes. Hence, we adjust it by decomposing the oil price changes into positive ($\dot{o}_t^{+}$) and negative components:[6]

$$\dot{o}_t^{+} = max\{\dot{o}_t^{+}, 0\} \Rightarrow \dot{o}_t^{+} = \begin{cases} \dot{o}_t & if\ \Delta o_t > 0 \\ 0 & otherwise \end{cases},$$

$$\dot{o}_t^{-} = m\dot{\imath}n\{\dot{o}_t^{-}, 0\} \Rightarrow o_t^{-} = \begin{cases} \dot{o}_t & if\ \Delta o_t \leq 0 \\ 0 & otherwise \end{cases}.\text{e}$$

The extended version of Equation (1) to include asymmetries can be written as:

$$INV_{i,t} = \beta_0 + \beta_1 INV_{i,t-1} + \beta_{oil}\dot{o}_{t-1}^{+} + \beta_{oil}\dot{o}_{t-1}^{-} + \sum_{k=1}^{k} \beta_k X_{i,t-1}^{k} + \beta_g GGDP_{t-1} + \beta_c Crisis_t + \tau_i + \delta_t + \varepsilon_{it}. \quad (2)$$

In this specification, asymmetry in the influence of oil price changes is captured by parameters β_{oil}^{+} and β_{oil}^{-}. If β_{oil}^{+} and β_{oil}^{-} are statistically equivalent, the conjecture of asymmetry is not statistically supported. Hence, we test the hypothesis of symmetry for the response of investment to oil price movements by using a Wald test of the null hypothesis ($\beta_{oil}^{+} = \beta_{oil}^{-}$) against the alternative ($\beta_{oil}^{+} \neq \beta_{oil}^{-}$).

To estimate models (1) and (2), we use a system GMM estimator as in Arellano and Bover (1995) and Blundell and Bond (1998). This estimator has two steps and yields asymptotically efficient and consistent parameters. It also controls for unobserved individual heterogeneity and potential endogeneity problems. The GMM estimates are

[6] Mork (1989) has implemented a similar adjustment to study asymmetry in the response of output to oil price changes.

generated using two to four lags of the explanatory variables as instruments and then the standard errors of these estimates are corrected using the procedure advocated by Windmeijer (2005).

3. Empirical results

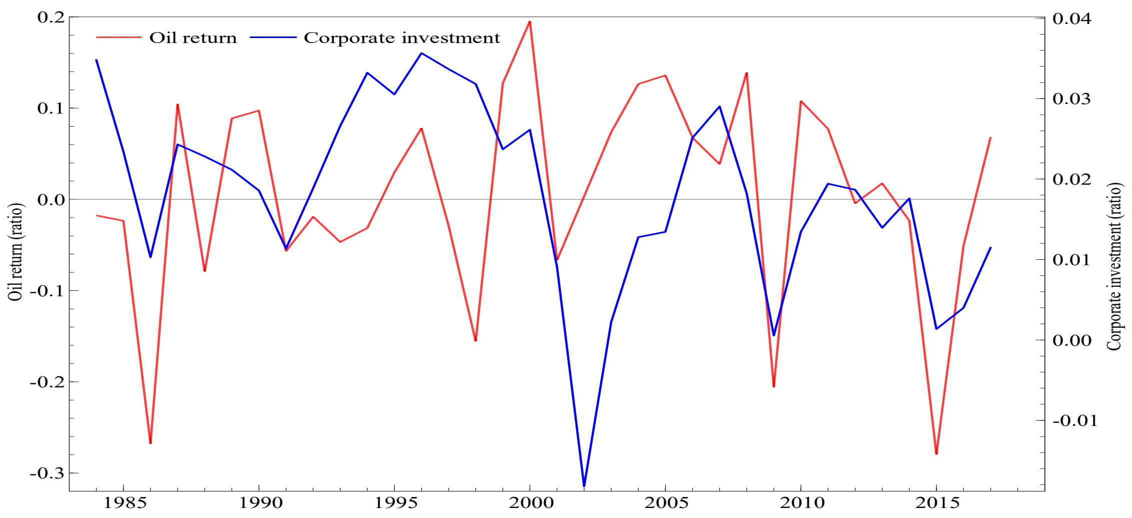
Table 2 shows descriptive statistics of corporate investment, oil price changes, and the rest of control variables in the model. The median company invests annually an average of 3.8% of its total assets over the sample period. The minimum capital spending is zero, which indicates some companies do not even compensate for depreciated capital over the year. The average highest capital spending is around 78% of total assets. The oil prices increase just under 1% annually over the sample period, with the biggest drawdown in 1986, when the oil prices dropped by more than 28%. The biggest increase in oil prices took place in 2000 (19.5%). Figure 1 displays the time series of annual oil price returns and corporate investments as a proportion of total assets over the sample period. Most of the time, company investments and oil returns move in the same direction, particularly during the periods when the US economy faced recession, such as in 1986, 2002, and 2008.

Table 2: Descriptive statistics of the variables for 1984–2017

Variable	Mean	Std. dev.	Min	25th percentile	Median	75th percentile	Max
INV_t	0.066	0.091	0.000	0.013	0.038	0.081	0.778
ΔO_{t-1}	0.009	0.109	-0.280	-0.047	0.018	0.089	0.195
$\dot{o}^{+}_{t-1}$	0.047	0.057	0.000	0.000	0.018	0.089	0.195
$\dot{o}^{-}_{t-1}$	-0.039	0.071	-0.280	-0.047	0.000	0.000	0.000
Lev_t	0.216	0.199	0.000	0.034	0.176	0.347	0.818
CF_t	0.004	0.226	-2.015	0.004	0.057	0.109	0.393
$Tobin\ Q_t$	1.898	1.813	0.383	1.015	1.287	2.025	30.872
$Prof_t$	0.045	0.214	-1.409	0.017	0.088	0.152	0.461
$Size_t$	5.609	2.400	-0.098	3.848	5.531	7.256	12.820
GDP_t	0.029	0.016	-0.025	0.019	0.029	0.040	0.072

Note: All variables are as defined in Table 1. The sample consists of 135,353 firm-year observations representing 15,411 firms over 1984–2017.

Figure 1: Oil price returns and corporate investment, 1984–2017



The median leverage is low and around 18% and the operating cash flows are around 5.7% of total assets. Higher profitability and low leverage can enhance the firm position in taking corporate investments. The median value of Tobin's Q, which reflects the ratio of market value to replacement costs of the firm's assets, is around 1.3, indicating growing prospects potential for the average firm in the market. On average, the sample companies are profitable and the median company generates profits around 8.8% of total assets. Given the median firm size of 252 million dollars, the median amount of profits is around 22.176 million dollars. Finally, the real GDP of the US economy increased by 2.9%, on average, during the sample period.

Table 3 presents the correlation matrix coefficients of our main variables. Column 1 shows the correlation of corporate investment with each of our explanatory variables. There is a negative correlation between corporate investments and oil indicating a negative sensitivity of investments to oil price changes. Investments are more correlated with company profitability, cash flow, and economic growth than with variables such as size, leverage, or Tobin's Q.

Table 3: Pearson correlation coefficients

	INV_t	ΔO_{t-1}	$\dot{o}^{+}_{t-1}$	$\dot{o}^{-}_{t-1}$	Lev_t	CF_t	$Tobin\ Q_t$	$Prof_t$	$Size_t$	GDP_t
INV_t	1.000									
ΔO_{t-1}	-0.011	1.000								
$\dot{o}^{+}_{t-1}$	-0.024	0.816	1.000							
$\dot{o}^{-}_{t-1}$	0.002	0.886	0.455	1.000						
Lev_t	-0.092	-0.026	-0.017	-0.027	1.000					
CF_t	0.132	0.010	-0.004	0.018	0.057	1.000				
$Tobin\ Q_t$	0.067	0.025	0.025	0.019	-0.217	-0.202	1.000			
$Prof_t$	0.139	0.006	-0.009	0.016	0.112	0.918	-0.200	1.000		
$Size_t$	-0.046	0.040	0.058	0.015	0.196	0.325	-0.213	0.339	1.000	
GDP_t	0.134	0.143	0.102	0.138	0.032	0.026	0.042	0.021	-0.171	1.000

Note: All variables are as defined in Table 1.

Table 4 presents estimates of six versions of Equation (2) we use to describe the response of US corporate investment to oil price changes in columns 1–6.[7] Columns 1, 3, and 5 do not differentiate between positive and negative oil price returns shocks. Oil returns have a positive influence on the investments of oil and gas firms and a negative influence on the capital spending of the other companies. This is not unexpected, as the revenues of oil and gas companies benefit from higher oil prices, unlike the revenues of non-oil ones.

The model estimates in columns 1, 3, and 5 are linear. In these models, the influence of oil price increases and decreases are described by the same parameter and, hence, they symmetric, which is not suitable for our purpose. Therefore, we decompose oil returns into positive and negative ones and re-estimate the model for the three samples. The

[7] The full sample includes oil and non-oil companies and is used to estimate models (1) and (2). The estimates are shown in columns 1 and 2. The parameters in columns 3 and 4 are generated from the sample excluding oil and gas companies. Finally, columns 5 and 6 show the estimates only for oil and gas companies. For each sample, we decompose the positive and negative oil price shocks and re-estimate the models. These estimates are shown in columns 2, 4, and 6, respectively.

parameter estimates of oil price increases are now different from those of oil price decreases and are shown in columns 2, 4, and 6.

Table 4: The asymmetric impact of oil prices on corporate investment (SYS GMM regressions)

	All firms		Exclude crude oil and gas firms		Crude oil and gas firms	
	(1)	(2)	(3)	(4)	(5)	(6)
INV_{t-1}	0.0829***	0.0833***	0.0863***	0.0867***	-0.0508***	-0.0513***
	(13.650)	(13.730)	(13.380)	(13.450)	(-4.300)	(-4.350)
ΔO_{t-1}	-0.0041***		-0.0053***		0.0702***	
	(-3.170)		(-4.090)		(6.900)	
$\dot{o}^{+}_{t-1}$		-0.0162***		-0.0173***		0.0562**
		(-6.530)		(-7.090)		(2.320)
$\dot{o}^{-}_{t-1}$		0.0030		0.0018		0.0780***
		(1.490)		(0.910)		(4.880)
Lev_{t-1}	-0.0971***	-0.0967***	-0.0939***	-0.0934***	-0.3780***	-0.3769***
	(-24.740)	(-24.620)	(-25.000)	(-24.860)	(-20.540)	(-20.360)
CF_{t-1}	0.0180***	0.0179***	0.0190***	0.0190***	0.0268	0.0273
	(6.830)	(6.800)	(7.390)	(7.360)	(1.310)	(1.340)
$Tobin\ Q_{t-1}$	0.0024***	0.0024***	0.0026***	0.0026***	0.0171***	0.0173***
	(7.000)	(7.030)	(7.580)	(7.600)	(5.150)	(5.270)
$Prof_{t-1}$	0.0149***	0.0148***	0.0089**	0.0088**	0.0928***	0.0926***
	(3.870)	(3.830)	(2.340)	(2.300)	(4.420)	(4.410)
$Size_{t-1}$	-0.0022**	-0.0021**	-0.0043***	-0.0041***	0.0265***	0.0267***
	(-2.190)	(-2.020)	(-4.150)	(-3.980)	(8.640)	(8.740)
GDP_{t-1}	0.1620***	0.1673***	0.1642***	0.1693***	0.5997***	0.5916***
	(14.110)	(14.510)	(14.380)	(14.770)	(6.600)	(6.560)
$Crisis_t$	-0.0003**	-0.0007***	0.0000***	-0.0004***	-0.0136**	-0.0141**
	(-2.690)	(-3.460)	(-2.100)	(-2.890)	(2.560)	(-2.650)
$Constant$	0.0694***	0.0691***	0.0790	0.0786***	0.0948***	0.0943***
	(11.790)	(11.740)	(13.020)	(12.960)	(5.230)	(5.200)
Sargan test	135.66	133.87	142.097	141.039	26.883	26.071
(p-value)	(0.3403)	(0.3512)	(0.398)	(0.390)	(0.766)	(0.750)
AR (2)	0.130	0.1298	0.241	0.229	0.082	0.089
(p-value)	(0.896)	(0.896)	(0.809)	(0.818)	(0.934)	(0.928)
W_{β}		26.73***		27.37***		0.40
(p-value)		(0.0000)		(0.0000)		(0.5275)
No. of firms	15,411	15,411	14,870	14,870	541	541
Observations	135,353	135,353	131,129	131,129	4,224	4,224

*Note: This table reports the regression results of the impact of oil prices on corporate investment. The dependent variable is corporate investment 〖(INV〗_t), defined as the ratio of gross capital expenditures to book value of total assets in the previous year. Detailed definitions of all variables are provided in Table 1. All regressions are estimated using the two-step system-GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998). We adopt the procedure of Windmeijer (2005) to correct the standard errors of the two-step GMM estimates. The t – 2 to t – 4 lags of the variables are used as instruments in the difference equation and the same lags of differenced variables are used. The regressions include industry-year dummy variables and standard errors are clustered at industry level. Sargan is a test statistic for the validity of the instruments used, where rejection implies that the instruments are not valid. AR(2) is test statistics for second order autocorrelations. W_β represents the Wald test for the null hypothesis (β_oil^+=β_oil^-) against the alternative (β_oil^+≠β_oil^-). In all regressions, the industry effects based on four -digit SIC codes. Numbers in parentheses indicate the robust t statistics. ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.*

Column 4 shows that the investment of non-oil and gas companies is more significantly affected by oil price increases than by price decrease. The estimated parameters indicate that, for every 1% increase in oil prices, corporates reduce capital spending by 1.73% of total assets. However, when oil prices fall by 1%, capital spending increases by only 0.18% of total assets. These asymmetries highlight the importance of the impact of oil price increase on US corporate investment. They also highlight the high probability that corporations will not be able to recover lost investments for a subsequent fall in oil prices. The antepenultimate row shows the Wald test statistics of the null that corporate investment responds equally to increases and decreases in oil price. The null of an equal response is rejected and, therefore, we conclude that the influence of oil on US corporate investments is asymmetric.

Column 6 reports the results for oil and gas companies. The parameters indicate that oil companies increase the proportion of capital spending by 8% and 6% following a 1% negative and positive change in the annual oil prices, respectively. It is clear that with an increase in oil prices, oil-producing company's profitability will increase, thereby encouraging more capital investments. The same effect is observed with a decrease in oil prices. As oil prices drop, revenues of crude oil and natural gas companies decline as well—and in order to maintain their profit against low break-even prices, it is reasonable to expect that these companies will increase capital expenditures especially in new technology and innovation in order to enhance efficiency and operational flexibility which in turn reduce the operating cost.

Table 5: Robustness checks: Alternative corporate investment measures (SYS GMM regressions)

	All firms	Exclude crude oil and gas firms	Crude oil and gas firms
	(1)	(2)	(3)
INV_{t-1}	0.1822***	0.1835***	0.1239***
	(14.720)	(14.550)	(13.210)
$\dot{o}^{+}_{t-1}$	-0.0543***	-0.0554***	0.0621**
	(-4.560)	(-4.580)	(2.060)
$\dot{o}^{-}_{t-1}$	0.0490*	0.0539*	0.0904*
	(1.390)	(1.720)	(1.830)
Lev_{t-1}	-0.1200***	-0.1228***	-0.1919***
	(-5.160)	(-5.230)	(-3.000)
CF_{t-1}	0.0343***	0.0332***	0.0260***
	(3.790)	(3.760)	(6.870)
$Tobin\ Q_{t-1}$	0.0783***	0.0948**	0.0169***
	(3.360)	(2.430)	(3.040)
$Prof_{t-1}$	0.0573***	0.0575***	0.0705***
	(3.940)	(3.940)	(2.740)
Size_{t-1}	0.1717***	0.1732***	0.1900***
	(11.430)	(11.250)	(6.160)
GDP_{t-1}	0.0573***	0.0547***	0.1717***
	(3.170)	(3.950)	(3.170)
$Crisis_t$	-0.0037***	-0.0027***	-0.0350***
	(-3.400)	-(2.980)	(2.520)
$Constant$	-0.0902***	-0.0811***	-0.0116***
	(-6.530)	-(7.350)	(-5.410)
Sargan test	50.811	48.311	20.500
(p-value)	(0.139)	(0.144)	(0.924)
AR (2)	0.0516	-0.0086	0.9131
(p-value)	(0.958)	(0.993)	(0.361)
W_β	25.10***	26.93***	1.15
(p-value)	(0.0000)	(0.0000)	(0.3165)
No. of firms	15,411	14,870	541
Observations	135,353	131,129	4,224

Note: In this table, we undertake robustness checks. The dependent variable is corporate investment 〖(INV〗_t), defined as the ratio change in net fixed assets plus depreciation to total assets in the previous year. The detailed definitions of all variables are provided in Table 1. All regressions are estimated using the two-step system-GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998). We adopt the procedure of Windmeijer (2005) to correct the standard errors of the two-step GMM estimates. The t − 2 to t – 4 lags of the variables used as instruments in the difference equation and the same lags of differenced variables are used.

*The regressions include industry-year dummy variables and standard errors are clustered at the industry level. Sargan is a test statistic for the validity of the instruments used, where rejection implies that the instruments are not valid. AR(2) is test statistics for second order autocorrelations. W_β represents the Wald test for the null hypothesis (β_oil^+=β_oil^-) against the alternative (β_oil^+≠β_oil^-). In all regressions, the industry effects are based on four -digit SIC codes. The numbers in parentheses indicate the robust t statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*

The null of symmetry in the influence of oil price increases and decreases is not rejected by the Wald test statistics and, therefore, we may conclude oil companies respond similarly to positive and negative oil price changes. The lack of asymmetry can be explained by the long-term nature of oil company investments. The irreversibility of these investments implies a lower sensitivity to the oil price, meaning companies may respond similarly to positive and negative oil changes.

Table 6: Robustness checks: Alternative estimation method (fixed effect regressions)

	All Firms	Exclude crude oil and gas firms	Crude oil and gas firms
	(1)	(2)	(3)
INV_{t-1}	0.0088***	0.0033	0.2212***
	(2.610)	(0.960)	(7.180)
$\dot{o}^{+}_{t-1}$	-0.0299***	-0.0311***	0.0895**
	(-4.090)	(-4.140)	(2.220)
$\dot{o}^{-}_{t-1}$	0.0188*	0.0189*	0.0322
	(1.840)	(1.800)	(0.600)
Lev_{t-1}	0.0360***	0.0362***	0.1092***
	(8.150)	(8.000)	(2.840)
CF_{t-1}	0.0151***	0.0145***	0.1502***
	(3.030)	(2.850)	(2.880)
$Tobin\ Q_{t-1}$	0.0030***	0.0030***	0.0236***
	(8.260)	(8.040)	(5.420)
$Prof_{t-1}$	0.0468***	0.0463***	0.0074***
	(7.540)	(7.310)	(3.140)
$Size_{t-1}$	0.0061***	0.0059***	0.0098**
	(9.150)	(8.630)	(2.160)
GDP_{t-1}	0.4632***	0.4615***	0.3660**
	(11.370)	(11.060)	(2.190)
$Crisis_{t}$	-0.0075***	-0.0075***	-0.0010**
	(-2.920)	(-2.880)	(0.050)
$Constant$	0.0715***	0.0705***	0.0477*
	(16.890)	(16.260)	(1.490)
W_{β}	22.54***	23.43	1.24
(p-value)	(0.0000)	(0.0000)	(0.2671)
No of firms	15,411	14,870	541
Observations	135,353	131,129	4,224

*Note: In this table, we undertake a robustness checks using the fixed effects method. The dependent variable is corporate investment 〖(INV〗_t), defined as the ratio change in net fixed assets plus depreciation to total assets in the previous year. The detailed definitions of all variables are provided in Table 1. The regressions consider only time dummies and standard errors are clustered at the industry level. W_β represents the Wald test for the null hypothesis (β_oil^+=β_oil^-) against the alternative (β_oil^+≠β_oil^-). In all regressions, the industry effects are based on four -digit SIC codes. The numbers in parentheses indicate the robust t statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively..*

The influence of the rest of the control variables on corporate investments in the US is as expected. For instance, companies tend to invest more when economic growth increases. US oil and non-oil corporates invest more following increases in cash flow and profitability. Moreover, Tobin's Q is positively correlated with company investment and, hence, corporates may expand their asset bases if the market valuation of their assets has increased relative to the assets' replacement costs. Size is found to negatively influence corporate investments.

To further validate the findings, we undertake two robustness checks in Tables 5 and 6. Particularly, we use an alternative measure of investment in Table 5, which is defined as the change in net fixed assets plus depreciation scaled by total assets in the previous year. Table 6 reports the results of Equation (2) using the fixed-effect method. We then re-estimate Equation (2) and find the results are quantitatively similar to the primary investment measure and use the fixed-effect method. In column 1, the coefficient on the positive oil price return is negative and its value is greater (in absolute term) than the coefficient on the negative oil price return. We re-run the regression models as above using Equation (2) on the samples sorted by industry classification (i.e., US oil and non-oil corporates). Again, the results reported in columns 2 and 3 of Tables 5 and 6 are quantitatively similar to those previously obtained.

4. Conclusion and Policy Implications

The costs and revenues of current and potential company investments are influenced by oil prices. Hence, company expansion, growth, and investment may be affected by oil price changes and fluctuations. Corporations are generally expected to invest less when oil prices are high and uncertain, while oil and gas firms are expected to expand and invest more. In the literature, the relationship between oil and corporate investments has been extensively explored.[8] In these studies, the response of investment to oil prices is linear and the different investment sensitivities to oil prices is not addressed. Therefore, we investigate whether corporate investment responds differently to oil price increases and decreases. This issue of asymmetric sensitivity to oil price is important, as it enables analysts to measure more accurately the responses of corporate investment to potential oil price changes. This is important for company growth prospects, whose value depends on assumptions regarding its capital spending. The issue is also important for modeling the investment decision of corporates and their dependence on the oil price.

Consistent with the literature, we find corporate investments are influenced by the oil price. More importantly, capital expenditure and spending respond differently to oil price increases and decreases. Specifically, an increase hurts assets expansion more than a decrease benefits corporate investments. These asymmetries indicate that the lost investment following an increase in oil price may not be recovered even when oil prices decline. For oil and gas companies, the response of investment is linear and symmetric.

These results highlight the importance of non-linear modeling for the influence of oil price changes on corporate investments. In particular, accounting for asymmetry when predicting the response of investment to oil price change becomes more accurate. Moreover, our results can potentially increase the shareholder value if firms manage the change of oil price (the increase or decrease in price) that exerts the largest effect on corporate investments.

[8] See, for instance, Edelstein and Kilian (2007), Hamilton (2009), Kilian (2009), Uri (1980), Mohn and Misund (2009), Elder and Serletis (2010), Yoon and Ratti (2011), Sadorsky (2011), Henriques and Sadorsky (2011), Sadath and Acharya (2015), Ratti et al. (2011), Wang et al. (2017), and Maghyereh and Abdoh (2020).

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CRYPTOCURRENCY AND STOCK MARKETS : COMPLEMENTS OR SUBSTITUTES? EVIDENCE FROM GULF COUNTRIES

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Abstract:
The main goal of this study is to examine whether the cryptocurrency market impacts the stock market returns in the Gulf countries. Understanding this impact is quite interesting to clarify whether the cryptocurrency market and the stock market are substitutes or complements for investors. The author compiles the data on the stock market of the Gulf countries with the cryptocurrency data on a daily basis over the period 2014-2019. Generalized Method of Moments with Instrumental Variable (IV-GMM) approach has been implemented as the main strategy to fulfill the objective of the paper. The results of this paper show that the Stock market and the cryptocurrency market are substitutes for investors in Gulf countries. In fact, each 10 percent increase in the cryptocurrency returns is associated with a decline in the stock market returns by 0.17 percent. The cryptocurrency market hampers the stock market indices in the Gulf countries. Having agreed upon in the literature that the stock market is affected by fundamental factors, market sentiment, technical factors, and anomalies, this study offers robust evidence that the cryptocurrency should be introduced as one of the main determinants of stock market prices and returns.

Keywords: Crytocurrency, Stock Market, Substitutes.

JEL classification:N2, E44, P33

1. Introduction

This decade has been characterized by a substantial expansion of virtual currencies. Bitcoin, which is considered as a Peer-to-Peer Electronic Cash System (Nakamoto, 2008), has served approximately 250 thousand transactions per day with a total market value \$3.5 billion (blockchain.com accessed on November 28th 2018).

Although such a substantial expansion of virtual currencies, there are no studies to devote a specific interest to find their impact on the stock market prices and returns. The existent literature provides evidence that the stock market returns are driven by four main factors: first, the fundamental factors that include an earning base and valuation multiple (Foster, 1973; Iliev, 2010 Edmans & al., 2012). Second, the technical factors that encompass different macroeconomic conditions (Bordo & al., 2009; Gorodnichenko & Weber, 2016). Third, the market sentiment factor that refers to animal spirits of investors and environmental context (Antweiler & Frank, 2004; Tetlock, 2007). Finally, anomalies that include the impact of different events (for example, day of the week) on the stock market prices (Szakmary & Kiefer, 2004; Gerlach, 2010; Robins & Smith, 2017).

This paper extends the previous literature by including a fifth factor that significantly explains the stock market returns which is the virtual money markets. In particular, the main hypothesis of this study is that virtual money currencies impacts the stock market returns.

More specifically, the main goal of this study is to find whether the cryptocurrency market has a significant impact on the equity markets in Gulf countries. Understanding this impact is quite interesting to clarify whether the cryptocurrency market and the stock market are substitutes (negative relationship) or complements (positive relationship) for investors. On one hand, if the cryptocurrency market and the stock market are substitutes, this might be a warning for policy-makers and academics to note that the higher the index of the cryptocurrency market, the lower the index of the stock market therefore the literature of the stock market should take into account the cryptocurrency market as one of the main determinants of the stock market returns. On the other hand, if the cryptocurrency market and the stock market are complements, therefore, we can note that investors are considering cryptocurrencies as part of their portfolio choice. As a result, if the investors in Gulf countries have positive animal spirits toward speculation and investment, they may place their savings in the stock market as well as in the cryptocurrency market.

In order to reach the goal of the study, the author compiles daily data on the stock market of the Gulf countries with the data on cryptocurrency market obtained from cryptocurrencycharts.com on a daily basis over the period 2014-2019. For the data on the stock market, the author uses the main indices of the Gulf countries: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates.[1] In particular, the data of stock market indices are mainly collected from: Tadawul All Share Index (TASI) that includes all stock indices in Saudi Arabia (168 listed equity), ADX: Abu Dhabi securities Exchange General Index (41 listed equity), KWSE: Kuwait Main Market index (187 listed equity), DFMGI: Dubai Financial Market General Index (33 listed equity), QE; Qatar Stock Exchange General (20 listed equity) and BAX: Bahrain All Share index (39 listed equity). Moreover, we resort to Federal Reserve Economic data (FRED) in order to have access to selected variables that are considered in the literature as the main determinants of the stock market returns.

Focusing on the Gulf countries in this study is quite interesting for several reasons: First, the stock market of Gulf countries is representative for the market capitalization of the Middle East region. Besides, the market cap of those six countries represents 86% of the stock market in the Arab World countries. Second, the economic expansion of Gulf countries

[1] According to United Nartions Classifications, the number of Gulf countries is seven: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates and Yemen. We note that the Yemen has been excluded as it does not have a public stock market and the data is not available.

is critically interesting for worldwide countries. Gulf countries are considered as main exporters of Oil worldwide and their economic indicators as well as their stock markets have a substantial impact on the economic trends of the other nations (Awartani &. Maghyereh, 2013). Third, unlike most of stock market indices, the stock market index of Gulf countries is negatively correlated with the cryptocurrency index at high levels. We can note that for Qatar the correlation reached 89 percent over the period 2014-2019[2]. Fourth, unlike an important number of countries, the Gulf countries issued warnings of purchasing cryptocurrency (Global Legal Research Directorate, 2018)[3]. The reason behind this warning is hard to be totally explained. However, this warning is expected to remain on the long-run. In fact, one of the reasons that may explain this expectation is that in the Islamic faith, economic transactions should be mainly based on real assets. Speculation which includes cryptocurrency transactions is not compliant with the Sharia Law that represents the cornerstone of the laws in those countries.[4]

As the main methodology, the author implements at a first stage the fixed effect model in order to test whether the cryptocurrency market impacts the stock markets of the Gulf countries. The results of this stage show a negative and significant relationship between the two markets. To deal with endogeinty issues, the author implements Generalized Method of Moments Instrumental Variable (IV/GMM) technique at a second stage. The results remain robust, However, the significance and magnitude of the coefficients changed.

Finally, the results of this paper show that each 10 percent increase in the returns of the cryptocurrency market is associated with a 0.17 percent decrease in the returns of the stock market in Gulf countries. The Stock market and the cryptocurrency market are substitutes in Gulf countries. This study is considered as a prior research that takes into account the significance of the cryptocurrency market as one of the main determinants of stock market returns in the Gulf countries. In fact, the cryptocurrency market index is able to hamper the stock market indices in the Gulf countries.

The rest of the study is organized as follows: the next section provides the literature review related to the stock market returns. The third section is devoted to explaining the data and methodology. Empirical findings are provided in the fourth section. The last section of the study is devoted for conclusion and discussion.

[2] Authors' calculations using stock market indices and cryptocurrency prices of Qatar over the period 2014-2019, on a daily basis.
[3] https://www.loc.gov/law/help/cryptocurrency/cryptocurrency-world-survey.pdf
[4] https://qz.com/1247409/bitcoin-cryptocurrencies-for-muslims-backed-by-gold-are-popping-up/

2. Literature

As previously mentioned, it has been well documented in the literature that the stock market prices and returns are driven by four main factors: the fundamental factors, the technical factors, the market sentiment factors, and the anomalies.

The fundamental factors including the earning base and the valuation multiples are clearly developed in the existing literature. Higher earnings per share and price earnings ratio impact the stock market prices (Foster, 1973; Iliev 2010; Edmans & al., 2012)

Regarding the technical factors, for a purpose to conciliate the macroeconomic environment and the stock market, Shiller & Grossman (1980) introduced the interest rate as one of the main determinants of the stock market prices. Besides, disinflation and low interest rate were always considered to be associated with stock market booms, especially in the United States during 1990s (Anari & Kolari, 2001; Campbell and Vuolteenaho, 2004; Bordo & Wheelock, 2007). Other studies have been developed to include other macroeconomic determinants such as the exchange rate, the banking development, and the trade openness (Garcia & Liu, 1999; Ito $ Hashimoto, 2004; Pan & al., 2007; Bordo & al., 2009; Gorodnichenko, 2016).

For the market sentiment factor, the previous studies highlighted an important relationship between the animal spirits of investors and the stock market prices. These studies assume that the animal spirits are mainly driven by the media and the news that mainly draw the status of the external environment in the stock market (Antweiler & Frank ,2004; Tetlock, 2007).

Previous studies have also identified the impact of regular and precise events on the stock market prices and returns. In fact, several calendar year effects which include January, Holidays, day-of the week and others have been documented in the previous empirical studies. It is noticeable that the impact of these events is critically dependent on the sample period (Szakmary & Kiefer, 2004; Gerlach, 2010; Robins & Smith, 2017).

This paper extends the previous literature by including a fifth factor that significantly explains the stock market prices and returns which is the virtual money markets. The main assumption of this study is that virtual money markets appeared nowadays to compete with the stock market. Controlling for the classical factors mentioned by the literature, this study tests the impact of virtual money markets on the stock market returns. Conspicuously, the two main hypotheses of this study are:

H1: Cryptocurrencies are one of the determinants of the stock market returns in the Gulf countries.

H2: The investors in the Gulf countries face a tradeoff between investing in the Stock market and the Cryptocurrency market. Therefore, the two markets might be considered as substitutes for potential investors.

3. Data

As previously mentioned, we compile the stock market data, obtained from the indices of Gulf countries, with the cryptocurrency market data obtained from cryptocurrencycharts.com on a daily basis over the period 2014-2019. Following Baur & Dimpfl (2018), the indices of top 20 cryptocurrencies (in terms of market cap) have been implemented in the study. Stationarity tests and Unit Root tests have been implemented before any econometric applications. Moreover, the author obtained the macroeconomic data from the Federal Reserve Economic data (FRED) on the country level. The following table presents the main variables that will be implemented in the next section.

Table 1: Definition and source of variables

Variable	Definition	Source
Log Prices	Log of prices in the stock market basis over Gulf countries.	Historical indices of each country from the stock market data of the country.
Returns	Returns are constructed as follows: $\ln(\frac{Price_t}{Price_{t-1}})$	Authors' construction using indices of each country from the stock market data of the country.
Openness	This variable represents the share of exports and imports from GDP per country.	Authors 'construction using FRED database.
Log Oil Exports	Total Oil exports per country in barrels per day in logarithm.	FRED database.
Log GDP	Constant GDP per country in US dollars.	FRED database.
Inflation	The growth rate of consumer price index (CPI) based on 2011 prices per country.	FRED database.
Log Domestic Credit	Domestic Credit from banks to private sector in millions of US dollars in logarithm.	FRED database.
Log Cryptocurrency Prices	Log of cryptocurrency prices.	Cryptocurrencycharts.com
Cryptocurrency returns	Returns are constructed as follows: $\ln(\frac{Price_t}{Price_{t-1}})$	Authors' construction using indices cryptocurrency indices from Cryptocurrencycharts.com

The following table represents the main descriptive statistics of these variables:

Table 2: Descriptive statistics of the variables for 1984–2017

Variable	Mean	Standard Deviation	Min	Max
Prices	6126.70	3047.40	1092.02	14350.50
Openness	34.70	34.80	50.20	164.20
Log Oil	14.35	0.99	13.19	15.83
GDP constant	3.90	2.50	0.23	9.77
Inflation	1.87	1.27	-0.85	4.20
Domestic Credit	71.20	15.40	44.29	103.77
Cryptocurrency Prices	2633.40	3822.089	120	19379

4. Methodology

At a first stage, the author implements Least squares to find the impact of cryptocurrency market on the stock market returns in Gulf countries. For the purpose of controlling the unobserved heterogeneity across countries, the author implements, at a second stage, a fixed effect model. The estimated specification from the fixed effect model can be written as follows:

$$return_{i,d} = \alpha + \beta X_{i,t} + \Phi\ Crypto\ return_d + \gamma_i + \varepsilon_{i,d} \tag{1}$$

$return_{i,d}$ is the return of the stock market for the country (i)at the day (d). While, $X_{i,t}$ is a matrix that includes the set of observables per country on a yearly basis. Φ is considered as the coefficient that detects the elasticity of stock market returns to Cryptocurrency returns. γ_i represents the fixed effect country. Finally, $\varepsilon_{i,d}$ is assumed to be Independent Identically Distributed (IID). Conspicuously, we are estimating the following specification:

$$\begin{aligned} Return_{i,d} = \alpha + \beta_1 Openess_{i,t} + \beta_2\ Oil\ Exports_{i,t} + \beta_3 GDP\ capita_{i,t} + \beta_4 Inflation_{i,t} \\ + \beta_5\ Domestic\ Credit_{i,t} + \Phi\ Crypto\ return_d + \gamma_i + \varepsilon_{i,d} \end{aligned} \tag{2}$$

In order to control for potential endogeneity between the two markets, the author specifies an IV-GMM specification. Conspicuously, the endogeneity arises from the fact that stock market returns are likely to be affected by the cryptocurrency returns. IV-GMM model overcomes this limitation by instrumenting the cryptocurrency returns by its two lag values. Robustness tests of the instruments and methodology are provided in the next section (Hansen test, Paap LM test and Paap Wald test).

For IV-GMM model, the first stage is specified as follows:

$$Crypto\ return_d = \alpha + L.Crypto\ return_{d-1} + L2.\ Crypto\ return_{d-2} + v_d \tag{3}$$

$L.Crypto\ return_{d-1}$ and $L2.\ Crypto\ return_{d-2}$ represent the first lag and second lag of cryptocurrency returns respectively.

Then the new values of cryptocurrency returns are inserted into the following new equation:

$$\begin{aligned} Return_{i,d} = \alpha + \beta_1 Openess_{i,t} + \beta_2\ Oil\ Exports_{i,t} + \beta_3 GDP\ capita_{i,t} + \beta_4 Inflation_{i,t} \\ + \beta_5\ Domestic\ Credit_{i,t} + \Phi\ Crypto\ return_d + \gamma_i + \varepsilon_{i,d} \end{aligned} \tag{4}$$

Further tests to test the robustness of the final specification (IV-GMM) will be implemented. In particular, we resort to Hansen J Statistic (Over identification test for instruments), under identification test by Kleibergen-Paap LM Statistic and Kleibergen-Paap Wald (Weak identification test). The results of the tests show that instruments are significant and strong and the problem of endogeneity has been resolved.

5. Empirical Findings

Table (5) provides the main empirical findings of the specifications mentioned in the previous section. The first two specifications provide the results of first stage estimations without and with fixed effect country. While, the last specification provides the results of IV-GMM estimation after instrumenting the cryptocurrency returns by their lag values. It is noticeable that the impact of cryptocurrency returns remains the same across the three specifications. While, the sign and magnitude of some variables vary after controlling the country unobserved heterogeneity and the endogeneity problem.

All interpretations will be based on the results of IV-GMM model that provides robust standard errors and exogeneity of independent variables. This can be well detected from the statistics of the tests in the last equation. We note that Hansen J Statistic is not significant which means that the null hypothesis of valid instruments cannot be rejected. While, Kleibergen-Paap LM Statistic is significant and shows that the null hypothesis of under-identified model is rejected. Finally, Kleibergen-Paap Wald has a quite high F statistic with significant P-value, which shows that the instruments are not weak.

Regarding the interpretation of coefficients, first the macroeconomic variables provide estimations that go in parallel with the findings of the existing literature. In particular, trade openness shows a significant and positive impact on the stock market returns and investments[5]. Moreover, the oil exports variable plays a significant role in determining the stock market returns in the Gulf countries. These results are similar to existent studies on Gulf countries (Arouri & Rault, 2012). Economic growth is associated with a higher level of returns in the stock market and investments (Segal & al., 2015; Montout & Sami, 2016; Sami & Eldomiaty, 2019). Besides, the development of the banking sector has a significant and positive impact on the stock market returns. On the other hand, inflation hampers the stock market returns. More specifically, inflation may have a substantial negative impact on the profits, production of the operating firms which can be transmitted to income and employment levels in the economy (Campbell and Vuolteenaho, 2004; Said & al.,2019; Ayad & Abd El-Aziz, 2018; Sami & El Bedawy, 2019).

Finally, cryptocurrencies have an adverse effect on the stock market returns in Gulf countries. This finding can be detected from the three specifications of the empirical models. As previously mentioned, the coefficient from IV-GMM is considered as the preferred one as it is corrected from all endogeinty and unobserved heterogeinty biasness . The last column of table (5) shows that each 10 percent increase in the cryptocurrency market is associated with a decrease in the stock market returns by 0.17 percent. Therefore, the higher the returns in the cryptocurrency market, the lower the returns in stock market in Gulf countries.

This finding is considered as an indicator that the cryptocurrency market is able to hamper the stock market returns in Gulf countries. Investors in those countries consider the stock market and the cryptocurrency market as substitutes rather than complements. Future capital flows are likely to be directed away from investments into corporations in benefit of the cryptocurrencies markets. Following the portfolio selection theory introduced by Markowitz (1952), this study shows that the cryptocurrency is considered

[5] See (Braun & Raddatz 2005; Niroomand et al. 2014 and Said & al., 2018) for further details and explanations of such a relationship.

nowadays as a part of the portfolio of investors. As a result, the cryptocurrency is likely to affect their decision to invest in the stock market[6].

Table 3: Regression results (Dependent variable= Stock Market Returns)

	(1) OLS	(2) Fixed Effects	(3) IV-GMM
Openness	0.028*	0.046*	0.520***
	(0.024)	(0.046)	(0.046)
Log Oil Export	-0.139***	2.420***	1.872***
	(0.036)	(0.063)	(0.094)
Log GDP constant	0.373***	0.199***	0.594***
	(0.050)	(0.044)	(0.039)
Inflation	-3.244***	-2.397***	-0.365***
	(0.384)	(0.179)	(0.105)
Log Domestic Credit	-0.217***	0.048***	0.034***
	(0.035)	(0.009)	(0.013)
Cryptocurrency Returns	**-0.013*** (0.004)**	**-0.028*** (0.003)**	**-0.017*** (0.001)**
Constant	11.021*** (0.164)	-25.338*** (1.190)	
Observations	3,447	3,447	1,994
R-squared	0.23	0.68	0.63
Hansen J Statistic (P-value)	------	------	0.2651
Kleibergen-Paap LM Statistic (P-Value)	------	------	0.0000
Kleibergen-Paap Wald (F statistic)	------	------	205
Country FE	NO	YES	YES

HAC standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1), Number of observations has been reduced in the third specification as the first two Lags of Cryptocurrency Returns have been used as the main instruments to control the correlation between Cryptocurrency returns and residual term.

4. Conclusion and Discussion

This study provides an estimation of the impact of cryptocurrency market on the stock market returns in Gulf countries over the period 2014-2019. At a first stage this paper shows that the macroeconomic variables impact the stock market returns in Gulf countries. Oil exports, Openness to trade, GDP per capita and banking development have a significant positive impact on the stock market returns. While inflation impacts negatively the stock market returns. Moreover, the author shows that each 10 percent increase in the returns of cryptocurrency, the stock market returns in Gulf countries decreases by 0.17 percent.

Unlike other countries, the situation of Gulf countries is quite interesting as legalizing cryptocurrency in those countries is complicated. In the Islamic faith, economic transactions should be mainly based on real assets. The speculation which includes the cryptocurrency transactions is not compliant with Sharia Law that represents the cornerstone of laws in those countries. As noted by Milton Friedman (2004) "the world is

[6] See Frijns & al. (2008) for further details about the portfolio choice theory.

flat" and isolating the impact of cryptocurrency is complicated. Therefore, policy-makers in Gulf countries should take into account that the cryptocurrency market affects the stock markets in their countries, even if these speculations are considered illegal in those countries. Regulators and policymakers also are invited to review their monetary and financial system in the light of the rapid growth of the cryptocurrency market and the increasing interactions between their potential investors and such a market. Besides, it is important to note that the investors have now more options to diversify their portfolios. The choice of such a portfolio is becoming more complex, especially with the appearance of new potential channels of investments associated with potentially higher returns.

This research has its limitations: on one hand, the results are merely focusing on the Gulf countries and cannot be generalized to other countries. Studies in other regions and countries should be developed. In particular, distinguishing the relationship between the two markets is interesting if some studies were developed to distinguish between the countries that have a legal system and illegal system of cryptocurrency. On the other hand, due to data constraints, the period of study is covering 2014-2019. Further studies on the long run may be able to consider larger time spans.

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PRICE CLUSTERING AFTER THE INTRODUCTION OF BITCOIN FUTURES

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Abstract

Economic theory suggests that introduction of derivative contracts can improve the informational efficiency of the underlying asset prices (Danthine, 1978). In this study, we examine the impact of the introduction of Bitcoin futures on price clustering in Bitcoin. Our findings suggest that price clustering in Bitcoin meaningfully decreases after the introduction of its futures contracts.

Keywords: Bitcoin, Cryptocurrency, Futures, Market Efficiency, Price Clustering

JEL classification: G10, G11, G12, G14

1. Introduction

Economic theory asserts that derivative contracts, such as futures, tend to act as an information enhancement mechanism and provide stability to the underlying assets (Danthine, 1978). A broad stream of empirical literature lends support to this theory. For instance, Skinner (1989) and Conrad (1989) find a decrease in the variance of underlying equity prices following the introduction of derivative contracts. Similarly, Damodaran and Lim (1991) study the options listings on CBOE and AMEX and find that listing of options leads to decrease in variance and an improvement in informational efficiency of underlying stock prices.

In this study, we extend this line of literature and examine the impact of the introduction of Bitcoin futures on the clustering of Bitcoin prices. Price clustering, a term coined by Harris (1991), refers to the instances whereby certain (round) pricing increments tend to be more commonly observed than the others. Since changes in prices should follow a random walk, clustered prices question the process of price discovery and in turn the notion of market efficiency (Fama, 1970). This phenomenon of price clustering has been observed in various markets including commodities, currencies, equities and fixed income. Urquhart (2017) documents clustering in daily Bitcoin prices on round increments and attributes it to the negotiation hypothesis (Harris, 1991). Baig, Blau and Sabah (2019) find evidence of price clustering in Bitcoin at the intra-day level. Building on the works of Harris (1991), Baig and Sabah (2019) show that price clustering is due to uncertainty and stocks that are more heavily traded by informed investors such as short sellers have lower instances of price clustering. Since the introduction of Bitcoin futures on December 10th, 2017 exogenously increased the possibility of institutional ownership and short selling[1], we hypothesize that price clustering in Bitcoin should decrease following this event. In a related study, Köchling, Müller and Posch (2019) use various autocorrelation tests to show that the efficiency of Bitcoin prices improved following the launch of its futures contracts. Another study by Blau, Griffith and Whitby (2020) suggests that introducing futures contracts improved the informational environment of the entire cryptocurrency market.

Using intraday data from top five cryptocurrency exchanges, we investigate clustering in Bitcoin prices before and after introduction of Bitcoin futures at the CBOE. To the extent that the introduction of Bitcoin futures improved the price discovery process in Bitcoin markets, we should expect a decrease in price clustering in Bitcoin *Post* the introduction of its futures contracts. The results from various time-series tests suggest that price clustering in Bitcoin indeed decreases after the introduction of its futures. These results remain robust to corrections for heteroscedasticity and serial correlation. Our results are also robust to different time windows surrounding the introduction of Bitcoin futures. Our findings indicate that the introduction of Bitcoin futures makes the Bitcoin market more informationally efficient. Therefore, governments should carefully design Bitcoin-related regulation to ease the Bitcoin futures trading in order to protect the consumers and investors.

2. Data and Methodology

We gather transaction level bitcoin data from https://bitcoincharts.com. This website provides data in several currencies from different active and inactive exchanges. We collect Bitcoin/USD data for 88 exchanges and keep the top five exchanges based on daily average trading volume. These five exchanges are: Bitfinex, Bitsta, Mtgox, Coinbase, and Btce. Each transaction record contains date, time, price and volume. We collect Bitcoin market capitalization, average transaction fee and turnover from https://bitinfocharts.com. We delete observations with price less than five dollars. Bitcoin futures were first introduced on 10 December 2017. We collect data from one year before to one year after the introduction of Bitcoin futures. Thus, our final sample spans from 11 December 2016 to 10 December 2018.

From transaction level data, we create one daily measure of price clustering, *CL_Ratio*, for the Bitcoin prices. The variable captures the percentage of daily transaction occurs at round increment of $0.05. We calculate our control variables as follows: *Market_Cap* is the closing Price multiplied by number of Bitcoin outstanding, *Transaction_Fee* is the average transaction fee for all the Bitcoin transactions during the day. Turnover is the trading volume scaled by no. of Bitcoins. Range Volatility is *Log (Maximum Price) – Log (Minimum Price)* using daily prices.

3. Results

Table 1 provides the statistics that summarize the sample. The mean Bitcoin price clustering at round increments of $0.05 is about 35% in our sample. In a world where changes in prices follow a random walk the mean price clustering would be about 20%. So, we have an abnormal level of Bitcoin price clustering in our sample that is consistent

[1] Figlewski and Webb (1993) show that derivatives improve the informational and transactional efficiency of the stock market by inhibiting the constraints to short selling activity.

with previous studies. The mean values for volume, market capitalization, transaction fee, price, range volatility and turnover are 0.03 million, 95.79 billion, 3.82, $5659.60, 0.08 and 1.81 respectively.

Table 1: Summary Statistics

	BTC					
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	**Obs**	**Mean**	**Median**	**Std.Dev**	**Minimum**	**Maximum**
CL_ratio	502	0.35	0.36	0.05	0.23	0.48
Volume (million)	502	0.03	0.02	0.02	0.01	0.16
Market_Cap (billion)	502	95.79	108.31	64.09	12.41	315.52
Transaction Fee	502	3.82	1.24	7.37	0.26	55.16
Price	502	5659.60	6247.88	3794.31	774.08	19039.01
Range Volatility	502	0.08	0.07	0.06	0.01	0.43
Turnover (*1000)	502	1.81	1.50	1.22	0.34	10.82

The data for BTC has been sourced from 5 exchanges (Bitfinex, Bitstamp, Mtgox, Coinbase, Btce). *CL_ratio* is clustering ratio calculated as a proportion of trades in a day carried out at $0.05 increments scaled by total trades in that day. Volume is the trading volume in a day. *Market_Cap* is the total market capitalization on close of market in a day. Transaction fee is the average fees for the Bitcoin transactions. Price is closing price. Range Volatility is Log (Maximum Price) – Log (Minimum Price) for the day. Turnover is the daily trading volume scaled by total number of Bitcoin outstanding. The data period is 11 Dec 2016 to 10 Dec 2018

In our first set of tests we run a time series regression as follows:

$$CL\_\text{-}\ Ratio\_t=\beta\_0+\beta\_1\ Post\_t+\beta\_2\ LN\_\_\ MarketCap\_t+\beta\_3\ Price\_t+\beta\_4\ RangeVolatility\ Post\ t+\beta\_5$$

$$Turnover\_t+\beta\_6\ Transaction\ Fee\_t+\epsilon\_t \qquad (1)$$

Post is an indicator variable that takes a value of one *Post* the launch of Bitcoin futures on the CBOE on December 10th, 2017. Table 2 presents the results from the time-series regressions following equation 1. Column 1 presents the results for 3-months before and after sample period, column 2 presents the results for 6-months before and after sample period, column 3 presents the results for 9-months before and after sample period while column 4 presents the results for 12-months before and after sample period. We use Newy-West standard errors with up to 20 lags in all our regression specifications. Our results are also robust to Eicker–Huber–White standard errors. According to our hypothesis we should observe a decrease in price clustering in Bitcoin *Post* the implementation of its futures contracts. Therefore, we should observe a negative and significant *Post* coefficient. In columns 1 and 2 we observe economically strong but statistically insignificant negative coefficients on *Post*. In column 3 we observe a both economically and statistically significant negative coefficient on *Post*. In economic terms we see about a 3.7% decrease in price clustering in the 9 months following the launch of its futures. This price clustering phenomenon further significantly decreases by about 4.1% in the 12 months' horizon as shown in column 4.

In sum, our results from Table 2 suggest that price clustering indeed decreases for Bitcoin *Post* the launch of its futures contracts. This decrease becomes stronger across time and is strongest at the 12-month horizon. This is consistent with market participants requiring time to understand and fully utilize the opportunity to realize the benefits of the Bitcoin futures market.

Table 2: Bitcoin Time Series Regressions

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
	3 Months Before After	**6 Months Before After**	**9 Months Before After**	**12 Months Before After**
	CL_Ratio	*CL_Ratio*	*CL_Ratio*	*CL_Ratio*
Post	-0.014	-0.010	-0.037***	-0.041***
	(0.009)	(0.017)	(0.013)	(0.011)
LN_Market_Cap	0.094***	-0.036	-0.000	-0.032**
	(0.025)	(0.023)	(0.027)	(0.015)
Price	-0.000	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Range Volatility	0.036	0.086	0.009	-0.042
	(0.066)	(0.092)	(0.088)	(0.087)
Turnover	12.580***	14.143***	23.043***	22.584***
	(3.123)	(4.906)	(5.193)	(4.925)
Transaction Fee	-0.001***	-0.001***	-0.000	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
Constant	-2.017***	1.177**	0.300	1.070***
	(0.610)	(0.568)	(0.650)	(0.359)
NW SE	Yes	Yes	Yes	Yes
R-squared	0.6875	0.4171	0.4665	0.465
Observations	126	251	379	502

The data for BTC has been sourced from 5 exchanges (Bitfinex, Bitstamp, Mtgox, Coinbase, Btce). Post is a dummy variable that takes a value of 1 after December 10th, 2017 (introduction of Bitcoin futures) and zero otherwise. *CL_ratio* is clustering ratio calculated as a proportion of trades in a day carried out at $0.05 increments scaled by total trades in that day. Volume is the trading volume in a day. *LN_Market_Cap* is the natural log of total market capitalization on close of market in a day Transaction fee is the average fees for the Bitcoin transactions. Price is closing price. Range Volatility is Log (Maximum Price) – Log (Minimum Price) for the day. Turnover is the daily trading volume scaled by total number of Bitcoin outstanding. The data period is 11 Dec 2016 to 10 Dec 2018. Standard errors are corrected using Newey-West error corrections with 20 lags.

In our final tests, we attempt to remove any general time-trends in our price clustering series in order to more robustly identify the impact of the introduction of Bitcoin futures on the price clustering phenomenon. To do so we follow Rapach, Ringgenberg and Zhou (2016) and de-trend our *CL_Ratio* series as follows:

$$CL\_-Ratio\_t=\beta\_0+\beta\_1\ Time\_t+\epsilon\_t \qquad for\ Time=1,\dots,T \tag{2}$$

Time is a counter variable that counts time across our time-series. We estimate equation (2) using ordinary least squares (OLS) for our sample that spans from 11 December 2016 to 10 December 2018 and take the fitted residuals $\widehat{U}$, as our de-trended measure of price clustering in Bitcoin.

Next, we run the following OLS specification:

$$U\hat{}\_t=\beta\_0+\beta\_1\ Post\_t+\beta\_2\ LN\_\_MarketCap\_t+\beta\_3\ Price\_t+\beta\_4\ RangeVolatility\_t+\beta\_5\ Turnover\_t+\beta\_6\ Transaction\ Fee\_t+\epsilon\_t \tag{3}$$

The sample period ranges from 12-months before and 12-months after the launch of Bitcoin futures. Dependent variable $\widehat{U}$ is the fitted residuals series obtained from equation (2). Our main independent variable is *Post* which is an indicator variable that takes a value of one *Post* the launch of Bitcoin futures on the CBOE on December 10th, 2017. The remaining control variables are defined the same way as in the earlier sections. Our regression specifications in columns (1) and (3) report Newy-West corrected standard errors, while regression specifications (2) and (4) report Eicker–Huber–White corrections. Our results are also robust to the use of a Tobit model.

Table 3: De-trended price clustering regressions surrounding the introduction of Bitcoin futures

Panel A: Time Trend Regressions				
	TIME	**CONSTANT**	**OBSERVATIONS**	**R-SQUARED**
CL_RATIO	-0.000***	0.390***	502	0.152
	(0.000)	(0.004)		

Panel B: De-trended Price Clustering Regressions				
	(1) *CL_Ratio*	**(2)** *CL_Ratio*	**(3)** $\widehat{U}$	**(4)** $\widehat{U}$
Post	-0.041***	-0.041***	-0.016*	-0.016***
	(0.011)	(0.005)	(0.009)	(0.005)
LN Market Cap	-0.032**	-0.032***	-0.006	-0.006
	(0.015)	(0.006)	(0.014)	(0.005)
Price	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Range Volatility	-0.042	-0.042	-0.041	-0.041
	(0.087)	(0.079)	(0.079)	(0.073)
Turnover	22.584***	22.584***	21.593***	21.593***
	(4.925)	(4.625)	(4.618)	(4.419)
Transaction Fee	-0.001	-0.001**	-0.001**	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Constant	1.070***	1.070***	0.092	0.092
	(0.359)	(0.132)	(0.343)	(0.126)
SE Type	Newy-West	White	Newy-West	White
Observations	502	502	502	502
R-squared	0.465	0.465	0.424	0.424

CL_Ratio is clustering ratio calculated as a proportion of trades in a day carried out at $0.05 increments scaled by total trades in that day. Time is a counter variable. $\widehat{U}$ are the residuals from the regression of *CL_Ratio* on the time counter variable. Volume is the trading volume in a day. *LN_Market_Cap* is the natural log of total market capitalization on close of market in a day. Transaction fee is the average fees for the Bitcoin transactions. Price is closing price. Range Volatility is Log (Maximum Price) – Log (Minimum Price) for the day. Turnover is the daily trading volume scaled by total number of Bitcoin outstanding. The data period is 11 Dec 2016 to 10 Dec 2018. Standard errors are corrected using Newey-West error corrections with 20 lags in columns (1) and (3) and using White's corrections in columns (2) and (4).

Panels A and B of Table 3 report the results from the estimation of equations (2) and (3) respectively. In panel A we find a significant negative coefficient on the Time variable which suggests that price clustering has a general negative trend across our sample. According to our hypothesis Bitcoin price clustering should decrease *Post* implementation of its futures contracts and this decrease is independent of any general time-trend and is solely driven by the exogenous increase in synthetic short selling due to its futures. In panel B columns (3) and (4) we report the estimates from equation (3).

In column (3) we incorporate the Newy-West corrections and find that our main independent variable of interest *Post* a negative and significant coefficient of 0.016, this coefficient is significant at ten percent level. It suggests that price clustering in Bitcoin significantly decreases in the twelve months following the introduction of Bitcoin futures contracts. In column (4) we incorporate White's standard errors and find that *Post* has an economically similar negative coefficient but is statistically significant at one percent level. We note that our results in columns (3) and (4) are weaker in comparison to columns (1) and (2) where we have our original *CL-Ratio* as a measure of price clustering. This is consistent with the findings of equation (2) that, during our sample period, price clustering generally had a decreasing trend in Bitcoin markets. This result is consistent with the findings of Baig, Sabah and Winters (2019) who find a similar decreasing time-trend in price clustering in equities. These results also suggest several paths for future research. For instance, researchers could study and quantify the reasons of this negative time-trend in price clustering. Baig, Sabah and Winters (2019) suggest that this negative time-trend may be explained by an increase in algorithmic and high frequency trading (HFT) in equities. A similar comparison could be a valuable contribution to the cryptocurrency literature.

In sum, our findings suggest that Bitcoin price clustering indeed strongly decreases *Post* the launch of its futures. Moreover, this decrease in price clustering is not solely due to any general trend or economy-wide factor, instead, it is largely driven by the exogenous shock to Bitcoin prices due to the introduction of its futures contracts on the CBOE.

4. Conclusion

Urquhart (2017) documents clustering in bitcoin prices and attributes it to the negotiation hypothesis (Harris, 1991). Baig and Sabah (2019) find that short selling activity improves the informational efficiency of stock prices by reducing daily and intra-day price clustering. Derivatives are purported to reduce transaction frictions and improve price discovery process of the underlying security by reducing short selling constraints. To the extent that the introduction of Bitcoin futures improved the price discovery process in Bitcoin markets, we should expect a decrease in price clustering in Bitcoin post the introduction of its futures contracts. The results from various time-series tests suggest that price clustering in Bitcoin indeed decreases following the launch of its futures contracts.

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TIME-VARYING RISK AVERSION AND THE PROFITABILITY OF MOMENTUM TRADES

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Abstract

We show that time-varying risk aversion serves as a significant predictor of stock market momentum in the U.S. and globally. Risk aversion is found to be a robust predictor of momentum returns even after controlling for various well-established stock market predictors and absorbs the predictive power of market volatility. Finally, we show that conditioning momentum trades based on the risk aversion state can help improve the risk/return profile of the conventional momentum strategy.

Keywords: Momentum, Risk aversion, Anomalies

JEL: C20, G10

1. Introduction

Pioneered by the works of Jegadeesh and Titman (1993) and Asness (1994), the momentum effect in stock returns has remained a puzzle in the academic literature without a definitive explanation for why this well-studied anomaly persists in stock returns, both in the U.S. and globally. The attempts to explain this anomaly include (i) Daniel et al. (1998), Hong and Stein (1999) based on overconfidence and underreaction to information; (ii) Nofsinger and Sias (1999), Demirer and Zhang (2019a) based on herding behaviour among investors; (iii) Hong et al. (2000) via gradual information diffusion; (iv) Hvidkjaer (2006) and Sadka (2006) based on how small traders and noise traders react to information; in addition to the risk-based explanations in Jegadeesh and Titman (2001), Avramov and Chordia (2006) and Liu and Zhang (2008), among others. A growing strand of the asset pricing literature, however, establishes a link between investor sentiment and market anomalies like size, value and momentum (e.g. Baker and Wurgler, 2006; Frazzini and Lamont, 2008 and Antoniou et al., 2013). Given that investor sentiment is closely related to risk aversion (e.g. Bams, et al., 2017) and the evidence that links investor sentiment to herding and speculative behaviour in financial markets (e.g. Lemmon and Ni, 2011; Blasco et al., 2012), this paper utilizes the recently developed measure of time-varying risk aversion by Bekaert et al. (2017) and examines (i) the role of time-varying risk aversion as a predictor of momentum returns; and (ii) whether or not the predictive power of risk aversion can be exploited as part of an investment strategy to enhance the profitability of the conventional momentum strategy.

The literature has offered several explanations to link sentiment to momentum and reversals in returns, although largely from a behavioural perspective. Earlier studies including Nofsinger and Sias (1999) and Sias (2004) show that asset returns follow the herd, while other studies including Dasgupta et al. (2011), Singh (2013), and Brown et al. (2014) document return reversals as a result of herding. The rationale is that herding drives correlated trading behaviour among investors, thus reinforcing trades by informed traders based on past performance, mimicked by noise (sentiment) traders. Considering that sentiment is a driver of herding tendencies among investors (e.g. Chiang and Lin, 2019) and that sentiment is closely related to risk aversion (e.g. Bams, et al., 2017), one possible channel that links time-varying risk aversion to momentum is therefore herd formation among investors, driven by sentiment spillovers across investors. This argument is indeed supported by a number of studies including Brown and Cliff (2005) and Baker and Wurgler (2006) relating sentiment to the comovement in the demand shocks of noise traders, which in turn, results in persistent mispricing. Baker and Wurgler (2007) further argue that subsequent market correction results in the predictability of contrarian patterns as sentiment dissipates in the long run. Accordingly, the literature offers ample arguments that link changes in risk preferences (via sentiment) to momentum and reversals in financial markets.

Another line of research proposes the gradual diffusion of information across the more and less informed traders as a driver of momentum (e.g. Hong and Stein, 1999). The underlying idea is that underreaction to news that is not fully arbitraged away by momentum traders, who condition their trades on past prices and not on all public information, eventually leads to momentum cycles with short-term profits and long-term losses for those traders. Building on this argument, Antoniou et al. (2013) argue that sentiment can drive momentum by affecting the pricing of past winners and losers asymmetrically due to a combination of cognitive dissonance that slows the diffusion of information and short-selling constraints that impede arbitrage forces to operate, which in turn, results in asymmetries in how information is priced out for the past winner and loser stocks. Arguing that optimistic sentiment will slow the diffusion of bad news for loser stocks (and vice versa for good news for winner stocks when sentiment is low), Antoniou et al. (2013) show that momentum will be stronger during high sentiment (optimistic) periods due to more severe arbitrage constraints as arbitrage would involve costly short selling of loser stocks during optimistic states.

In the case of the emerging literature on risk aversion, a number of recent studies establish a close link between time-varying risk aversion and a global financial cycle that drives capital flows and stock market valuations (e.g. Miranda-Agrippino and Rey, 2015; Rey, 2018). Xu (2017)and Demirer et al. (2018) further show that risk aversion serves as a significant driver of return comovement across global stock markets. Clearly, from an economic perspective, one can establish a close link between changes in investors' risk appetite and their tendency to be involved in risky trades such as momentum trading. This argument is indeed supported by the evidence that links investor sentiment to herding and speculative behaviour in financial markets (e.g. Lemmon and Ni, 2011; Blasco et al., 2012). Furthermore, given the recent evidence in Demirer and Zhang (2019b) that investor herding significantly contributes to stock market momentum, particularly via its effect on how past loser stocks perform in subsequent periods, one can argue that the market's state with regards to the level of risk aversion can explain (perhaps predict) the profitability of momentum trades as investors' tendency to herd would be closely linked to changes in risk attitudes.

Clearly, as Guiso et al. (2018) note, risk aversion can fluctuate due to changes in wealth, background risk, and emotions that alter risk appetite. To address this distinction, Bekaert et al. (2017) derive a formulation for time-varying risk aversion based on a utility function in the hyperbolic absolute risk aversion (HARA) class. As the authors note, this measure of risk aversion that we utilize in our tests distinguishes the time variation in economic uncertainty (i.e. the amount of risk) from the time variation in changes in risk preferences (i.e. the price of risk). To that end, the availability of the measure of time-varying risk aversion presents an interesting opening, allowing us to examine the role of risk aversion as a determinant of momentum returns independently from the effect's economic uncertainty.

Examining monthly momentum returns for the U.S. and global stock markets, our findings suggest that time-varying risk aversion indeed plays a primary role in the subsequent performance of momentum trades. While positive market states contribute to the profitability of momentum trades, we also find that momentum payoffs are significantly greater during periods of low-risk aversion, consistently both in the U.S. and globally. Further analysis shows that time-varying risk aversion absorbs the predictive power of market volatility as a predictor and is robust to the inclusion of various well-established stock market predictors in our models. Finally, we show that the predictive power of risk aversion over momentum returns can be exploited in a conditional momentum strategy based on the level of risk aversion. We observe that the conditional momentum strategy offers a more favourable risk-adjusted return (implied by the information ratio) compared to the conventional momentum strategy, suggesting that conditioning momentum trades based on the risk aversion state can help improve the risk/return profile of the conventional momentum strategy. The remainder of the paper is organized as follows. Section 2 discusses the data and methodology. Section 3 presents the empirical results and Section 4 concludes.

2. Data and Methodology

We utilize monthly Fama-French U.S. and global (ex U.S.) momentum returns over January 1991 through December 2016, obtained from Kenneth French's data library.[1] The time-varying risk-aversion series, originally developed by Bekaert et al. (2017), is obtained from Nancy Xu's website.[2] Based on a set of six financial instruments including term spread, credit spread, a detrended dividend yield, realized and risk-neutral equity return variance and realized corporate bond return variance, this recently proposed measure of risk-aversion distinguishes the time variation in economic uncertainty (the amount of risk) from time variation in risk aversion (the price of risk), thus provides an unbiased representation of dynamic changes in the risk preferences of investors in financial markets. Our sample period is governed by the availability of the risk aversion data. As will be discussed later, we also use several control variables in our predictive regressions, based on the well-cited study of Goyal and Welch (2008).[3]

We first examine mean Fama-French U.S. (*USmom*) and global momentum (*Gmom*) returns during high vs low-risk aversion states. We define a month to be in high (low) risk aversion state if the lagged 3-month risk aversion is greater (smaller) than the lagged 12-month risk aversion.[4] In addition, following Wang and Xu (2015), we define a month to be in a positive (negative) market state if the lagged 36-month market return is positive (negative).[5] We then perform a two-way sort based on market and risk aversion states, allowing us to see if momentum payoffs vary with risk aversion state after controlling for the market state. Next, we run various predictive regressions in the form

$$mom_t = a + b \cdot X_{t-1} + \varepsilon_t \tag{1}$$

[1] Data publicly available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[2] We thank Nancy Xu for providing the data on risk aversion https://www.nancyxu.net/risk-aversion-index.
[3] Data on predictor variables are available on Amit Goyal's website at http://www.hec.unil.ch/agoyal/.
[4] Robustness checks with alternative lags for the risk aversion index to determine the risk aversion state yield similar results and are available upon request.
[5] Note that we have two different proxies for markets returns, U.S and global market returns obtained from Ken French's website, to examine U.S. and global momentum, respectively.

where *mom* is the U.S. (global) momentum return in month t, and X_{t-1} is the set of predictor variables. The predictors include MKT (lagged 36-month return), VOL (lagged 12-month market volatility), default spread, term spread, Treasury yield, and dividend yield for month *t-1*. Finally, risk aversion is the lagged 3-month risk aversion index to be consistent with our earlier definition of high/low-risk aversion states.[6]

3. Empirical Results

Table 1 presents the mean momentum payoffs obtained from two-way sorts. We observe in Panel A that both U.S. and global momentum payoffs are significantly higher during periods of low-risk aversion. For example, mean U.S. momentum payoffs are 0.917% and -0.259% during low and high-risk aversion periods, respectively. Comparing the results in Panels B and C, consistent with Wang and Xu (2015), higher momentum payoffs are found during positive market states. However, when we further sort the samples based on the level of risk aversion, we see that low-risk aversion is the primary determinant of momentum profitability, particularly for the U.S.

Table 1: Momentum during high and low-risk aversion states

	U.S. Momentum			Global Momentum (ex U.S.)		
Panel A: Mean returns conditional on the level of risk aversion						
	Overall	**High R.A.**	**Low RA**	**Overall**	**High R.A.**	**Low R.A.**
Mean	0.476*	-0.259	0.917***	0.708***	0.443	0.866***
t-stat	(1.720)	(-0.460)	(3.210)	(3.450)	(1.150)	(3.700)
N	312	117	195	312	117	195
Panel B: Mean returns during POSITIVE market states, conditional on the level of risk aversion.						
	Overall	**High R.A.**	**Low RA**	**Overall**	**High R.A.**	**Low R.A.**
Mean	0.771***	0.284	1.065***	0.956***	0.906***	0.988***
t-stat	(2.950)	(0.600)	(3.470)	(4.440)	(2.920)	(3.370)
N	263	99	164	229	89	140
Panel C: Mean returns during NEGATIVE market states, conditional on the level of risk aversion.						
	Overall	**High R.A.**	**Low RA**	**Overall**	**High R.A.**	**Low R.A.**
Mean	-1.108	-3.249	0.136	0.022	-1.029	0.557
t-stat	(-1.050)	(-1.290)	(0.180)	(0.050)	(-0.830)	(1.540)
N	49	18	31	83	28	55

Note: This table reports the mean U.S. Fama-French (*USmom*) and global (*Gmom*) momentum returns for the period January 1991 through December 2016. Panel A reports the mean momentum returns independent of market state, however conditional on high and low-risk aversion. We define a month to be in high (low) risk aversion state if the lagged 3-month average risk aversion is greater (smaller) than the lagged 12-month average risk aversion. Panels B and C report the momentum returns during positive and negative market states, respectively, conditional on high and low-risk aversion. A month is in positive (negative) market state if the lagged 36-month market return is positive (negative). The panel reports the results from two-way sorts for the market state and risk aversion state. The t-stats (in

[6] For robustness, we have also tried alternative definitions for risk aversion and found qualitatively similar results. Results are available upon request.

parenthesis) and number of observations (N) are reported for each group. ***,**, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Interestingly, in Panel C, we observe positive mean momentum payoffs during low-risk aversion months even when the market is in a negative state, providing the initial evidence that risk aversion can indeed be the primary driver of momentum payoffs even after controlling for the state of the market. This evidence is further supported visually in Figures 1a and 1b with positive spikes in lagged risk aversion values associated with major crashes in momentum payoffs in both plots. Likewise, we observe that downward movements in risk aversion values are closely linked to positive spikes in momentum payoffs.

Figure 1a: Monthly U.S. momentum returns and lagged risk aversion.

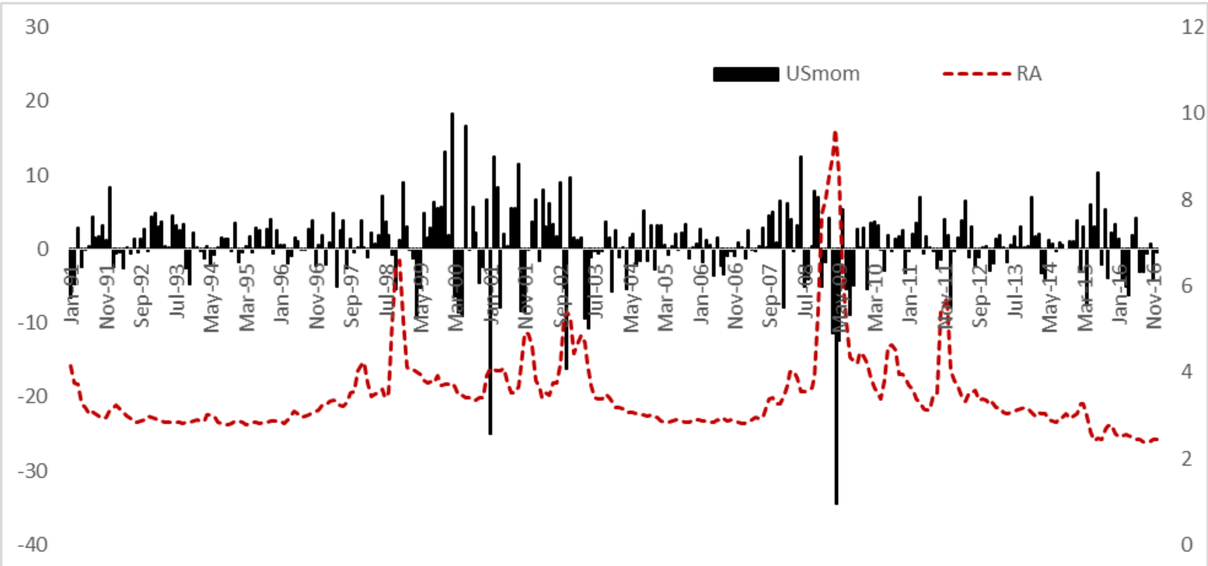
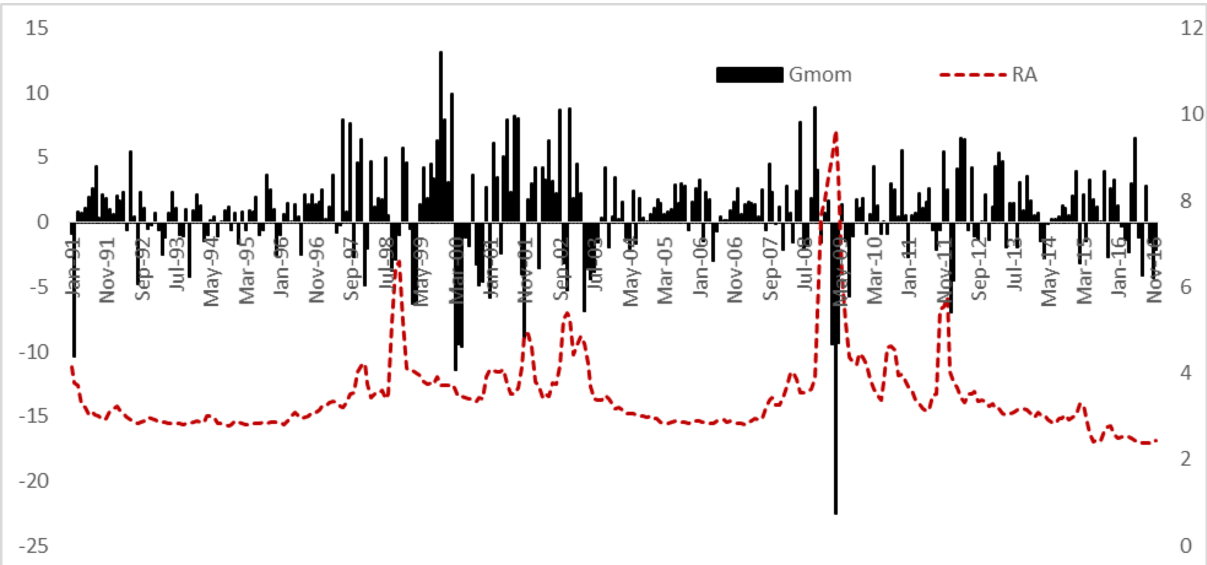


Figure 1b: Monthly global momentum returns and lagged risk aversion



Note: The figures plot monthly U.S. (*USmom*) and global (*Gmom*) momentum returns along with lagged risk aversion (R.A.). Risk aversion series is computed as the average risk aversion over months (t, t-3).

The formal predictive tests, presented in Table 2, further confirm the predictive power of risk aversion over momentum returns both for the U.S. and global markets. While the market return (MKT) positively predicts momentum returns, consistent with the results in Table 1 (and those documented in Wang and Xu, 2015), we observe that risk aversion is a significant, negative predictor for momentum payoffs. Interestingly, while market volatility (VOL) comes out significant when used in the model alone, it loses its significance when risk aversion is introduced to the model, suggesting that risk aversion absorbs the predictive power of market volatility. Finally, we see that risk aversion remains highly significant even after controlling for various stock market predictors based on Goyal and Welch (2008). Overall, our findings show that risk aversion is a robust predictor of momentum returns, with a high level of risk aversion predicting negative momentum payoffs.

Table 2: Predictive Regressions

	U.S. Momentum					Global Momentum (ex U.S.)		
MKT	1.179***		0.634	1.426***	0.637**		-0.019	0.672
	(3.33)		(1.65)	(2.91)	(2.19)		(-0.05)	(1.53)
VOL		-0.445***	0.236	-0.094		-0.409***	-0.134	-0.133
		(-2.64)	(1.05)	(-0.39)		(-3.06)	(-0.75)	(-0.71)
Risk			-1.371***	-1.292***			-0.727***	-0.738**
Aversion			(-3.66)	(-2.97)			(-2.70)	(-2.20)
Default				1.167				0.562
Spread				(1.08)				(0.70)
Term				0.899**				0.637**
Spread				(3.11)				(2.57)
Treasury				-0.123				-0.001
Yield				(-1.12)				(-0.01)
Div Yield				-0.109***				-0.081***
				(-3.75)				(-3.38)
Intercept	-0.562	2.233***	3.759***	-17.337***	0.333	2.493***	3.881***	-12.470***
	(-1.36)	(3.10)	(3.04)	(-3.11)	(1.17)	(4.05)	(3.63)	(-2.69)
N	312	312	312	312	282	282	282	282
Adj. R^2	0.032	0.019	0.073	0.111	0.013	0.029	0.048	0.082

Note: The table reports the results of the predictive regressions of U.S. (*USmom*) and global (*Gmom*) momentum returns against risk aversion, after controlling for various predictors. MKT is the lagged 36-month stock market return, and VOL is the lagged 12-month stock market volatility. Stock market variables are based on the U.S. (Global) market index when the dependent variable is *USmom* (*Gmom*). Risk Aversion (R.A.) is the lagged 3-month average of the risk aversion index. Control predictor variables include lagged values for Default_Spread, Term_Spread, Treasury_Yield, and Div_Yield based on Goyal and Welch (2008). ***,**, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

As noted earlier, the literature offers ample evidence that links investor sentiment to stock market momentum and reversals, largely from a behavioural perspective. Therefore, to explore the possible role of sentiment in our predictive models, we utilize two alternative sentiment proxies that are well-cited in the literature, namely the sentiment indexes by Baker and Wurgler (2006) and Huang et al. (2015).[7] Table 3 presents the results.

Table 3: Controlling for Sentiment

	U.S. Momentum				Global Momentum (ex U.S.)			
	M1	M2	M3	M4	M5	M6	M7	M8
MKT		1.454***		1.408***		0.653		0.672
		(2.93)		(2.86)		(1.46)		(1.53)
VOL		-0.107		-0.125		-0.105		-0.144
		(-0.43)		(-0.51)		(-0.55)		(-0.76)
Risk Aversion		-1.283***		-1.269***		-0.623*		-0.686*
(R.A.)		(-2.76)		(-2.73)		(-1.74)		(-1.96)
PLS	0.565	-0.505			0.219	-1.757		
	(1.32)	(-0.21)			(0.69)	(-0.96)		
PLS * R.A.		0.248				0.484		
		(0.40)				(1.03)		
BWS			0.937**	-0.362			0.617*	-1.438
			(2.09)	(-0.15)			(1.86)	(-0.74)
BWS * R.A.				0.202				0.485
				(0.32)				(0.98)
Default Spread		1.173		1.49		0.237		0.935
		(1.01)		(1.30)		(0.27)		(1.11)
Term Spread		0.888***		0.927***		0.652***		0.643**
		(2.98)		(3.12)		(2.62)		(2.49)
Treasury Yield		-0.120		-0.111		-0.009		0.013
		(-1.08)		(-1.00)		(-0.10)		(0.15)
Div Yield		-0.101***		-0.103***		-0.079***		-0.064**
		(-3.37)		(-3.32)		(-3.16)		(-2.35)
Intercept	0.554*	-16.034***	0.249	-16.847***	0.738***	-12.633**	0.558**	-10.181**
	(1.96)	(-2.76)	(0.402)	(-2.90)	(3.51)	(-2.57)	(2.54)	(-2.02)
N	312	312	312	312	312	282	312	282
Adj. R^2	0.002	0.108	0.011	0.107	-0.002	0.079	0.008	0.082

Note: The table reports the results of the predictive regressions of U.S. (*USmom*) and global (*Gmom*) momentum returns against risk aversion, after controlling for various predictors. MKT is the lagged 36-month stock market return, and VOL is the lagged 12-month stock market volatility. Stock market variables are based on the U.S. (Global) market index when the dependent variable is *USmom* (*Gmom*). Risk Aversion (R.A.) is the lagged 3-month average of the risk aversion index. B&W Sentiment (**BWS**) is the investor sentiment of Baker and Wurgler (2006), and **PLS** is the sentiment index of Huang et al. (2015). Consistent with the construction of R.A., we use the lagged 3-month average of both proxies for investor sentiment. Control predictor variables include lagged values for Default_Spread, Term_Spread, Treasury_Yield, and Div_Yield based on Goyal and Welch (2008). ***,**, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

While the PLS sentiment index of Huang et al. (2015) is not significant by itself in Models 1 and 5, we see in Models 3 and 7 that the sentiment proxy of Baker and Wurgler (2006) indeed has predictive power over momentum returns. However, we also see in Models 2, 4, 6 and 8 that

[7] We thank an anonymous reviewer for the suggestion to control for sentiment.

risk aversion retains its predictive power even in the presence of sentiment proxies. It must, however, be noted that the sentiment proxies of Baker and Wurgler (2006) and Huang et al. (2015) are, by construction, based on the information contained in the closed-end fund discount rate, share turnover, number of initial public offerings (IPOs), first-day returns of IPOs, dividend premium, and the equity share in new issues. As Huang et al. (2015) note, the predictive power of these sentiment indexes is primarily driven by the cash-flow channel and not the discount rate channel that relates to changes in risk preferences. Given our findings in Table 3, one can argue that risk aversion indeed captures the time variation in discount rates that is driven by the changes in risk preferences.

To provide further insight into the risk aversion-momentum relationship, we present in Table 4, the results of the predictive regressions for winner and loser portfolio returns separately. Winner (loser) portfolios refer to the highest (lowest) decile portfolios sorted on their past returns as computed by Ken French. The findings in Table 4 suggest that the predictive power of risk aversion over momentum profitability largely stems from the predictive information it captures over the performance of past loser stocks.

Table 4: Asymmetric Predictability.

	U.S. Momentum		**Global Momentum (ex U.S.)**	
	Winner Stocks	**Loser Stocks**	**Winner Stocks**	**Loser Stocks**
MKT	-0.408	-1.834***	-0.335	-1.016
	(-0.79)	(-2.77)	(-0.57)	(-1.49)
VOL	0.329	0.423	-0.064	0.0678
	(1.31)	(1.32)	(-0.26)	(0.23)
Risk Aversion	1.113**	2.405***	0.482	1.223**
	(2.42)	(4.09)	(1.08)	(2.35)
Default Spread	-4.732***	-5.899***	-1.201	-1.763
	(-4.14)	(-4.04)	(-1.12)	(-1.41)
Term Spread	-0.359	-1.258***	-0.029	-0.667*
	(-1.17)	(-3.22)	(-0.09)	(-1.73)
Treasury Yield	-0.079	0.044	0.023	0.023
	(-0.68)	(0.29)	(0.19)	(0.17)
Div Yield	0.085***	0.194***	0.027	0.108***
	(2.79)	(4.96)	(0.86)	(2.92)
Intercept	16.72***	34.059***	5.609	18.094**
	(2.83)	(4.52)	(0.90)	(2.51)
N	312	312	282	282
Adj. R^2	0.042	0.121	-0.016	0.049

Note: The table reports the results of the predictive regressions of U.S. (*USmom*) and global (*Gmom*) winner and loser portfolio returns against risk aversion, after controlling for various predictors. Winner (loser) portfolios refer to the highest (lowest) decile portfolios sorted on their past returns. MKT is the lagged 36-month stock market return, and VOL is the lagged 12-month stock market volatility. ***,**, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

We observe that risk aversion positively predicts the subsequent performance of past losers, even after controlling for the other traditional predictors employed in the literature. While dividend yield seems to be a robust predictor for both U.S. and global loser portfolios, risk aversion is also found to capture positive predictive power over the subsequent performance of loser portfolios for the U.S. and global markets. Interestingly, in the case of the U.S., risk aversion comes out as a significant predictor for both the winner and loser portfolios; however, considering that the predictive coefficient is larger for loser portfolios (2.405) compared to winner portfolios (1.113), we conclude that the negative predictive power of risk aversion over momentum returns is primarily driven by its positive predictive power over the subsequent performance of loser stocks.

Finally, we examine whether the predictive power of risk aversion over momentum returns has any economic implications. For this purpose, given the finding that high-risk aversion predicts lower momentum returns, we propose a conditional (based on risk-aversion) momentum strategy that adopts a contrarian strategy (i.e. buy loser and sell winner stocks) at the beginning of month (t), if risk aversion is high over the preceding 3 month period; otherwise, adopt the conventional momentum strategy. In this strategy, the decision is made at the beginning of month t given the level of risk aversion in the previous period and the switch to the contrarian strategy when the market is in high-risk aversion state is based on the negative predictive relationship between risk aversion and momentum returns so that high-risk aversion predicts lower momentum returns.

Table 5: The out-of-sample performance of the risk aversion-based momentum strategy

	U.S.		Global (ex U.S.)	
	Conditional Momentum	**Conventional Momentum**	**Conditional Momentum**	**Conventional Momentum**
Panel A: Risk aversion state based on the past 3-month average				
Mean	1.016%	0.476%	0.718%	0.708%
Std. Deviation	4.408%	4.899%	4.279%	3.626%
Information Ratio	0.231	0.097	0.168	0.195
Panel B: Risk aversion state based on the past 6-month average				
Mean	1.155%	0.476%	1.03%	0.708%
Std. Deviation	4.189%	4.899%	3.948%	3.626%
Information Ratio	0.276	0.097	0.261	0.195

Note: The table reports the average monthly out-of-sample payoffs for the conditional (based on risk-aversion) momentum strategy and the conventional momentum strategy. The conventional momentum strategy buys (sells) past winner (loser) stocks based on past performance over months (t-2, t-12). The conditional (based on risk-aversion) momentum strategy adopts a contrarian strategy (i.e. buy loser and sell winner stocks) at the beginning of month (t), if risk aversion is high over the preceding 3-month period; otherwise, adopt the conventional momentum strategy. **Mean** and **Std. Dev.** are the mean and the standard deviation of monthly returns for the corresponding investment strategy. **Information ratio** is computed as the ratio of mean return to standard deviation. Panels A and B report the findings when the risk aversion state is defined based on the average risk aversion for the past 3 and 6 months, respectively, compared to the average 12-month risk aversion.

Table 5 reports the average monthly out-of-sample payoffs for the conventional and the conditional momentum strategy based on risk-aversion. For robustness checks, Panels A and B in the table report the findings when the risk aversion state is defined based on the average risk aversion for the past 3 and 6 months, respectively, compared to the average 12-month risk aversion. We observe that the conditional momentum strategy offers a more favourable risk-adjusted return (implied by the information ratio) compared to the conventional momentum strategy, suggesting that conditioning momentum trades based on the risk aversion state can help improve the risk/return profile of conventional momentum trades. Accordingly, one can conclude that the predictive power of time-varying risk aversion over momentum returns has significant economic implications with the potential to improve the profitability of the conventional momentum strategy.

4. Conclusion

This paper examines the predictive power of time-varying risk aversion over the profitability of momentum strategies for the U.S. and globally. We show that risk aversion is a robust predictor of momentum returns even after controlling for various well-established stock market predictors and the market state. Further analysis shows that risk aversion absorbs the predictive power of market volatility and negatively predicts subsequent momentum returns. Examining possible asymmetries in predictability patterns, we further find that the negative predictive power of risk aversion over momentum returns is primarily driven by its positive predictive power over the subsequent performance of past loser stocks. Finally, our findings indicate that the predictive relationship between time-varying risk aversion and momentum returns can be exploited in a conditional strategy based on the level of risk aversion, implied by improved risk/return tradeoffs offered by the conditional momentum strategy compared to the conventional momentum strategy. For future research, it would be interesting to examine investor holding data and explore whether changes in risk aversion affect buy and sell trades for past loser and winner stocks in an asymmetric manner during high and low-risk aversion states as noted by Antoniou et al. (2013).

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THE COST OF INNOVATION AND DECREASING BOOK EQUITY OF U.S. FIRMS

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Abstract

This study documents that book equity of U.S. firms has decreased dramatically over time and such decrease is systematic across various industries and firm size. Our analysis shows that intangible capital investment explains a significant portion of the decrease in book equity even after controlling for the concurrent effect of leverage and profitability on book equity, and the effect of intangible capital investment on book equity increased in recent years. Further analysis shows that intangible capital contributes to a decrease in book equity mostly through the channel of changing firm characteristics rather than changing sensitivity over time. Our findings suggest that investors must incorporate the effect of intangible capital investment into their valuation analysis, as indexes or investment strategies relying on indicators constructed by book equity may be biased and misleading.

Keywords: Book Equity, Intangible Assets, Innovation

JEL: G30, G31

1. Introduction

Many of America's largest companies currently have a book value that is small relative to their market value. Some firms[1], including AutoZone and McDonald's, even report a negative book value. Such empirical regularity has been noticed by some recent studies. For example, Jan and Ou (2012), Brown et al. (2008) and Luo et al. (2019) have documented the systematic increase in the frequency of firms with negative book equities across various industries and sizes. Although negative book equity firms are extreme examples, the rapid increase in such firms may indicate a shift in or reshaping of entire distributions of book equity of U.S. firms, a topic that has not been discussed in prior literature. Our study is thus motivated to fill this gap by studying aggregate trends in the book equity (B.E.) of U.S. firms over the past four decades. Specifically, our paper intends to address the following general questions: Has the book equity of U.S. firms systematically decreased over time? If so, what are the possible driving forces?

[1] Other noticeable long-time negative book equity firms include Revlon and DirecTV before it merged with AT&T

In our analysis, we first document that the book equity (B.E.) of U.S. firms has been consistently decreasing since the 1960s. The average book equity of U.S unregulated firms decreased from 61% of total asset in 1960 to 43% in 2017. Such a decrease is prevalent among firms from different industries and with different size in a consistent pattern. There are a few potential reasons that can be implied from previous literature for such a trend. First of all, it is well documented in finance and accounting literature [2]that the frequency of reported losses has increased significantly over recent decades. The systematic decrease in earnings on income statement may lead to a decrease in book equity on the balance sheet through decreased retained earnings. Secondly, as pointed out by Graham et al. (2015), unregulated firms dramatically increased their debt financing, and aggregate leverage of U.S. firms more than tripled over the past century. As corporate debt financing squeezes the room for equity financing in firms' capital structure, it is not surprising to observe the decreasing trend of book equity along with the increasing trend of leverage.

In this paper, we argue that another possible reason for decreasing B.E. is the increased impact of intangible capital investment. Specifically, we contend that, although profitability and leverage are important determinants of firms' book equity, firm's investment on intangible capital also play a critical role in regulating its book equity even after controlling for the effect of profitability and leverage. As a gauge of a firm's net asset, book equity should proxy for the abandonment value of firms because the bulk of book value is made up by fixed capital assets, such as factories, machines, land and office buildings, as well as current assets. Such proxy works fine in the non-digital age when firms' assets are mostly tangibles. However, as we are moving toward a knowledge-based economy, the complexity of valuing a firm's assets has increased dramatically, and problem raises with the old book equity measurement due to what it leaves out: investment in knowledge and intangibles such as human capital, research and development, and relationships with customers and suppliers. By their nature, these intangible assets are difficult to value and are not directly reflected by book equity. Nonetheless, the heavy research, marketing, and networking activities cause firms to incur expenditure which will reduce the tangible assets on the balance sheet while creating an off-balance sheet intangible asset. The more intangible assets that a firm acquires or develops, the faster book value of equity should decrease. As a result, we should obtain a negative relationship between intangible capital investment and book equity.

To test this conjecture, we use a newly developed proxy for intangible capital by Peter and Taylor (2017) and investigate how it related with book equity using a sample of non-regulated firms over past four decades. Our main findings confirm that a significant portion of the secular decrease in B.E. can be explained by an increase in intangible capital under various model specifications. In addition, we find that the explanatory power of intangible capital has been increasing over time, and there is a fundamental shift in the sensitivity of B.E. to intangible capital investment. In further analysis, we isolate the effect of changing firm characteristics from that of changing sensitivity of explanatory variables and show that both are important to explain the variation of B.E. in our sample.

Our findings have several empirical implications. First, BE is widely used by investors to differentiate value stocks from growth stocks in the form of price-to-book ratios. Although many previous studies have shown that buy-and-hold value stocks represent

[2] See Collins et al. (1999), Burgstahler and Dichev (1997) and Barth et al. (1998)

a winning strategy, recent findings suggest that value stocks have lagged behind the general market and are far behind growth stocks. Our finding suggests that such empirical observations may be due to measurement errors, as the B.E. of U.S. firms has systematically changed over time. Second, our intangible-capital-based explanation suggests that the increasing discrepancy between market value and book value is due to the intangible nature of investment in knowledge and human capital. As the industrial age gives way to the digital age, intangible capital investment matters increasingly as the crucial driver of corporate innovation and its long-term viability. As a result, accounting rules must be modified so that book value can reflect past intangible capital investment activities for more useful comparisons across stocks.

We organize the remainder of the paper as follows. Section 2 provides an overview of the long-term trend of book equity. In section 3, we develop and test main hypotheses using various model specifications—section 4 focus on identifying and quantifying driving forces of decreasing book equity. Then we performed a robustness check in Section 5. Conclusions are in Section 6.

2. An Overview of Long-Term Trend of Book Equity

We start with an overview of the long-term trend of book equity for unregulated U.S firms. In this analysis, our sample comprises public-traded firms, excluding financial (SIC codes 6000-6999), utility (SIC codes 4900-4999), firms classified as public service, international affairs, or non-operating establishments (SIC codes greater than 9000)[3] and non-US firms (FIC = USA), from 1960 to 2017. Following previous literature (Fama and French, 2008), the book equity is defined as the sum of shareholders' book equity and balance sheet deferred taxes and investment tax credit, subtracting the book value of preferred stock. We standardize B.E. using the total asset.

Figure 1 shows the B.E. has decreased significantly between 1960 and 2017. Average (Median) BE dropped by nearly 26% (23%), from 0.61 (0.62) in 1960 to 0.45 (0.48) in 2017. To test whether such a decrease is industry-specific, in Figure 2, we evaluate the trend across different industry classifications (defined as in Fama-French 12 industry codes). The results suggest that the secular decrease in book equity is persistent for firms from all industries and that such trend is more pronounced for firms within industries that have gone through technological transformation or known for R&D intensive, such as the manufacturing (FF12=3), chemical (FF12=5), pharmaceutical (FF12=10) and Information Technology (FF12=7) industries. In particular, for the information technology industry, the B.E. is consistently lower than in other industries and continue decreasing. The findings from Figure 2 suggest that one possible explanatory factor for decreasing B.E. over time is intangible-driven innovation: in an increasingly knowledge-based economy, typical firms switch from investing in tangible assets to intangible assets. Under current accounting rules, however, intangible investments are expensed rather than capitalized for most firms. As a result, balance sheets fail to reflect the true value of B.E., especially for firms heavily invested in unrecorded intangible capital.

It is also possible that observed long term trend of B.E. is driven by firms with a particular size. In figure 3, we further examine the trend of B.E. by firm size quintiles. Firm size is

[3] This sample restriction is required by Peter and Taylor (2017) in order to use their intangible capital investment measurement.

measured by sales standardized by total assets. Figure 3 illustrates the time series trend of average B.E. sorted by firm size quintiles during our sample period. Similar to Figure 1 and Figure 2, we observe that B.E. decreased over time in all firm size quintiles. In particular, the decrease in B.E. is more pronounced for firms fall into top and bottom size quintiles. Also, the B.E. for the largest firms in our sample (quintiles=5) is systematically lower than that of relatively smaller firms.

Figure 1: The secular trend in book equity overtime

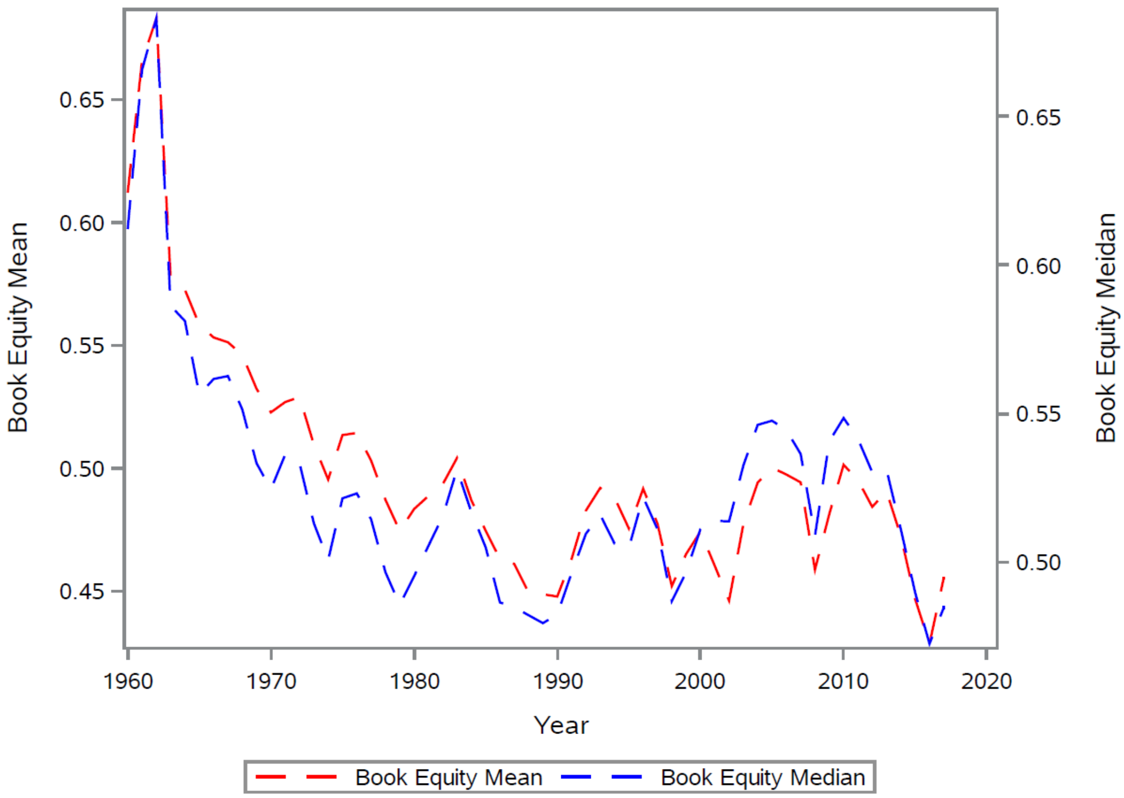
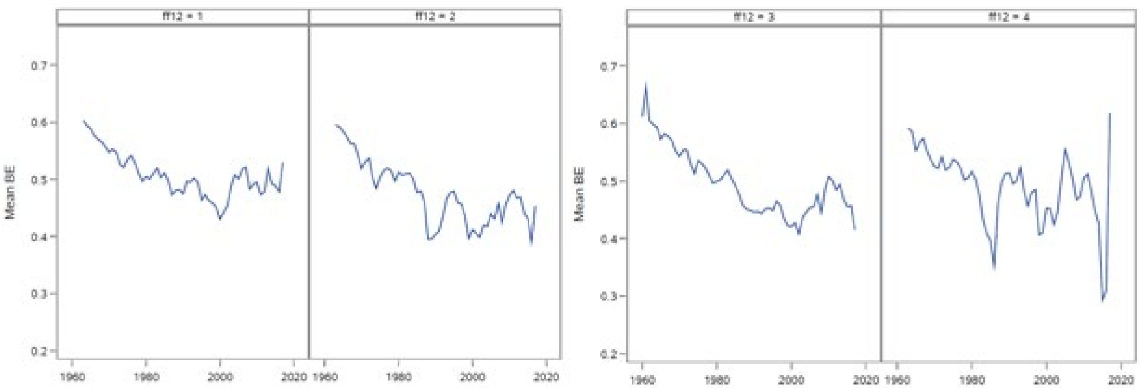


Figure 2: The secular trend in book equity by industry



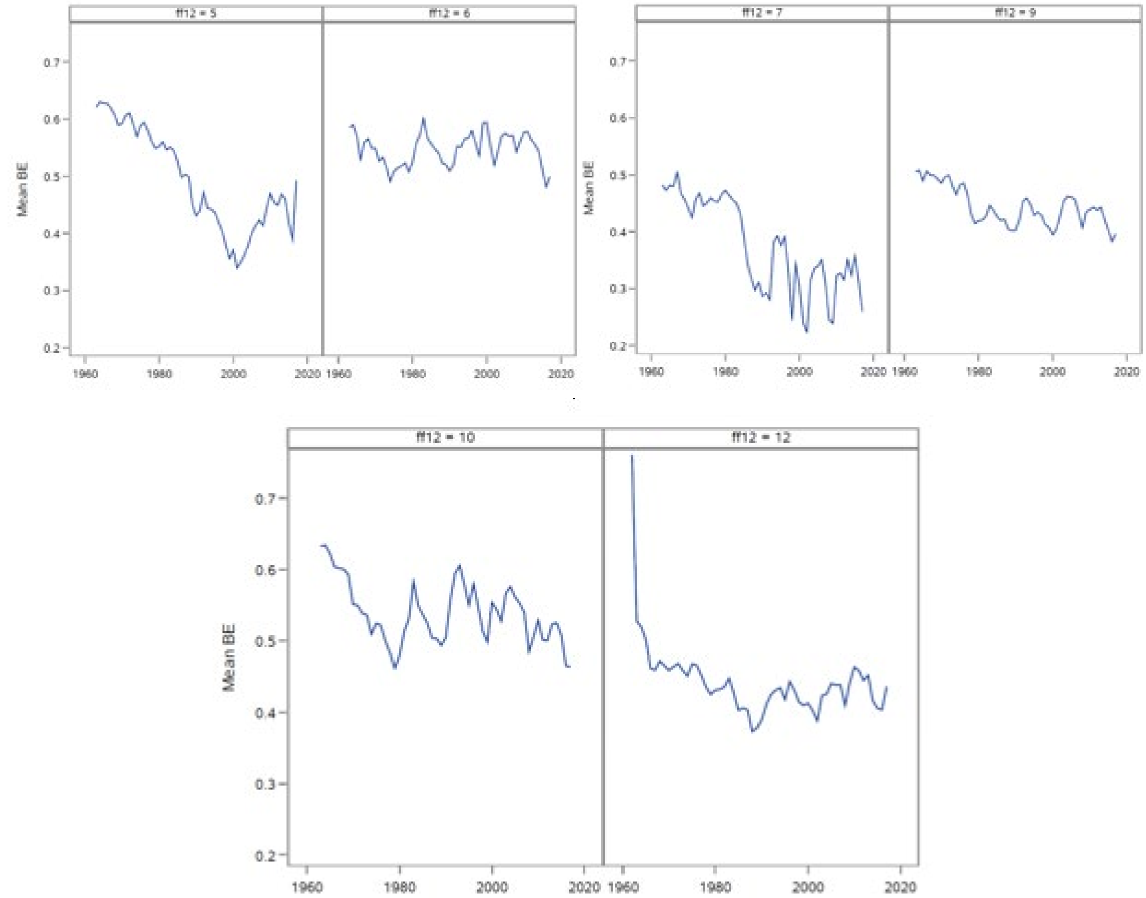
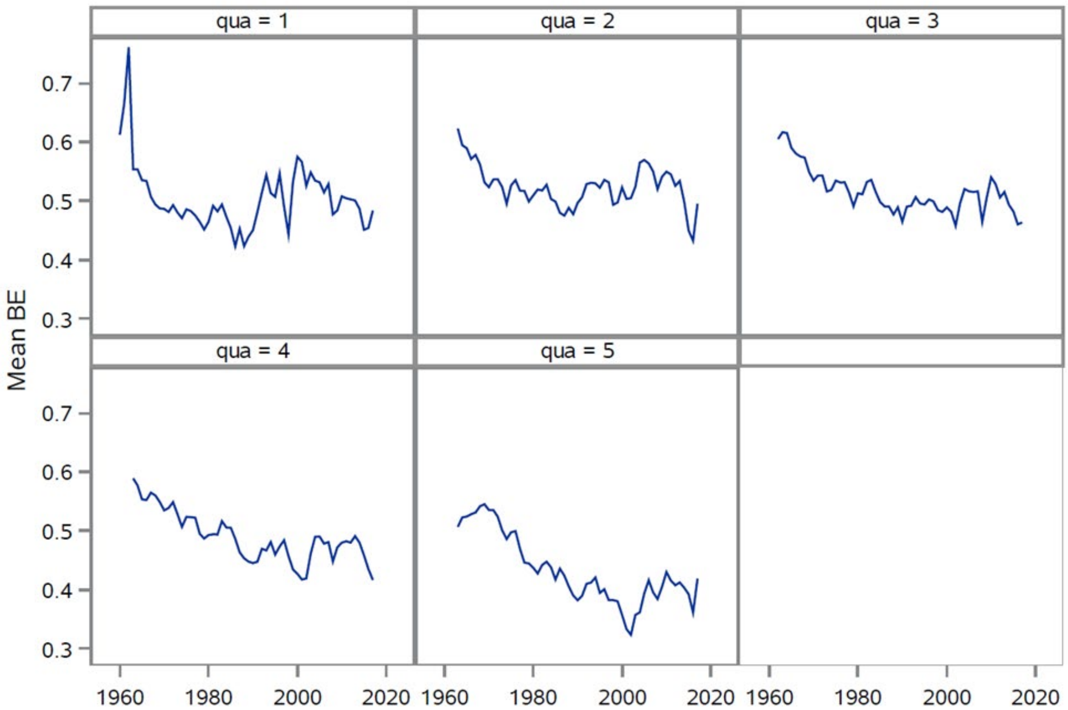


Figure 3: The secular trend in book equity by size quintiles



3. How Intangible Investments Affect Book Equity

3.1 Hypothesis development

The decreasing trend of B.E., as documented in the previous section, is interesting. Such observation coincides with two previously documented stylized empirical regularities with respect to firm characteristics. First, several studies have documented a downward shift in average earnings among firms in recent decades (Fama and French (1995), Opler and Titman (1994)). As the direct consequence, retained earnings are decreased over time and, assuming other factors unchanged, B.E. of average firms is affected negatively. Second, debt usage of unregulated firms has dramatically increased over time (Graham et al. (2015) and Philippon (2009)). This shift was largely driven by a systemic change in financial leverage, and firms of all sizes and all industries are affected. DeAngelo and Roll (2014) also find that over 1950 to 2008, leverage increased more frequently than it decreased among firms, which is the evidence of wholesale abandonment of conservative leverage. If the majority of firms are prone to more debt financing over time, then we should observe a gradually contracting equity portion on the balance sheet along with an expanding debt section.

Although both profitability and leverage may explain some variation in book equity observed in our sample, they are not the only factors. In this paper, we argue that investment in intangible capital also plays an important role in explaining long term variation in book equity. Many industries nowadays are transferring from tangible-based ones to information- and technology-based ones. Accordingly, the value of a firm within these industries lies as much in its intangible investments as in tangible assets. However, under the current accounting rule, not every dollar of intangible investments can be ascribed to a well-defined asset and reflected by net asset as measured by book equity. In other words, the book value of equity is not adjusted to reflect past intangible investment which is increasing across firms from many different industries. As a result, the decreasing book equity is the mere consequence of increasing intangible capital investment due to systematic industrial transformation. Therefore, based on previous discussion and observations, it led us to make the following broad prediction that we test in the paper:

Hypothesis 1: *Intangible capital investment is negatively related to book equity.*

3.2 Methods and data

The main variable of interest, intangible capital investment, is based on a newly developed proxy for intangible capital by Peters and Taylor (2017)[4]. This measurement, denoted as K^{int} in their studies, is intended to capture the replacement cost of firms' intangible capital both purchased externally, such as goodwill and intangibles reported on the balance sheet and created internally within the firm, such as R&D (which is referred to as knowledge capital) and SG&A (which is referred to as organization capital). We standardize intangible capital investment at firm level as calculated by Peters and Taylor (2017) using total assets for each firm. One limitation of using this measurement is that we can only use observations starting in 1975 in our regression analysis because the Federal Accounting Standards Board (FASB) only require firms to report R&D after 1974.

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[4] We appreciate authors for sharing the data through WRDS

To control for other firm characteristics that are related to book equity, we also include a set of control variables in our empirical analysis. These variables include the following: *profitability*, defined as operating income before depreciation over book assets; *firm size*, defined as the natural log of a firm's total assets; *share repurchase*, defined as the ratio of share repurchases to total assets; *industry sales volatility*, calculated as the standard deviation of sales over total assets for 5 years' rolling window for each industry (3 digit SIC code); *tangibility*, defined as property, plant and equipment to book assets; *leverage*, calculated as total debt over total assets; *capital expenditure*, measured by capital expenditure divided by total asset, and *dividend dummy*, which takes the value of 1 if the firm pays a dividend in that year and 0 otherwise. Our final sample consists of 129,444 firm-year observations between 1975 and 2017. We winsorized all regression variables at the 1% level to remove outliers.

We test *hypothesis 1* using the empirical model generally specified below:

$$BE_{i,t} = \alpha \ + \beta_0 Intangible\ Capital_{i,t-1} + \beta_1 X_{i,t-1} + \varepsilon_{i,t} + \gamma_j + \delta_t \quad (1)$$

where B.E. is the book equity-to-asset ratio for firm i in year t, Intangible capital is the standardized replacement cost of firms' intangible capital calculated by Peters and Taylor (2017), and X is a vector of control variables as introduced previously. All independent variables are lagged 1 year to mitigate the reverse causality problem. Equation 1 also include industry (γ_j) and year fixed effect[5] (δ_t).

3.3 Summary Statistics

Panel A of Table 1 displays descriptive statistics for all the variables for the full sample. The mean (median) book equity-to-asset ratio is 0.48 (0.51). The mean (median) intangible capital is 0.56 (0.45), suggesting that off-balance-sheet intangible assets are accounting for a large portion of the total asset on average. The average leverage, industry sales volatility, capital expenditure and profitability are 0.25, 0.06, 0.07 and 0.10, respectively. Panel B of Table 1 reports pairwise correlation coefficients. It appears that intangible capital is negatively related to book equity, and the correlation coefficient is significant at the 1% level. Variables that are positively related with book equity are share repurchase, dividend dummy, and profitability; Variables that are negatively related with book equity are leverage, size, industry sales volatility, tangibility, and capital expenditure. All correlation coefficients are significant at the 1% level.

To visualize how intangible capital investment and book equity comoves during our sample period, in figure 4, we plot the time series trend of both variables calculated as the average per year. The figure demonstrates that, as book equity decreased over the past 4 decades from over 51% of total assets in 1975 to less than 40 % of total assets in 2016, average intangible capital has steadily increased from less than 44% of total assets to over 60% of total assets. The findings from Figure 4 suggest that one possible explanatory factor for decreasing book equity over time is an investment in innovation and intangible assets. In an increasingly knowledge-based economy, typical firms switch from investing in tangible assets to intangible assets. Under current accounting rules, however, intangible investments are expensed rather than capitalized for most firms. As a result, balance sheets fail to reflect the true value of net asset measured by book equity, especially for firms heavily invested in unrecorded intangible capital.

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[5] The use of pooled OLS with a single intercept is rejected by Breusch and Pagan (1980) LaGrange multiplier test. Hausman (1978) test suggest that fixed effects are the preferred specification for these data.

Table 1: Summary Statistics

This table displays descriptive statistics of all financial variables over the sample period 1975-2017 in Panel A and Pearson correlation coefficient in Panel B. All variables are winsorized at the 1% level. Our sample consists of 129,444 firm-year observations, and we exclude financial (SIC codes 6000-6999), utility (SIC codes 4900-4999), firms classified as public service, international affairs, or non-operating establishments (SIC codes greater than 9000) and non-US firms (FIC = USA). Book equity is defined as the sum of shareholders' book equity and balance sheet deferred taxes and investment tax credit, subtracting the book value of preferred stock, standardized by the total asset. Profitability, defined as operating income before depreciation over book assets; firm size, defined as the natural log of a firm's total assets; share repurchase, defined as the ratio of share repurchases to total assets; industry sales volatility, calculated as the standard deviation of sales over total assets for 5 years' rolling window for each industry (3 digit SIC code); tangibility, defined as property, plant and equipment to book assets; leverage, calculated as total debt over total assets; capital expenditure, measured by capital expenditure divided by total asset, and dividend dummy, which takes the value of 1 if the firm pays a dividend in that year and 0 otherwise.

Panel A: Full Sample (1975-2017)

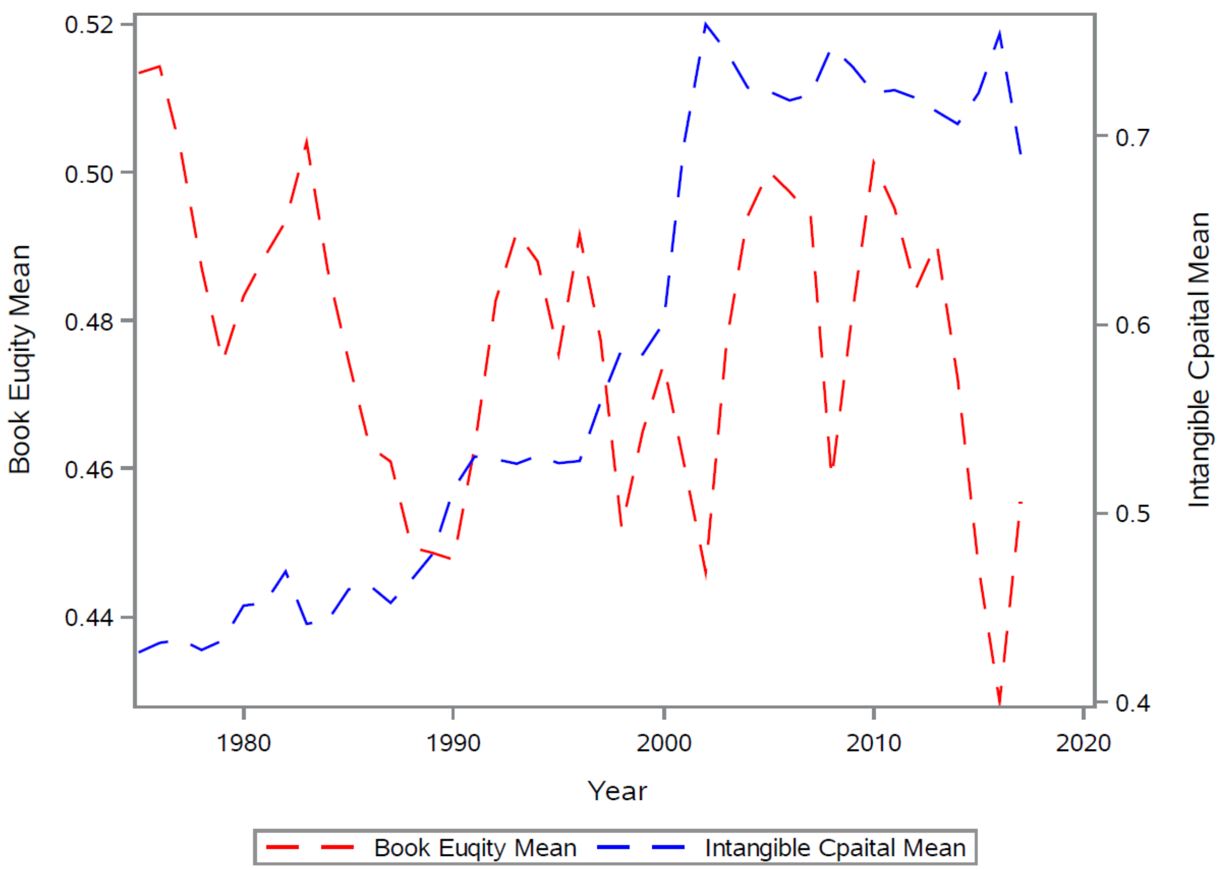
Variable	Mean	Median	Std Dev	Min	Q1	Q3	Max	N
BE	0.48	0.51	0.30	-0.77	0.34	0.68	0.94	129,444
Intangible Capital	0.56	0.45	0.51	0.00	0.22	0.73	3.10	129,444
Leverage	0.25	0.22	0.23	0.00	0.06	0.38	1.05	129,444
Repurchase	0.01	0.00	0.03	0.00	0.00	0.00	0.21	129,444
Size	5.08	4.88	1.98	1.28	3.60	6.41	10.17	129,444
Dividend	0.39	0.00	0.49	0.00	0.00	1.00	1.00	129,444
Industrial Sales Volatility	0.06	0.05	0.05	0.01	0.03	0.08	0.28	129,444
Tangibility	0.32	0.26	0.23	0.02	0.14	0.45	0.91	129,444
Profit	0.10	0.12	0.17	-0.73	0.06	0.18	0.41	129,444
Capital Expenditure	0.07	0.05	0.08	0.00	0.02	0.09	0.41	129,444

Panel B: Pearson Correlation Coefficients

Variable	B.E.	Intangible Capital	Leverage	Repurchase	Size	Dividend	Industrial Sales Volatility	Tangibility	Profit
Intangible Capital	-0.09***								
Leverage	-0.41***	-0.16***							
Repurchase	0.03***	0.06***	-0.06***						
Size	-0.06***	-0.15***	0.3***	0.18***					
Dividend	0.12***	-0.14***	0.13***	0.06***	0.33***				
Industrial Sales Volatility	-0.06***	-0.06***	0.06***	-0.02***	0.03***	0.06***			
Tangibility	-0.11***	-0.4***	0.21***	-0.09***	0.01***	0.1***	0.06***		
Profit	0.21***	-0.34***	0.08***	0.15***	0.22***	0.31***	0.02***	0.09***	
Capital Expenditure	-0.01***	-0.26***	0.06***	-0.05***	-0.09***	-0.01***	0.02***	0.57***	0.09***

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 4: Book equity V.S. intangible capital over Time



3.4 OLS results and the cross-sectional relationship between intangible investments and book equity

The results from the univariate analysis suggest that intangible investments may be an important explanatory variable for variation of book equity. In this section, we formally test this possibility as described in *Hypothesis 1* using regression analysis. We start by examining the pooled cross-sectional regression as specified in equation (1).

Table 2 reports the regression results. In all regressions, the t-statistics are calculated based on robust standard errors clustered by the firm (Petersen, 2009). Model 1 is the regression on intangible capital only. As shown, the coefficient on the intangible capital stock is negative and significant at the 1% level, consistent with the correlation coefficient reported in Table 1. In Model (2), we added all control variables in the regression and examined the effect of intangible capital on B.E. To control for unobserved, time-invariant factors; we also control for firm fixed effects in this specification. The coefficient on intangible capital remains negative and statistically significant at the 1% level. Also, notice that the effect of intangible capital on book equity increased as the absolute value of coefficient increased significantly. The explanatory power of the model also improved as adjusted R-square increased from 0.0086 to 0.6327. We re-estimated model (2) using lagged changes (first difference) regressions in models (3). In this new specification, the coefficient on intangible capital remains negative and statistically significant.

Among other variables in all specifications, we find that the signs and magnitudes of independent variables are consistent with prior literature and our expectations. Specifically, firms' book equity ratios are generally positively associated with profitability, dividend dummy and capital expenditures. Book equity is negatively related to leverage, share repurchase, and tangibility. Note that both the negative coefficient of leverage and positive coefficient of profitability are significant at 1 % level, providing the evidence that the negative effect of intangible capital on book equity is distinct from effects from leverage and profitability and remain significant even after we have controlled these effects.

Table 2: Cross-sectional relationship between intangible capital and book equity

This table provides regression results of book equity on intangible capital and other control variables over the sample period 1975-2017. All variables are winsorized at the 1% level. Our sample consists of 129,444 firm-year observations, and we exclude financial (SIC codes 6000-6999), utility (SIC codes 4900-4999), firms classified as public service, international affairs, or non-operating establishments (SIC codes greater than 9000) and non-US firms (FIC = USA). Book equity is defined as the sum of shareholders' book equity and balance sheet deferred taxes and investment tax credit, subtracting the book value of preferred stock, standardized by the total asset. Profitability, defined as operating income before depreciation over book assets; firm size, defined as the natural log of a firm's total assets; share repurchase, defined as the ratio of share repurchases to total assets; industry sales volatility, calculated as the standard deviation of sales over total assets for 5 years' rolling window for each industry (3 digit SIC code); tangibility, defined as property, plant and equipment to book assets; leverage, calculated as total debt over total assets; capital expenditure, measured by capital expenditure divided by total asset, and dividend dummy, which takes the value of 1 if the firm pays a dividend in that year and 0 otherwise.

Model	***1***	***3***	***4***
Dependent Variable	***BE***	***BE***	***Change_BE***
Intercept	*0.5039**** *(0.0036)*	*0.6683**** *(0.0156)*	*-0.0105**** *(0.0005)*
Intangible Capital	*-0.0547**** *(0.0053)*	*-0.1204**** *(0.0066)*	*-0.1078**** *(0.0066)*
Leverage		*-0.2078**** *(0.0052)*	*-0.2098**** *(0.0048)*
Repurchase		*-0.1576**** *(0.0254)*	*-0.1370**** *(0.0155)*
Size		*0.0038* *(0.0027)*	*0.0312**** *(0.0040)*
Dividend		*0.0454**** *(0.0039)*	*0.0114**** *(0.0019)*
Industrial Sales Volatility		*0.0162* *(0.0251)*	*0.0164* *(0.0145)*
Tangibility		*-0.1039**** *(0.0155)*	*-0.1309**** *(0.0149)*
Profit		*0.2948**** *(0.0129)*	*0.2781**** *(0.0085)*
Capital Expenditure		*0.0914**** *(0.0178)*	*0.0387*** *(0.0122)*
Firm F.E.	*No*	*Yes*	*No*
Industry F.E.	Yes	No	Yes
Year F.E.	Yes	Yes	Yes
Adjusted R^2	0.0086	0.6327	0.1799

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

3.5 The evolving effect of intangible investments and book equity over time

In this section, we turn our focus to analyze how the effect of intangible capital on book equity evolving over time. As we discussed in previous sections, in an increasingly knowledge-based economy, many industries are transforming from tangible-based to intangible-intensive ones. As we plotted in Figure 4, the intangible capital investments for average firms are consistently increasing over our sample period. Some recent literature (e.g. He and Wintoki 2016) also document that R&D intensity increased across all industries between 1980 and 2012. One implication emerges from these findings: the effect of intangible capital on book equity deepens over time, and there is a fundamental shift in the association between intangible capital and book equity that could explain a considerable portion of the decrease in book equity in recent years. This conjecture thus leads us to make the following hypothesis:

Hypothesis 2: *Intangible capital investment has become an increasingly important determinant of book equity in recent years.*

To test this hypothesis, we estimate equation (1) for successive five-year periods between 1975 and 2015 and compare the changing effect of intangible capital on book equity while controlling other firm characteristics that might also have an increasing impact on book equity. The results are reported in Table 3.

As shown in the table, the effect of intangible capital has increased dramatically during our sample period. Across all regressions, the estimated coefficients are consistently negative and significant at 1% level. The absolute values of the estimated coefficient on intangible capital increased from 0.0326 in the 1975-1980 period to 0.1158 in the 2001-2005 period, then dropped slightly to 0.099 in the 2011 – 2015 period. But even with the slight drop in most recent subperiod, the magnitude of the effect of intangible capital on book equity has increased 204% between 1975 and 2015. In contrast, although the coefficients on leverage are consistently negative and statistically significant over time, the magnitude of effect has decreased. The absolute values of the estimated coefficient on leverage decreased from 0.4326 in 1975-1980 to 0.3573 in the 2011 – 2015 period, a 17% decrease. Similarly, for profitability, although estimated coefficients are consistently positive and significant, the magnitude of effect has decreased by 46% from 0.579 in the 1975-1980 period to 0.3146 in the 2011 – 2015 period. Among all other variables, industry sales volatility and tangibility exhibit similar patterns as intangible capital, with an increasingly negative effect on book equity, but the magnitude is much smaller.

Table 3: The evolving effects of intangible capital on book equity

This table provides regression results of book equity on intangible capital and other control variables for successive five-year periods between 1975 and 2015. All variables are winsorized at the 1% level. Our sample consists of 129,444 firm-year observations, and we exclude financial (SIC codes 6000-6999), utility (SIC codes 4900-4999), firms classified as public service, international affairs, or non-operating establishments (SIC codes greater than 9000) and non-US firms (FIC = USA). Book equity is defined as the sum of shareholders' book equity and balance sheet deferred taxes and investment tax credit, subtracting the book value of preferred stock, standardized by the total asset. profitability, defined as operating income before depreciation over book assets; firm size, defined as the natural log of a firm's total assets; share repurchase, defined as the ratio of share repurchases to total assets; industry sales volatility, calculated as the standard deviation of sales over total assets for 5 years' rolling window for each industry (3 digit SIC code); tangibility, defined as property, plant and equipment to book assets; leverage, calculated as total debt over total assets; capital expenditure, measured by capital expenditure divided by total asset, and dividend dummy, which takes the value of 1 if the firm pays a dividend in that year and 0 otherwise. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

	1	2	3	4	5	6	7	8
Dependent Variable for all regressions is BE	**1975-1980**	**1981-1985**	**1986-1990**	**1991-1995**	**1996-2000**	**2001-2005**	**2006-2010**	**2011-2015**
Intercept	0.7467***	0.8261***	0.8608***	0.8496***	0.9132***	0.8867***	0.8706***	0.8869***
	(0.0082)	(0.0091)	(0.0086)	(0.0087)	(0.0109)	(0.0110)	(0.0121)	(0.0268)
Intangible Capital	-0.0326***	-0.0484***	-0.0690***	-0.0702***	-0.1196***	-0.1158***	-0.0883***	-0.0990***
	(0.0047)	(0.0057)	(0.0049)	(0.0047)	(0.0051)	(0.0052)	(0.0053)	(0.0121)
Leverage	-0.4326***	-0.4583***	-0.3785***	-0.3769***	-0.3592***	-0.3203***	-0.3229***	-0.3573***
	(0.0072)	(0.0078)	(0.0067)	(0.0062)	(0.0069)	(0.0066)	(0.0070)	(0.0162)
Re-purchase	-0.0366	-0.1265	0.2417**	-0.1803**	0.0572	-0.0374	-0.3458***	-0.5821***
	(0.0713)	(0.0666)	(0.0783)	(0.0570)	(0.0688)	(0.0537)	(0.0618)	(0.1216)
Size	0.0055***	-0.0064***	-0.0157***	-0.0093***	-0.0046**	-0.0057***	-0.0073***	-0.0081*
	(0.0012)	(0.0014)	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0016)	(0.0034)
Dividend	0.0990***	0.1138***	0.1015***	0.0624***	0.0589***	0.0235***	0.0390***	0.0324**
	(0.0041)	(0.0049)	(0.0048)	(0.0049)	(0.0060)	(0.0056)	(0.0056)	(0.0121)
Industrial Sales Volatility	0.0165	-0.2619***	-0.2711***	-0.3946***	-0.5154***	-0.4056***	-0.3736***	-0.3327**
	(0.0377)	(0.0419)	(0.0511)	(0.0532)	(0.0489)	(0.0527)	(0.0528)	(0.1190)
Tangibility	-0.1035***	-0.0614***	-0.1426***	-0.1443***	-0.2784***	-0.2164***	-0.1664***	-0.1379***
	(0.0104)	(0.0112)	(0.0109)	(0.0111)	(0.0135)	(0.0142)	(0.0144)	(0.0311)
Profit	0.5790***	0.4983***	0.2827***	0.3362***	0.2823***	0.2372***	0.2435***	0.3146***
	(0.0154)	(0.0154)	(0.0147)	(0.0128)	(0.0145)	(0.0160)	(0.0173)	(0.0331)
Capital Expenditure	0.0771**	0.0610*	0.3246***	0.1633***	0.3165***	0.1352**	0.0237	0.0323
	(0.0238)	(0.0298)	(0.0314)	(0.0314)	(0.0453)	(0.0436)	(0.0475)	(0.1137)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.3303	0.2947	0.2615	0.2456	0.2440	0.2367	0.2245	0.2283

4. How Much of the Change in Book Equity Can be Attributed to Intangible Capital?

The results from Table 3 suggest that the effect of intangible capital on book equity has increased over recent decades. However, we also observe that other firm characteristics, such as profitability and leverage, exhibit time-varying effects on book equity during the sample period. In this section, we turn our analysis to identify and quantify the main driving forces of decreasing book equity among various firm characteristics. Specifically, we investigate how firm characteristics change and how the sensitivity of book equity to firm characteristics change, respectively, affect book equity levels over time.

We start with the first possible source for the aggregate decrease in book equity: changing firm characteristics. To isolate the effect of changing firm characteristics, we must hold the sensitivity of independent variables constant and only use time-varying firm characteristics to calculate changes in book equity. Since we are holding sensitivity constant, the resulting changes in book equity are solely due to changing firm characteristics. In an effort to track the evolution of such effect, we perform separate calculations on each of the three most recent decades ((i.e., the 1990s, 2000s and 2010s). Specifically, for each of three decades, we estimate regression models as in Model 2 of Table 2 for a sample consist of firms during the previous 10 years, which we call the base period. For example, to evaluate how changing firm characteristics affect book equity during the 1990s, we estimate model 2 using sample firms during the base period (1980- 1989) and record the estimated coefficients, assuming the estimated coefficients during the base period persist during 1990s. We then calculate the change in the mean value for each firm characteristics variable between the base period (1980-1989) and 1990s. Lastly, we multiply calculated change by the estimated coefficient from the base period for each firm characteristics to obtain the change in book equity due to each firm characteristics variable for the 1990s. To make sure that we use the most recent information when estimating coefficients, we use a rolling base period for each decade. For example, the base period for the 2000s is the ten-year-period between 1990 and 1999, and the base period for 2010s is the ten-year-period between 2000 and 2009. Table 4 reports the main results of our analysis.

Panel A of Table 4 report changes of mean firm characteristics for each decade. It appears that intangible capital, on average, is consistently increasing over each decade, with the incremental amount maximized during the 2000s. Similarly, repurchase and size are also consistently increasing each decade. In contrast, tangibility and capital expenditure are steadily decreasing over time. Panel B of Table 4 presents the results of the effect of changing firm characteristics on book equity for each decade. Holding sensitivity constant, increasing intangible capital alone result in book equity ratio to decrease by 0.8%, 1.44% and 0.4% for each decade. Beside intangible capital, changes in repurchase and capital expenditure also contribute to a decrease in book equity, but the magnitude is much smaller relative to that of intangible capital. In contrast, the effect of leverage and probability are time-sensitive. For leverage, its variation contributes to a decrease in book equity only during the 2010s. For profitability, its variation contributes to a decrease in book equity during the 1990s and 2000s but not 2010s.

Table 4: Decrease in book equity and Changing Firm Characteristics

This table presents the decomposed effect of changing firm characteristics on decreasing book equity for each of the three most recent decades ((i.e., 1990s, 2000s and 2010s). For each decade, we first estimate a regression as in Equation 1 for a sample consist of firms during previous 10 years, which we call the base period. We then calculate the change in mean value for each firm characteristic variable between base period and that decade. Lastly, we multiply calculated change by estimated coefficient from base period for each firm characteristic to obtain the change in book equity due to each firm characteristic variable. We use rolling base period for each decade. For example, the base period for 2000s is the ten-year-period between 1990 and 1999, and the base period for 2010s is the ten-year-period between 2000 and 2009.

Panel A
Change of Firm Characteristics from Corresponding Base Period

Decades	Intangible Capital	Leverage	Repurchase	Size	Dividend	Sales Volatility	Tangibility	Profitability	Capital Expenditure
1990s	12.19%	-4.39%	0.46%	0.649	-29.16%	-1.89%	-3.87%	-4.91%	-1.09%
2000s	16.81%	-4.65%	0.71%	0.818	-6.07%	1.09%	-5.73%	-3.85%	-2.04%
2010s	3.36%	1.08%	0.35%	0.797	11.47%	0.30%	-0.49%	1.44%	-0.57%

Panel B
Effect of Changing Firm Characteristics on Book Equity

Decades	Intangible Capital	Leverage	Repurchase	Size	Dividend	Sales Volatility	Tangibility	Profitability	Capital Expenditure
1990s	-0.80%	0.83%	-0.05%	-0.001	-1.20%	0.04%	0.35%	-1.78%	-0.07%
2000s	-1.44%	0.94%	-0.09%	-0.003	-0.32%	0.00%	0.38%	-1.43%	-0.07%
2010s	-0.40%	-0.21%	-0.04%	-0.001	0.47%	0.01%	0.05%	0.45%	-0.05%
Average	-0.88%	0.52%	-0.06%	-0.001	-0.35%	0.02%	0.26%	-0.92%	-0.06%

We next move to calculate the contribution of decreasing book equity due to changing sensitivity for each firm characteristic variable. In this practice, we must hold each firm characteristic variable constant and only use time-varying sensitivity of independent variables to calculate changes in book equity. The resulting changes in book equity are solely due to the changing sensitivity of each independent variable since we are holding firm characteristics constant from the base period. Similar to prior analysis, for each recent decade (the 1990s, 2000s and 2010s), we first calculate the mean value for each firm characteristic variable and assume these values persist into each decade. We then estimate Model 2 for each decade and its corresponding base period, respectively, and calculate the change in coefficient for each independent variable. Lastly, we multiply the calculated change of sensitivity by the mean value for each firm characteristic variable from the base period to obtain the change in book equity due to the changing sensitivity of individual firm characteristics.

Table 5: Decrease in book equity and changing sensitivity of book equity on firm characteristics

This table presents the decomposed effect of changing sensitivity of book equity on firm characteristics for each of the three most recent decades ((i.e., 1990s, 2000s and 2010s). For each decade, we first calculate the mean value for each firm characteristic variable and assume these values persist into each decade. We then estimate Equation 1 for each decade and its corresponding base period, respectively, and calculate the change in coefficient for each independent variable. Lastly, we multiply calculated change of sensitivity by mean value for each firm characteristic variable from base period to obtain the change in book equity due to changing sensitivity of individual firm characteristics. We use rolling base period for each decade. For example, the base period for 2000s is the ten-year-period between 1990 and 1999, and the base period for 2010s is the ten-year-period between 2000 and 2009.

Panel A
Change of sensitivity of Firm Characteristics from Corresponding Base Period

Decades	Intangible Capital	Leverage	Repurchase	Size	Dividend	Sales Volatility	Tangibility	Profitability	Capital Expenditure
1990s	-0.43%	-18.80%	5.83%	-0.012	4.14%	-31.15%	-5.16%	-4.34%	17.45%
2000s	-3.19%	-13.83%	10.92%	-0.001	-1.08%	-47.31%	-18.47%	-10.99%	19.77%
2010s	3.08%	-13.19%	-30.57%	-0.006	-0.39%	-39.85%	-5.10%	-5.21%	-7.05%

Panel B
Effect of Changing sensitivity of Firm Characteristics on Book Equity

Decades	Intangible Capital	Leverage	Repurchase	Size	Dividend	Sales Volatility	Tangibility	Profitability	Capital Expenditure
1990s	-0.18%	-15.85%	0.04%	-0.050	2.47%	-2.17%	-1.86%	-0.61%	1.51%
2000s	-1.67%	-11.12%	0.11%	-0.007	-0.35%	-2.32%	-6.05%	-1.06%	1.52%
2010s	2.07%	-10.06%	-0.55%	-0.036	-0.10%	-2.38%	-1.39%	-0.30%	-0.41%
Average	0.08%	-12.34%	-0.13%	-0.031	0.67%	-2.29%	-3.10%	-0.66%	0.87%

Table 5 reports the results. In panel A of Table 5, we find that estimated coefficient, although consistently negative during each decade and its corresponding base period[6], become less negative in the 2010s. As a result, the changes of sensitivity remain negative during the 1990s and 2000s but become positive 3.08% during 2010s (the coefficient on intangible capital become less negative from 2000s to 2010s). In contrast, sensitivities of leverage, size, industry sales volatility, tangibility and profitability consistently become more negative each decade. Panel B of Table 5 presents the

[6] In untabulated results, the estimated coefficients on intangible capital are consistently negative for 1990s, 2000s and 2010s

results on the effect of changing sensitivity on book equity while holding firm characteristics constant. Unlike the effect of changing firm characteristics, we observe that changing sensitivity of intangible capital leads to a decrease in book equity ratio by 0.18% and 1.67% during the 1990s and 2000s but causes book equity to increase by 2.07% during 2010s. In contrast, changing sensitivities of leverage, size, industry sales volatility, tangibility and profitability are the main driving forces to bring down the book equity during each of three decades.

5. Robustness

One concern about our main findings on the relationship between intangible capital and book equity is that our sample covers firm-year observations over 40 years and sample composition could systematically shift over time. To address this issue, we form a subsample of firms that survived the entire period between 1975 and 2015 and re-estimate equation 1 for the subsample as well as successive five-year periods between 1975 and 2015 as reported in Table 2 and Table 3. The results are presented in Table 6 below.

Column 1 of Table 6 shows the estimated coefficients of regression using full sample period for surviving firms. Similar to model 2 in Table 2, we control for unobserved, time-invariant factors by adding firm fixed effects in this specification. As shown, the coefficient on intangible capital remains negative and statistically significant at the 1% level for such a restricted sample of survivors. Column 2 to column 9 report regression results for subsamples for each five-year period between 1975 and 2015. Similar to those reported in Table 3, the coefficients on intangible capital are consistently negative and significant at 1% level in all subsamples except for the 1975-1980 period and 2006-2010. The absolute values of the estimated coefficient on intangible capital increased from 0.0055 in the 1975-1980 period to 0.0735 in the 2011 – 2015 period, suggesting the magnitude of the effect of intangible capital on book equity has increased 120% between 1975 and 2015. The increase is slightly lower than that reported using the full sample but still impressive and economically significant. Overall, our main results remain valid in the more restricted sample of survivors.

Table 6: Robustness check using restricted survivor sample

This table presents the regression results of the cross-sectional relationship between intangible capital and book equity as in equation 1 for the subsample of firms that survived the entire period between 1975 and 2015 as well as successive five-year periods between 1975 and 2015 as reported in Table 2 and Table 3. we exclude financial (SIC codes 6000-6999), utility (SIC codes 4900-4999), firms classified as public service, international affairs, or non-operating establishments (SIC codes greater than 9000) and non-US firms (FIC = USA). Book equity is defined as the sum of shareholders' book equity and balance sheet deferred taxes and investment tax credit, subtracting the book value of preferred stock, standardized by the total asset. profitability, defined as operating income before depreciation over book assets; firm size, defined as the natural log of a firm's total assets; share repurchase, defined as the ratio of share repurchases to total assets; industry sales volatility, calculated as the standard deviation of sales over total assets for 5 years' rolling window for each industry (3 digit SIC code); tangibility, defined as property, plant and equipment to book assets; leverage, calculated as total debt over total assets; capital expenditure, measured by capital expenditure divided by total asset, and dividend dummy, which takes the value of 1 if the firm pays a dividend in that year and 0 otherwise. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively

	1	2	3	4	5	6	7	8	9
Dependent Variable for all regressions is BE	**1975-2015**	**1975-1980**	**1981-1985**	**1986-1990**	**1991-1995**	**1996-2000**	**2001-2005**	**2006-2010**	**2011-2015**
Intercept	0.4956***	0.5999***	0.6208***	0.7273***	0.8199***	0.8207***	0.8465***	0.8487***	0.8733***
	(0.0576)	(0.0183)	(0.0237)	(0.0259)	(0.0220)	(0.0220)	(0.0255)	(0.0236)	(0.0269)
Intangible Capital	-0.0918***	-0.0055	-0.0314**	-0.0316*	-0.0643***	-0.0716***	-0.0312*	-0.0281	-0.0735***
	(0.0246)	(0.0114)	(0.0117)	(0.0153)	(0.0123)	(0.0128)	(0.0153)	(0.0147)	(0.0151)
Leverage	-0.2261***	-0.2857***	-0.2888***	-0.2951***	-0.2724***	-0.3183***	-0.2672***	-0.2467***	-0.2557***
	(0.0151)	(0.0135)	(0.0180)	(0.0212)	(0.0174)	(0.0176)	(0.0209)	(0.0171)	(0.0195)
Repurchase	-0.3468***	0.0804	-0.2824	-0.0659	0.0080	-0.3333**	-0.0704	-0.1174	-0.2614
	(0.0700)	(0.1909)	(0.1523)	(0.1367)	(0.1469)	(0.1079)	(0.1544)	(0.1104)	(0.1351)
Size	0.0151*	0.0009	-0.0059*	-0.0247***	-0.0388***	-0.0291***	-0.0357***	-0.0336***	-0.0345***
	(0.0073)	(0.0019)	(0.0024)	(0.0028)	(0.0024)	(0.0023)	(0.0028)	(0.0027)	(0.0030)
Dividend	0.0643***	0.0810***	0.1095***	0.1470***	0.1156***	0.0673***	0.1186***	0.1255***	0.1475***
	(0.0128)	(0.0089)	(0.0115)	(0.0131)	(0.0107)	(0.0097)	(0.0108)	(0.0106)	(0.0115)
Industrial Sales Volatility	0.0020	-0.0493	0.2087*	-0.3387***	-0.2168	-0.1578	-0.1957*	-0.3131***	-0.3632***
	(0.0595)	(0.0759)	(0.0871)	(0.0948)	(0.1173)	(0.1059)	(0.0968)	(0.0889)	(0.0912)
Tangibility	0.1118**	0.0763***	0.0606*	0.0256	0.0516	0.0381	0.0055	0.0641*	0.0648*
	(0.0406)	(0.0229)	(0.0272)	(0.0332)	(0.0286)	(0.0271)	(0.0322)	(0.0301)	(0.0322)
Profit	0.3777***	0.7078***	0.6983***	0.5575***	0.6010***	0.7067***	0.3057***	0.1232	0.2596***
	(0.0490)	(0.0386)	(0.0455)	(0.0597)	(0.0588)	(0.0594)	(0.0734)	(0.0664)	(0.0768)
Capital Expenditure	0.0198	-0.4347***	-0.1036	0.2493*	0.0156	0.1246	0.4017**	0.1461	-0.2854
	(0.0633)	(0.0646)	(0.0825)	(0.1226)	(0.1065)	(0.0956)	(0.1362)	(0.1337)	(0.1459)
Firm F.E.	Yes	No	No	No	No	No	No	No	No
Industry F.E.	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.5539	0.3867	0.2995	0.2628	0.3494	0.3285	0.2663	0.2816	0.2635

5. Conclusion

We document that the book equity of U.S. firms has decreased dramatically over time. Such a systematic decrease may reflect overall companies' attitudes on intangible assets. We find that intangible capital investments play an essential role in explaining decreasing book equity. The negative relationship between intangible capital and book equity is persistent across many model specifications. We also find that the negative effect is more pronounced in recent years. To understand how intangible capital affects book equity and compare it with other explanatory variables, we isolate the effect of changing firm characteristics from the effect of changing the sensitivity of firm characteristics on book equity. Our analysis shows that intangible capital contributes to a decrease in book equity mostly through the channel of changing firm characteristics. The changing sensitivity of intangible capital explains the decrease in book equity during the 1990s and 2000s but not 2010s. In contrast, changing sensitivities of leverage, size, industry sales volatility, tangibility and profitability are the main driving forces to bring down the book equity during the 2010s. Our findings call for a revision of accounting standards to clearly define the boundaries of intangible assets and reflect such assets in book value. Investors also must incorporate the effect of intangible capital into their valuation analysis, as indexes or investment strategies relying on indicators constructed by book equity may be biased and misleading.

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AN INVESTIGATION OF THE PRESENCE OF ANOMALIES IN DIGITAL ASSET MARKETS: THE CASE OF BITCOIN

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Abstract

This paper examines the cryptocurrency Bitcoin to determine if there is evidence of the weekday effects, such as the Monday effect, during the period between 2 January 2011, and 10 September 2019. The study shows that Bitcoin exhibits a Monday effect at the 10% level of significance and a Tuesday and Sunday effect at the 1% significance level. The S&P 500 stock index also showed a Monday effect but did not exhibit a Tuesday or Sunday effect. The study also examined if there was a Month of the Year effect and found that Bitcoin exhibited a May and November effect at the 10% significance level.

Keywords: Anomalies, EMH, Seasonality, Bitcoin, Cryptocurrency

JEL: G11, G12, G14, G17

1. Introduction

Since the Efficient Market Hypothesis (EMH) was first introduced (Fama, 1970), there has been a significant amount of research focused on the validation of as well as challenging the basic premise of this theory. Many studies have focused on the existence of market anomalies, which are a key challenge to the EMH. Market anomalies suggest that the market is not as efficient as suggested by the EMH. While there has been extensive research conducted on equity markets, national currencies and other financial instruments, there is a need to develop further insight into emerging instruments such as cryptocurrencies to determine if these markets have matured and are operating efficiently. This study examines seasonality in cryptocurrencies, specifically focusing on daily and monthly anomalies that are present in Bitcoin from January 2011 through September 2019. Bitcoin was created on 3 January 2009, as an entirely digital cryptocurrency that is free of a central bank or single administrator (Nakamoto, 2008). While not the only cryptocurrency in circulation, Bitcoin serves as the most prominent representative of this market both in terms of trading volume and acceptance as a means of payment around the globe. As Bitcoin has continued to mature over the past decade, it is critical that we attain further insight into its efficiency in the market and performance in relation to other established currencies such as the USD.

The remainder of this paper is organized as follows: Section 2 provides the review of pertinent academic literature, Section 3 details the data set and methodology utilized in this study, Section 4 reports the empirical results, and finally, Section 5 provides a summary of the paper content and the conclusion.

2. Literature Review

Market seasonality, which includes various aspects of market anomalies, such as the weekend effect, Monday effect, and day-of-the-week effect, has been thoroughly studied since the 1970s, with the initial focus on equities markets. In studies conducted by Cross (1973), French (1980), and Gibbons and Hess (1981) there have been documented market anomalies, such as the Monday effect in equity markets, with each study providing evidence to support lower market returns on Mondays than on the other days of the week. Further studies have been performed to examine if the Monday effect could also be detected in other markets, such as the foreign exchange market. Yu, Chiou, and Jordan-Wagner (2008), for example, studied the effect in the Yen, British Pound, and USD. The authors did not find evidence to support a noticeable Monday effect in the period studied; however, they did find that Tuesdays seem to exhibit the largest increase in exchange rates for the week. It is notable that the period of analysis in their study, which dates 1994 through 2003, coincided with a relatively healthy economy, which may explain the lack of a Monday downturn in the currency markets of the time.

In further studies, Arsad and Coutts (1996) discovered a statistically significant Monday effect when there was negative news in the stock market based on the Financial Times Industrial Ordinary Shares Index of the London International Stock Exchange. The study covered an extended period from 1935 through 1994, which was broken into 12 equal periods over the 60 years examined. The authors observed that the downturn on Mondays was significant when there was negative market news present, defined by an overall downturn in the stock market, and inconsistent when there was positive news, defined by an overall upturn in the stock market. Patell and Wolfson (1982) and Penman (1987) also provided validity to the negative news argument, concluding that positive news tends to occur during trading hours, while negative news tends to occur after hours and on weekends, leading to more downturns on Mondays.

As suggested in the findings of Yu, Chiou, and Jordan-Wagner (2008), studies often find evidence of time or day-of-the-week effect in currency markets for days other than Monday. Thatcher and Blenman (2001) studied the USD/GBP market and saw a drop in exchange rates on Wednesdays. Their work is supported by earlier studies conducted by Goodhart and Figlioli (1991), and Lyons (1995), who reported a time-of-the-day effect in intra-day trading. Levi (1978), Bossaerts and Hillion (1991) and Bessembinder (1992) all found a day-of-the-week effect in various currency markets. Some of the conclusions of these studies attribute the effects to asymmetries in bid-ask spreads, measurement errors, and new information arrival. No study to date has been able to define the reason for the day-of-the-week-effect definitively, and as such, it is plausible that all the proposed explanations contribute in part to the effect. McFarland, Pettit, and Sung (1982) conducted a study on eleven foreign currency pairs and found that dollar-denominated price changes are significant on Mondays and Wednesdays and low on Thursdays and Fridays for all eleven currencies being traded.

Connolly (1989) found that the day-of-the-week effect tends to be inconsistent over time. Research provides evidence that the impact can be measurable in one period, and then no longer present in another period. The effect also tends to reverse itself at times, becoming negative on Friday and positive on Monday, as was highlighted in a study conducted by Brusa, Liu, and Schulman (2000). In another study, Kamara (1997) found that the effect seems to have diminished in U.S. equity markets with the introduction of the S&P 500 futures contract.

While there has been a substantial amount of research conducted regarding market seasonality in equity and standard currency markets, there has been minimal focus on cryptocurrency markets as they have evolved into mainstream products. One of the first studies of the cryptocurrency market to test for market efficiency was conducted by Urquhart (2016), which provided one of the first insights into the market efficiency of Bitcoin and concludes that Bitcoin returns do not provide evidence to support that it is weak-form efficient. In 2017, Nadarajah and Chu ran multiple tests and concluded that Bitcoin is largely weak form efficient over their estimation period. Also, in 2017, Kurihara and Fukushima examined Bitcoin for weekly price anomalies, with the results showing that the Bitcoin market is not efficient.

Early studies of the cryptocurrency markets, and more specifically of Bitcoin, were focused on the general efficiency of the market as these currencies have begun to mature over time. More recent studies have focused directly on market anomalies to determine whether specific evidence can be found to both support and explain the inefficiencies noted in earlier studies. In 2018, Hattori and Ishida tested for arbitrage activities by investors in the Bitcoin futures market and reported findings that support the existence of market efficiency. Aharon and Qadan (2018) studied Bitcoin from 2010 to 2017 and provide initial evidence about the existence of the day-of-the-week effect anomaly not only in returns but also in volatility. Further evidence is provided by Caporale and Plastun (2018). They studied the day-of-the-week effect of cryptocurrency markets using several techniques. They found that Bitcoin exhibits a reverse Monday effect with Monday returns being significantly higher than other days of the week. This finding is further supported by Ma and Tanizaki (2019), who also find that Bitcoin has a higher mean return and volatility on Monday than other days of the week. In another study, Fraz, Hassan, and Chughtai find evidence of higher returns on Monday than on other days of the week, further supporting the potential existence of the reverse Monday effect.

The purpose of this paper is to determine if there are day-of-the-week and month-of-the-year effects in cryptocurrency markets, specifically Bitcoin, from July 2010 through September 2019. We will employ the same statistical procedures developed by Connolly (1989) as the basis for this analysis to evaluate our theory.

3. Data and Methodology

3.1 Data

The data of this study covers daily closing values of Bitcoin and the S&P 500 from 2 January 2011 to 10 September 2019. To collect the data, we select January 2011 as the starting date, which is two years after the introduction of Bitcoin to provide the market with sufficient time to become familiar and to adjust with the trading of digital currency and new assets.

To explore the presence of an anomaly in the Bitcoin market, we examine both the-day-of-the-week and the-month-of-the-year effect to shed light on the behaviour of these markets in the context of market efficiency.

3.2 Methodology

We define the daily changes in the daily closing value of Bitcoin and the S&P 500 as:

$$Rt= ln\ (Pt/Pt\text{-}1) * 100 \qquad (1)$$

where: Rt is the daily log return, Pt is the closing value of the Bitcoin and S&P 500 index on day t, and Pt-1 is the closing value of the Bitcoin and S&P 500 index on day t-1.

We perform an Augmented Dickey-Fuller to test for stationarity of the time- series used, and the results indicate that the calculated daily changes are stationary of the first order. The results are not presented here to conserve space but are available from the authors upon the request.

In line with the commonly used methodology in the finance literature (for instance, see Bush and Stephens, 2016), we use the following regression models to examine the presence of the day-of-the-week and the month-of-the year effects in series used:

For the day-of-the-week effect, we employ the following regression:

$$Rt = \alpha 1D1+ \alpha 2D2+ \alpha 3D3+ \alpha 4D4+ \alpha 5D5+ut \qquad (2\text{-}1)$$

$$Rt = \alpha 1D1+ \alpha 2D2+ \alpha 3D3+ \alpha 4D4+ \alpha 5D5+ \alpha 6D6+ \alpha 7D7 + ut \qquad (2\text{-}2)$$

where Rt is the daily change of Bitcoin or daily return of the S&P 500 and D1 – D5 are dummy variables for the five days of the week. It follows that if t is a Monday, then D1 = 1 otherwise D1 = 0, if t is a Tuesday, then D2 = 1 otherwise D2 = 0, if t is a Wednesday, then D3 = 1 otherwise D3 = 0, and so forth. We use model 2-1 for S&P 500(with five-day trading per week and Model 2-2 for Bitcoin (with seven-day trading per week). The as are coefficients to be estimated and ut. is a random error term. If the estimated coefficient a 1, in 2-1, is statistically significantly negative for Bitcoin and S&P 500, then the results imply the presence of a traditional Monday effect.

For month-of-the-year effect, we estimate the following model:

$$Rt = \alpha 1D1+\alpha 2D2+\alpha 3D3+\alpha 4D4+\alpha 5D5+ \alpha 6D6+\alpha 7D7+\alpha 8D8+\alpha 9D9+\alpha 10D10+ \alpha 11D11+\alpha 12D12+ ut \quad (3)$$

where Rt is the daily return in day t, as defined earlier; a s are coefficients to be estimated; Ds are dummy variables for the twelve months of the year, such that dummy variable takes the value of 1 in January and zero in the other month of the year, dummy variable takes the value of 1 in February and zero in the other month of the year, and so on. Finally, ut is a random error term.

4. Empirical Results

The empirical findings of the analysis suggest statistically significant positive returns in the Bitcoin market on Monday, which is consistent with Perry and Mehdian (2001), as a reversal of the traditional Monday effect. The findings also suggest that there are significant positive returns in the Bitcoin market in April, May, and November. The results of the Bitcoin analysis have been compared to the S&P 500 index as a base as the S&P 500 index is widely considered efficient in order to provide further perspective to support the findings. As such, the research shows a positive return on Monday for the S&P 500 index, which is likely driven by the bull run that has been present in U.S. equity markets since the end of the 2008 recession. The means and standard deviations, in parentheses, of the weekly and monthly series, are displayed in tables 1 and 2. As can be seen from Table 1, daily mean and volatility measured by standard deviation are significantly higher for Bitcoin compared to the S&P 500 in all days of the week. In addition, the same conclusion is observed in the case of monthly data, where the monthly standard deviation of Bitcoin is higher compared to the S&P 500 over all months of the year. It is notably that the volatility in the Bitcoin market is substantially higher in January, August, and September than during the other months of the year. It is also important to note that Bitcoin has a negative average return during June, July, August, and September, which is notable as these average negative returns occurred with the backdrop of a U.S. equity market bull run in play. Both of these findings would suggest that further research should be conducted to assess these specific results in more detail.

Table 1: Daily Summary Statistics (in daily percent change) for S&P and Bitcoin

Day	S&P	Bitcoin
Monday	0.11905723 *(0.89772784)*	0.65157367 *(5.68301653)*
Tuesday	0.01818258 *(0.90582155)*	0.61008925 *(8.72744464)*
Wednesday	0.03882869 *(0.90747814)*	0.22944375 *(5.67211905)*
Thursday	0.03096718 *(0.94233403)*	0.26897888 *(5.26948043)*
Friday	0.0103063 *(0.9485828)*	0.40384325 *(6.20264308)*
Saturday	-	0.21629026 *(4.38435922)*
Sunday	-	0.4718197 *(5.51850004)*

Table 2: Monthly Summary Statistics (in daily percent change) for S&P and Bitcoin

Month	S&P	Bitcoin
January	-0.0615281 *(1.37885433)*	2.78831672 *(9.53640299)*
February	0.02828287 *(1.25329554)*	1.34286649 *(5.40096028)*
March	0.09324123 *(0.81058649)*	0.91149278 *(4.79714111)*
April	0.07734207 *(0.71501794)*	0.55113005 *(4.54934694)*
May	0.04900005 *(0.63792663)*	0.18622891 *(4.57377319)*
June	0.03498444 *(0.80597085)*	-0.18426177 *(4.74695729)*
July	-0.0175688 *(1.15686775)*	-0.64311727 *(5.22736441)*
August	0.03498444 *(0.80597085)*	-1.50261287 *(7.0547035)*
September	0.05631579 *(0.44725544)*	-1.1612101 *(9.46684975)*
October	0.05163683 *(0.88646837)*	0.38990625 *(2.71853763)*
November	-0.0241971 *(1.07231335)*	0.2465542 *(2.71722759)*
December	0.07396224 *(0.80347047)*	0.08277347 *(2.76843245)*

The results provided in Table 3 contain the estimated coefficients and corresponding statistics from the estimation using the data pertaining to the day of the week effect analysis. For the S&P 500 index, we can see a statistically significant reverse Monday effect 1% level of significance as the Monday effect would be distinguished by a negative average return for this day of the week. Similarly, Bitcoin also exhibits a reverse Monday effect at the 1% level, however in contrast we see a positive return on Tuesday and Sunday that is significant at the 10% level.

Table 3: Regression of Day-of-the-week effect in the S&P and Bitcoin

Index	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
S&P	0.11844787 (2.62669853)***	0.0192521 (0.44673131)	0.05360717 (1.24391651)	0.02695893 (0.6206783)	-0.0183365 (0.4216874)	-	-
Bitcoin	0.65303137 (2.15849235) ***	0.53558821 (1.77030246)*	0.04157198 (0.13725822)	0.20890139 (0.68972977)	0.29444668 (0.97217467)	0.13378185 (0.44219484)	0.43002701 (1.42138654) *

Notes: T-Statistic is given in parentheses *** significant at 1 percent and *significant at 10 percent

The results provided in Table 4 contain the estimated coefficients and corresponding statistics from the estimation using the data pertaining to the month of the year effect analysis. The results provide evidence to show that Bitcoin displays positive returns that have statistical significance at the 1% level in April, May and November. As a means of comparison, the S&P 500 index does not provide return results in any month that have an appropriate level of statistical significance.

Table 4: Regression of Month-of-the-year effect in the S&P and Bitcoin

Month	S&P	Bitcoin
January	-0.0615281 (-0.9090758)	0.20077538 (0.52035122)
February	0.067882 (0.9751663)	0.33506945 (0.82858242)
March	0.10329564 (1.57543421)	0.04639244 (0.12023567)
April	0.07734207 (1.1520551)	0.86883152 (2.2151415) ***
May	0.04900005 (0.74349179)	0.92824394 (2.40573756) ***
June	0.03498444 (0.52807136)	0.26924533 (0.68645819)
July	-0.0175688 (-0.264497)	0.2033305 (0.52697336)
August	0.05010905 (0.77591679)	-0.04201559 (-0.10889216)
September	0.05631579 (0.82061822)	-0.23386456 (-0.57374438)
October	0.05163683 (0.74819853)	0.2017098 (0.49287508)
November	-0.0241971 (-0.3384432)	0.85452771 (2.05407262) ***
December	0.07396224 (1.04079473)	0.3244825 (0.79286846)

Notes: T-Statistic is in parentheses *** significant at 1 percent

5. Conclusion

As can be supported by the output of the study, Bitcoin exhibits market anomalies at a time when the stock market, as represented by the S&P 500 stock index, primarily does not. While the result is not entirely unexpected, there is still a need to understand these results further to identify the root cause of this disconnect. There are many potential explanations for this disconnect, such as the difference in the method and system Bitcoin and the S&P 500 index are traded, where Bitcoin trades in a continuous market while the S&P 500 trades during open market hours and only on weekdays. Another difference is that the S&P 500 is backed by stocks that are regulated and have real assets that back the companies in the index as well as earning records that can be studied by investors, while Bitcoin is a purely speculative asset and there is lack comprehensive government regulation at this time. One last difference is that Bitcoin has not been studied by the investing world to the same extent as U.S. equities and has no existing intrinsic valuation model that can support the development of the expected market value based on other factors outside of market supply and demand.

The final output of the study has provided evidence that Bitcoin does display statistically significant market anomalies during the tested period, which is not consistent with the U.S. equity market during that same period. While there is evidence of market anomalies present, we have provided multiple potential explanations for these deviations from the efficiency that is worthy of further assessments and additional research in the future. As cryptocurrencies overall and Bitcoin specifically are newer instruments to financial markets, we would expect that over time these instruments will stabilize and perhaps become more efficient with this increased level of maturity.

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BANK CONCENTRATION AND ECONOMIC GROWTH NEXUS: EVIDENCE FROM OIC COUNTRIES

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Abstract

This paper examines the relationship between bank concentration and economic growth in Organization of Islamic Cooperation (OIC) countries. This is done using the system GMM estimators on a panel data sample consisting of 41 countries and 650 observations. Our analysis reveals that bank concentration impacts negatively on economic growth, and this relationship is non-linear. Furthermore, the impact of bank concentration on economic growth is found to be dependent on the country's income but not corruption levels. Nevertheless, different concentration measures provide somehow different results, and thus policymakers should be careful when making policy recommendations. However, it seems reasonable to conclude that bank concentration should be controlled as much as possible to promote economic growth in OIC countries.

Keywords: Bank concentration, financial development, economic growth, OIC countries, corruption, income level.

JEL: O1, O4, L1, P52, C23, D4, F43, G21

1. Introduction

Even though the literature provides conflicting views, a functional banking sector is an important component in the stable financial system. It plays a key role in the economic development of a country and its economic growth. A well-functioning banking sector is especially important for developing countries. However, in the last two decades, the world witnessed the global trend of bank consolidation. This raises the issue of bank concentration and its impact on economic growth to the forefront of academic discussion.

As of now, two major views emerged from the literature. The first view is in favour of a competitive banking structure as it generally leads to efficiency, cheaper credits, and widely available to all (Di Patti & Dell'Ariccia, 2004). On the contrary, the second view supports a robust or monopolistic banking structure. Under this view, bank concentration may stimulate economic growth as these banks are more capable of information collection, screening and monitoring borrowers (Abuzayed & Al-Fayoumi, 2016; Cetorelli & Gambera, 2001; De Guevara & Maudos, 2011; Di Patti & Dell'Ariccia, 2004; Jackson & Thomas, 1995; Petersen & Rajan, 1995).

However, despite overwhelming literature on finance–growth nexus in general and bank concentration–economic growth in particular, this issue has not been adequately addressed within the Organization of Islamic Cooperation (OIC) member countries. This motivated us to investigate this relationship within OIC member countries, which we view essential for several reasons. First, theoretical, and empirical results offered by the literature are far from being conclusive as the results yield contradictory conclusions. In other words, whether bank concentration contributes to overall economic growth or not is unclear as the current discussion on the topic is far from being complete. Second, the literature under review is primarily concerned with developed and developing countries. They focus more on U.S. and EU banks, thus largely ignoring OIC countries. Third, from an economic point of view, the majority of the OIC countries belong to the least developed and developing countries groups. At the same time, overall financial development is at very low levels, and there is an overwhelming corruption that may explain their overall underdevelopment. Fourth, it is argued that banks are the primary source of business finance in most of the countries (Deesomsak, Paudyal, & Pescetto, 2004; Ito, 2006; Lee & Hsieh, 2013a, 2013b; Mlachila, Park, & Yabara, 2013; Moyo, Nandwa, Oduor, & Simpasa, 2014). The same is true for OIC countries that have banking sector more developed than stock markets. Finally, it is worth looking at this relationship to see if results will be similar or different as compared to other studies covering different sets of countries. Since the OIC countries are heterogeneous in nature and consist of developing and emerging economies, the impact of bank concentration on economic growth may be reflected in different ways. Consequently, discovering these ways is crucial for a better understanding of the topic and coming up with policy recommendations.

Having said that, this paper seeks to remedy these issues through analysis of the existing literature and contribution to this growing area of research by exploring the impact of bank concentration on economic growth within OIC member countries. Using a panel data set consisting of developing and emerging economies of different financial structures and sizes, we will therefore test:

i. Does bank concentration impact economic growth within the OIC member countries positively or negatively?
ii. Furthermore, as there is a discrepancy between the sample countries and their socio-economic and financial development, we will also study whether these relationships differ once we split the data set into two subcategories, namely: (i) emerging and developing economies; and (ii) corrupted and less–corrupted countries.

The remainder of the paper is organized as follows: Section 2 provides a literature review; Section 3 describes the data and methodology used; Section 4; analyses empirical results; Section 5 is left for concluding remarks.

2. Literature Review

A large and growing body of literature has investigated the finance–growth nexus. The global trend of bank consolidation brought up another critical dimension on the topic by exploring bank concentration and economic growth relationship. In this regard, there are two primary, but contradicting views. On one side, some support a competitive banking structure as it promotes competitive market practices that lead to efficiency. Greater competition in the banking industry, among other things, makes credit cheaper and more available to all borrowers (Di Patti & Dell'Ariccia, 2004).

In contrast, a banking structure that is highly concentrated and with monopolistic power, in their view and according to economic theory, will be detrimental to economic growth. In general, a monopoly is associated with inefficient resource allocation where optimal levels and prices of products and services are not reached. Recent evidence suggests that banks with monopoly power tend to extract excessive rents from firms through higher loan rates, reduce credit availability in general, lead to financial barriers to entering markets, promote moral hazard problem and credit rationing by banks (Cetorelli & Strahan, 2006; Diallo & Koch, 2017; Fisman & Raturi, 2004; Guzman, 2000; Hannan, 1991; Stiglitz & Weiss, 1981).

A number of studies have found that a more competitive banking sector is conducive to firm creation, credit access (especially for new and small firms), and overall industrial and economic growth as a concentrated banking sector creates financial impediments for new firms (Beck, Demirgüç-Kunt, & Maksimovic, 2003; Black & Strahan, 2002; Carlin & Mayer, 2003; Cetorelli & Gambera, 2001; Cetorelli & Strahan, 2006; Claessens & Laeven, 2005). Similarly, Shaffer (1998) finds a positive association between household income growth and the number of banks in the market using U.S. cross-sectional data.

One of the rare studies focusing on the causality between banking concentration and economic growth and covering some of the OIC countries in the sample is a study by Ghasemi & Abdolshah (2014). By covering 15 countries over the period 2004–2011, they found a bi-directional relationship whereby bank monopoly power harms economic growth, and economic growth promotes bank monopoly power.

On the other side, Jackson and Thomas (1995), Petersen and Rajan (1995), and Cetorelli and Gambera (2001) find that local bank concentration helps small business firms in the U.S. to alleviate credit constraints more effectively. Similar findings are reported by Abuzayed and Al-Fayoumi (2016) for 15 Middle East and North African (MENA) countries and De Guevara and Maudos (2011)[1].

It has been argued that banks with monopolistic power (bank concentration) may spur economic growth as they are more capable of information collection, screening, and monitoring borrowers. These banks can sustain long-lasting relationships with their clients promoting financial stability since excessive competition between banks can result in a sort of financial instability (Di Patti & Dell'Ariccia, 2004).

Thus, contrary to the common wisdom that banking competition unequivocally leads to overall welfare, Cetorelli (2001) finds that there might be specific channels through which it may have adverse economic effects. Other studies also support this view (see Dewatripont & Maskin, 1995; Petersen & Rajan, 1995; Rajan & Zingales, 2001). In fact, based on the literature reviewed, Cetorelli (2001) further concludes that when it comes to the most desirable banking market structure neither extreme – monopoly or perfect competition – may be the best option. This is further substantiated by Deidda and Fattouh (2005) who claim that banking concentration exerts two opposite effects on growth: economies of specialization and duplication of banks' investment in fixed capital. The former is beneficial, and the latter is detrimental to economic growth (Deidda & Fattouh, 2005).

In short, it can be seen then that the current discussion on the topic is far from being complete. Furthermore, most studies on the topic have only focused on U.S. and EU markets in general and Organization for Economic Co-operation and Development (OECD) countries. The

[1] *De Guevara and Maudos (2011) find that bank market power increases economic growth only up to a certain point (an inverted–U–shape relationship).*

existing literature fails to address the issue from less-developed countries' points of view, and this analysis is necessary for a better understanding of the topic. Hence, this study provides an exciting opportunity to advance our knowledge of the bank concentration-economic growth relationship by looking at the issue using OIC countries as a sample. Not only that our study will investigate this relationship on the whole sample, but it will also divide the sample into two broad categories to get additional insights into this relationship. These two categories are: (i) developing– and emerging economies; and (ii) corrupted and less–corrupted countries within the OIC countries sample.

3. Data and Methodology

3.1 Sample Selection and Data Collection

Table 1: Selected OIC countries

No.	Country Name	No.	Country Name	No.	Country Name
1	Afghanistan	15	Jordan	29	Pakistan
2	Albania	16	Kazakhstan	30	Qatar
3	Algeria	17	Kuwait	31	Saudi Arabia
4	Azerbaijan	18	Kyrgyz	32	Senegal
5	Bahrain	19	Lebanon	33	Sierra Leone
6	Bangladesh	20	Libya	34	Sudan
7	Benin	21	Malaysia	35	Togo
8	Burkina-Faso	22	Mali	36	Tunisia
9	Cameroon	23	Mauritania	37	Turkey
10	Comoros	24	Morocco	38	Uganda
11	Egypt	25	Mozambique	39	United Arab Emirates
12	Gabon	26	Niger	40	Uzbekistan
13	Gambia	27	Nigeria	41	Yemen
14	Indonesia	28	Oman		

Initially, we wanted to include all 57 OIC member countries for the period between 2000 and 2015. However, after collecting the data, we had to drop certain countries and years for which there was no sufficient data. The inclusion of a country into our sample is subject to specific criteria. First, we include only those countries that have data for our dependant and independent variables, namely real per capita GDP, and concentration measures. Those countries that are missing these data are excluded from our sample. Second, we include only those countries that have at least three years of continuous observations. [2]Since we are using the GMM method, it is a minimum requirement for data to be processed. Hence, we removed single and two–year observations from our sample. Finally, to reduce the effect of possibly spurious outliers, we eliminate them in all variables by winsorizing at the 1st and 99th percentiles within each country (Beck et al., 2013). After applying these criteria, our final sample comes to a list of 41 countries and 650 observations. Table 1 presents the full sample of selected countries.

Furthermore, several studies investigated whether the effect of bank concentration/competition on economic growth is different when applied to developed and developing countries. The OIC group of countries provides a mixture, consisting of a majority

[2] *Beck et al. (2013) included countries with at least 2 years of continuous observations. However, since we are using GMM method, we opted for at least 3 years of continuous observations.*

of underdeveloped and developing countries with few countries belonging to the group of high–income countries. Thus, the sample offers a unique opportunity to investigate the hypothesis that bank concentration has a different effect on economic growth due to different economic development. As a result, we split our sample into two subcategories: developing– and emerging economies. Based on the World Bank classifications, countries are classified into four income categories, namely: low income, lower middle income, upper middle income, and high income. For this study, we combined low and lower-middle-income countries into developing economies.

Similarly, we combined upper middle income and high-income countries into emerging economies. The detailed classifications, according to the World Bank methodology, is presented in Table 2. Out of 41 countries in our sample, 25 or 60.98% fall under the developing economies group, while the remaining 16 or 39.02% of countries fall under the emerging economies group. We go a step further and investigate our sample from a corruption point of view. As a proxy measure of a level of corruption, we use control of corruption (estimate) data provided by the World Governance Indicator, the World Bank.

Table 2: Developing and Emerging Economies - OIC countries

Developing Economies		Emerging Economies	
Low Income	**Lower Middle Income**	**Upper Middle Income**	**High Income**
Afghanistan	Bangladesh	Albania	Bahrain
Benin	Cameroon	Algeria	Kuwait
Burkina-Faso	Comoros	Azerbaijan	Oman
Gambia	Egypt	Gabon	Qatar
Mali	Indonesia	Jordan	Saudi Arabia
Mozambique	Kyrgyz	Kazakhstan	United Arab Emirates
Niger	Mauritania	Lebanon	
Sierra Leone	Morocco	Libya	
Togo	Nigeria	Malaysia	
Uganda	Pakistan	Turkey	
Yemen	Senegal		
	Sudan		
	Tunisia		

Finally, the data will be obtained from BankFocus (earlier known as BankScope) database of Bureau van Dijk's company, International Monetary Fund, UNESCO Institute for Statistics and several World Bank's databases, namely the World Development Indicators, the Global Financial Development and the World Governance Indicators as pointed out in Table 3.

Table 3: Summary of All Variables

VARIABLES	SIGN	DEFINITION	SOURCE
DEPENDENT VARIABLE(S)			
Economic Growth	Gpc	The real per capita GDP.	WDI[a]
INDEPENDENT VARIABLE(S)			
Measures of Market Structure Concentration			
Concentration ratio 5-bank	CR5	A measure of the degree of competitiveness of the banking sector, proxied by the total assets of the five largest commercial banks as a share of total commercial banking assets.	BankFocus
Concentration ratio 3-bank	CR3	A measure of the degree of competitiveness of the banking sector, proxied by the total assets of the three largest commercial banks as a share of total commercial banking assets.	BankFocus
Herfindahl-Hirschman Index	HHI	HHI is defined as the sum of the square of the market shares (based on total assets) of all the banks that compete in the market.	WITS[b]
Measures of Market Power Concentration			
Lerner index	LI	A measure of market power in the banking market. It is defined as the difference between output prices and marginal costs (relative to prices).	BankFocus
Boone indicator	BI	A measure of the degree of competition, calculated as the elasticity of profits to marginal costs.	BankFocus
CONTROL VARIABLE(S)			
Country-Specific			
Gross capital formation	GCF	The net increase in physical assets (investment minus disposals) within the measurement period, and it can be measured as a ratio of GDP.	WDI
Trade openness	TO	The sum of exports and imports of goods and services measured as a share of GDP.	WDI
Government size	GS	Measured by the ratio of the government's final consumption expenditure to GDP.	WDI
Financial development P	FIN_p	A ratio of private credit by deposit money banks and other financial institutions to GDP.	IFS[c]
Financial development L	FIN_l	A ratio of liquid liabilities to GDP.	IFS
Inflation (GDP deflator)	I	Inflation-adjusted by the GDP deflator.	IMF[d]
Financial crisis	C	A dummy variable to capture the effect of the global financial crisis 2008-2009.	GFD
Developing economies	DEV	A dummy variable to capture the effect of a country's income level.	WDI
Corrupted countries	COR	A variable to capture the effect of corrupted countries.	WGI[e]
Bank-specific			
Bank non-interest income	BNI	Bank's income generated by noninterest related activities as a percentage of total income.	GFD
Bank cost to income	BCI	It measures overhead costs relative to gross revenues.	GFD[f]
Bank net interest margin	BNIM	The difference between the interest charged by the bank and the interest paid out to lenders.	WDI

[a] The World Development Indicators (WDI). The World Bank.
[b] The World Integrated Trade Solution (WITS). The World Bank.
[c] International Financial Statistics (IFS), International Monetary Fund (IMF)
[d] International Monetary Fund, International Financial Statistics and data files using World Bank data on the GDP deflator.
[e] World Governance Indicators (WGI). The World Bank.
f The Global Financial Development (GFD). The World Bank.

3.2 Descriptive Analysis: Overview

First of all, it is essential to note here that due to a potentially non-linear relationship between economic growth and control variables, and in line with prevailing literature, we transform all control variables (except crisis) into natural logarithm forms. Hence, we will use these variables in natural logarithm forms throughout the study (Naceur, Blotevogel, Fischer, & Shi, 2017).

Table 3 provides a summary of all variables, while Table 4 presents the summary statistics of our sample (in level forms). [3]The average GDP per capita (Gpc) is 7,697.77 US$ (constant 2010), [4]but there is wide cross–country variation in the sample with a low of 256.54 US$ to a high of around 72,670.96 US$. The lowest GDP per capita was recorded in 2000 by Mozambique, while the highest was recorded in 2011 by Qatar.

Table 4: Summary of Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Gpc	650	7,697.77	13,921.72	256.54	7,2670.96
CR5	534	83.22	14.74	33.42	100.00
CR3	639	70.87	18.03	23.32	100.00
HHI	549	0.13	0.10	0.03	0.67
LI	518	0.32	0.13	-0.39	0.64
BI	609	-0.06	0.17	-2.54	0.34
GCF	623	24.68	8.09	1.10	61.47
TO	633	76.15	34.71	21.45	220.41
GS	622	14.11	4.78	0.95	30.00
FIN_p	613	28.52	24.31	1.32	119.58
FIN_l	613	47.12	39.41	8.36	242.33
BNI	610	38.61	13.76	3.22	82.75
BCI	610	52.92	14.55	21.03	139.47
BNIM	648	4.96	2.69	0.57	18.63
I	649	7.08	9.85	-25.96	73.84
COR	557	-0.60	0.57	-1.64	1.57

Notes: Gpc is the real GDP per capita. CR5 is the 5-bank concentration ratio. CR3 is the 3-bank concentration ratio. HHI is the Herfindahl-Hirschman Index. LI is the Lerner index. BI is the Boone indicator. GCF is the gross capital formation. TO is the trade openness. GS is the government size. FIN_p is the ratio of private credit to GDP FIN_l is the ratio of liquid liabilities to GDP. BNI is the bank noninterest income to total income ratio. BCI is the bank cost to income ratio. BNIM is the bank net interest margin. I is the inflation (GDP deflator). COR is the control for corruption (estimate).

In addition, the average concentration ratio measured by CR5 is about 83% with a low of about 33% and a high value of 1 (i.e. 100%). The lowest point was recorded by Nigeria in 2001, while the highest was recorded by several countries (19 countries, to be precise). When measured by CR3, the average concentration ratio for our sample is about 71% with a low of about 23% and high values of 1 (i.e. 100%). The lowest concentration was found in the case of Nigeria in 2002. After that period, the concentration ratio in Nigeria was also on the rise, reaching the highest value of 71.09% in 2006. Similar to the CR5 case, the highest concentration point, and hence the highest concentration was recorded by 14 OIC member countries. Consequently, it can be concluded from the data before us that there is an overwhelming concentration of the banking sector in OIC countries. Similar findings are evidenced by the other measures of bank concentration/competition as well.

[3] *Please note that the data presented in this descriptive section are based on winsorized dataset to eliminate spurious outliers as explained briefly in the previous section.*

[4] *Here, for simplicity purposed we explain certain descriptive statistics using level forms for the data. Such is the case of GDP per capita.*

Table 5: Correlation Between Main Dependent and Independent Variables

Appendix B: Correlation coefficients of all variables

	Gpc	CR5	CR3	HHI	LI	BI	GCF	TO	GS	FIN_p	FIN_I	BNI	BCI	BNIM	I	COR	C	DEV
Gpc	1.0000																	
CR5	0.1432	1.0000																
CR3	0.1282	0.9108	1.0000															
HHI	0.0469	0.2687	0.2103	1.0000														
LI	0.4538	0.1892	0.0972	0.0809	1.0000													
BI	0.0972	0.1074	0.1147	-0.1639	0.1548	1.0000												
GCF	0.0701	0.0489	0.0873	0.1754	0.2915	0.1017	1.0000											
TO	0.3858	0.1826	0.2984	-0.0167	0.3093	0.1530	0.2095	1.0000										
GS	0.0344	0.3738	0.2928	0.0756	0.3561	0.1710	0.1732	0.2217	1.0000									
FIN_p	0.2379	-0.0978	0.0028	-0.2078	0.0008	0.1206	0.0240	0.6855	0.2188	1.0000								
FIN_I	0.0646	-0.1818	-0.0774	-0.1941	-0.1411	0.0858	0.0299	0.3990	0.1649	0.7775	1.0000							
BNI	-0.1070	0.1670	0.0926	0.0912	-0.0380	-0.0788	0.0068	-0.1546	-0.0166	-0.3414	-0.3120	1.0000						
BCI	-0.6178	-0.0463	-0.0441	0.1750	-0.5875	-0.2607	-0.2862	-0.4171	-0.0666	-0.3368	-0.1639	0.1986	1.0000					
BNIM	-0.3577	-0.1599	-0.1359	0.1034	-0.0760	-0.2597	-0.0607	-0.3626	-0.2599	-0.5789	-0.5088	0.0212	0.3954	1.0000				
I	0.1376	-0.0145	0.0274	-0.0341	0.0202	-0.0245	0.0333	-0.0035	-0.1731	-0.1820	-0.1890	-0.0107	-0.1210	0.1491	1.0000			
COR	0.1746	0.0051	0.0113	-0.0231	0.0091	-0.1393	0.0378	0.1075	-0.0022	0.0398	-0.1581	-0.1268	-0.0433	-0.1311	0.1522	1.0000		
C	-0.0391	0.0413	0.0621	0.0050	-0.0726	-0.0561	0.0335	-0.0012	-0.0326	0.0230	-0.0033	-0.0324	0.0183	0.0433	-0.0244	-0.0044	1.0000	
DEV	-0.5424	-0.0700	-0.1469	0.0706	-0.3489	-0.1787	-0.2327	-0.5579	-0.1576	-0.4318	-0.3847	0.3087	0.5987	0.3635	-0.1228	-0.0215	0.0356	1.0000

Notes: Gpc is the real GDP per capita. CR5 is the 5-bank concentration ratio. CR3 is the 3-bank concentration ratio. HHI is the Herfindahl-Hirschman Index. LI is the Lerner index. BI is the Boone indicator. GCF is the gross capital formation. TO is the trade openness. GS is the government size. FIN_p is the ratio of private credit to GDP FIN_I is the ratio of liquid liabilities to GDP. BNI is the bank noninterest income to total income ratio. BCI is the bank cost to income ratio. BNIM is the bank net interest margin. I is the inflation (GDP deflator). COR is the control for corruption (estimate). C is the crisis dummy variable. DEV is the dummy variable representing a developing economy.

The presence of the overwhelming bank concentration within the OIC member countries should not come as a surprise as overall underdevelopment is also evident from some indicators. One of them is the financial development variables used in this study. Measured as a ratio of private credit by deposit money banks and other financial institutions to GDP, the average financial development is around 28%, with a minimum and maximum being 1.32% and 119.58% respectively. When liquid liabilities measure financial development to GDP ratio, the average is around 47%, while a minimum and maximum are 8.32% and 242.33% respectively. Another indicator that shows the overall underdevelopment of our sample countries is the gross capital formation (GCF) variable. Its average is 24.68% of GDP, with a low value of 1.10 % for Sierra Leone recorded in 2000, and a high value of 61.47% for Mauritania recorded in 2005. Furthermore, Table 5 provides a correlation matrix among the study variables.

3.3 Data Descriptions

After reviewing the existing literature, it is evident that there are standard measures when it comes to measuring the economic growth of a country. Following Beck, Degryse, and Kneer (2014), as economic growth proxy, this study uses the real per capita GDP (Gpc). The data source of these variables is the World Development Indicators (WDI) Database.

When it comes to bank concentration/competition measures, several of them have been used in the literature. Perhaps the simplest and probably the most frequently used measure of bank concentration is the *k bank concentration ratio*. CR3 and CR5 are the most commonly used, representing the cumulative market share of the *k* largest banks in a country to the assets of the whole banking industry (Davis, 2007). Another measure is HHI index that takes into consideration the size distribution of all banks in the market making it better than the *k bank concentration ratio* (Carbó, Humphrey, Maudos, & Molyneux, 2009).

One of the most popular non–structural measures of market power is the Lerner index (LI), developed by Abraham P. Lerner (1934). In essence, the Lerner index, or degree of monopoly power, measures a bank's/firm's market power by calculating the difference between output prices and marginal costs (relative to prices), following the methodology described in Demirgüç-Kunt and Martínez Pería (2010).[5]

The usage of the Lerner index has several advantages over other measures of concentration /competition, especially those structural ones discussed earlier. Not only that the Lerner index can measure the market power of individual firms or specific products, but it can also measure the market power of the whole industry or market. As a result, it is considered as the only available measure of competition at the bank level (Berger, Klapper, & Turk-Ariss, 2009; Coccorese, 2009; Repkova, 2012).

other non–structural measure of competition is the Boone indicator (BI). While challenging the theoretical foundations of the Lerner's index, Boone (2004, 2008) proposed a macro–level index of competition that caters for some shortcomings of the Lerner index.[i6]

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[5] *Mathematically it is expressed as follows: Lerner Index = (P-MC)/P. Marginal cost is calculated using estimated translog cost function with respect to output and prices are calculated as total bank revenue over assets. For details see Demirgüç-Kunt and Martínez Pería (2010).*

[6] *Boone (2004, 2008) argued that the theoretical foundations of the existing price cost margin (PCM) measure of competition are not robust and proposed a macro–level index of competition. According to the Lerner index that is based on PCM, as competition increases in a given market/industry its PCM will decrease and finally reach zero in perfect competition. This may not be the case, Boone (2004, 2008) argues saying that in some cases a more intense*

Several country-specific control variables are used as well. For example, gross capital formation (GCF) is a control variable that reflects the overall economic development of a country. Levine & Renelt (1992) and Islam (1995) find a significantly positive effect of gross domestic investment (now known as capital formation) as a share of GDP on growth. Trade openness (TO), measured as the sum of exports and imports of goods and services as a share of GDP, is found to contribute positively to economic growth in a number of the existing empirical literature (Beck et al., 2014; Beck & Levine, 2004; Dollar, 1992; Dollar & Kraay, 2004).

The government size (GS) is the most frequently used variable as it measures overall economic development and government policies. In this study, we use the ratio of the government's final consumption expenditure to GDP. The financial crisis dummy (C) is used as an indicator of macroeconomic development. It takes the value of one for the year 2008 and 2009 and zeroes otherwise to capture the effect of the global financial crisis on economic growth. During a financial crisis, banks are faced with a few challenges that make them fragile. This brings about uncertainty in the market and increases overall risk.

As a financial development indicator, we use two measures:

i. a ratio of private credit by deposit money banks and other financial institutions to GDP (FIN_p) and it captures the allocation of credit by deposit money banks and other financial institutions relative to the size of the economy;
ii. a ratio of liquid liabilities to GDP (FIN_l) that measures banks' ability to mobilize funds or banking sector's size (see Abuzayed & Al-Fayoumi, 2016; Compton & Giedeman, 2011; Law & Singh, 2014). Both these ratios can be considered as part of overall institutional as well as banking development.

It is worth mentioning here that we opt for these two measures of financial development for mainly two reasons, namely:

i. financial development plays a crucial role in our study, and one of the objectives is the interaction between this variable and bank concentration measures;
ii. this approach can also be considered as a part of robustness check for the overall results.

As for ban-specific control variables, we use bank noninterest income (BNI), bank cost to income ratio (BCI), and bank net interest margin (BNIM). The BNI measures bank efficiency, overhead costs relative to gross revenues, with higher ratios indicating lower levels of cost-efficiency. The BCI measures overhead costs relative to gross revenues with higher ratios indicating lower levels of cost-efficiency. It is argued that bank efficiency and its stability promote economic growth through its impact on bank efficiency and stability (Beck et al., 2013). Finally, the BNIM is a measure of the difference between the interest paid and the interest received by banks. It is used as an indicator of the macroeconomic development of a country as it reflects the banks' efficiency.[7]

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competition may lead to higher PCM instead of lower margins. In this scenario, as further elaborated by Van Leuvensteijn et. al. (2011), "more efficient banks may have a higher PCM (skimming off part of the profits stemming from their efficiency lead), the increase of their market share may raise the industry's average PCM, contrary to common expectations" (p. 3158).

[7] *Boone (2004, 2008) argued that the theoretical foundations of the existing price cost margin (PCM) measure of competition are not robust and proposed a macro–level index of competition. According to the Lerner index that is based on PCM, as competition increases in a given market/industry its PCM will decrease and finally reach zero in perfect competition. This may not be the case, Boone (2004, 2008) argues saying that in some cases a more intense*

We use inflation as a control variable for overall macroeconomic conditions is inflation and a proxy for monetary (in)stability. Countries with high inflation tend to have financial systems that are generally underdeveloped and prone to financial crises (Boyd, Levine, & Smith, 2001; Demirgüç-Kunt & Detragiache, 1998).

Table 6: Expected impact of variables

	Variables	Sign	Expected Impact
DEPENDENT VARIABLE(S)			
	GDP per capita growth rate	*Gpc*	
INDEPENDENT VARIABLE(S)			
Concentration Measures	***Measures of Market Structure Concentration***		
	Concentration ratio – 5 top banks	*CR5*	+ | -
	Concentration ratio - 3 top banks	*CR3*	+ | -
	Herfindahl-Hirschman Index	*HHI*	+ | -
	Measures of Market Power Concentration		
	Lerner index	*LI*	+ | -
	Boone indicator	*BI*	+ | -
CONTROL VARIABLE(S)			
Bank-Specific	***Bank-specific***		
	Bank noninterest income (%)	*BNI*	+ | -
	Bank cost to income ratio (%)	*BCI*	-
	Bank net interest margin (%)	*BNIM*	+
Country-Specific	***Macroeconomic developments***		
	Inflation (GDP deflator)	*I*	-
	Financial crisis '08 & '09 (Dummy)	*C*	-
	Trade openness	*TO*	+
	General economic development		
	Human capital accumulation	*HC*	+
	Gross capital formation	*GCF*	+
	Government size	*GS*	+ | -
	Financial development		
	Private credit by banks to GDP (%)	*FIN_p*	+ | -
	Liquid liabilities to GDP (%)	*FIN_l*	+ | -
	Policy variables		
	Institutional development	*ID*	+
	Subgrouping		
	Developing economies (dummy)	*DEV*	+ | -
	Corrupted countries (dummy)	*COR*	-

On top of that, we divided our sample into two sub-groups and introduced a dummy variable for each sub-group. The overall level of socio-economic development of a country may result in different effects of bank concentration on economic growth. Bank concentration has a significantly negative impact on economic growth low–income countries only (Abuzayed & Al-Fayoumi, 2016; Deidda & Fattouh, 2005; A. I. Fernández, González, & Suárez, 2010). Consequently, we introduced a dummy variable that takes the value of 1 for developing economies and 0 for emerging economies. Similarly, we introduced a corruption dummy (COR) variable to see how corruption level affects economic growth. A few studies indicate that corruption may have a positive effect on developing processes in the case of countries with excessive bureaucratic and regulatory obstacles (Bardhan, 1997; Leff, 1964). Overwhelming opinion, however, is that corruption has adverse effects not just on economic

competition may lead to higher PCM instead of lower margins. In this scenario, as further elaborated by Van Leuvensteijn et. al. (2011), "more efficient banks may have a higher PCM (skimming off part of the profits stemming from their efficiency lead), the increase of their market share may raise the industry's average PCM, contrary to common expectations" (p. 3158).

growth but also on political and institutional developments of a country (Bardhan, 1997; Robinson, 1998; Voskanyan, 2000).

Finally, Table 6 shows the expected impact of independent and control variables on economic growth.

3.4 Methodology

3.4.1 Baseline Empirical Methods

To assess the impact of the bank concentration on economic growth within the OIC member countries we will use a variant of the models used by Berger et al. (2009), Alin & Bogdan (2011), Fu et al. (2014), Fernández & Garza–García (2015) and Abojeib (2017). For example, Abojeib (2017) used this model to investigate the relationship between competition and stability. Hence, our baseline model is as follows:

$$Gpc_{i,t} = \alpha Gpc_{i,t-1} + \beta CON_{i,t} + \delta B_{i,t} + \theta C_{i,t} + \tau_t + \nu_i + \varepsilon_{i.t} \qquad (1)$$

where,

$Gpc_{i,t}$ is the real per capita GDP of country *i* at time *t*, and where *i* denotes the cross-sectional dimension (i.e. country), and *t* denotes the time dimension (i.e. year).

$Gpc_{i,t-1}$ the lagged dependent variable is included to account for persistency in real per capita GDP.

$CON_{i,t}$ represents the concentration measure of country *i* at time *t* as measured by one of the concentration measures.

$B_{i,t}$ is a vector of bank-specific control variables

$C_{i,t}$ is a vector of country-specific control variables

τ_t is a year dummy to control for time-varying standard shocks

ν_i is a dummy to control for time-invariant country-specific factors, and

$\varepsilon_{i,t}$ is a residual value.

The sign and magnitude of β in the estimations' results using the model in *Eq. 1* would indicate the nature of the relationship between bank concentration and economic growth. This is because the marginal effect of bank concentration on economic growth is equal to the partial derivative of *Gpc* with respect to *CON* or mathematically:

$$\frac{\partial Gpc}{\partial CON} = \beta \qquad (2)$$

The above model assumes that the relationship between concentration and economic growth is linear. However, several studies show that this relationship may be non–linear, after all. For instance, see Cetorelli & Gambera (2001), di Patti & Dell'Ariccia (2004), Berger *et al.* (2009), Fernández *et al.* (2010), Soedarmono (2010) and Ma & Song (2017). Hence, to investigate this empirically, we will use the following models for bank concentration–economic growth non-linear relationship:

$$\mathrm{Gpc}_{i,t} = \alpha \mathrm{Gpc}_{i,t-1} + \beta_1 \mathrm{CON}_{i,t} + \beta_2 \mathrm{CON}_{i,t}^2 + \delta \mathrm{B}_{i,t} + \theta \mathrm{C}_{i,t} + \nu_i + \varepsilon_{i.t} \quad (3)$$

In this case, we want to see whether the effect of bank concentration is only demonstrated up to a certain limit after which its effect might change. In this case, the marginal effect of bank concentration on economic growth would be as follows:

$$\frac{\partial \mathrm{Gpc}}{\partial \mathrm{CON}} = \beta_1 + 2 * \beta_2 \mathrm{CON} \quad (4)$$

The above equation represents a line with an intercept (β_1) and a slope ($2*\beta_2$) indicating that for each value of CON, the value of marginal effect would be different. The marginal effect would be zero when $CON = \frac{-\beta_1}{2\beta_2}$, which is called the inflection point or threshold level. However, depending on results from *Eq. 4* above, the marginal effect would be positive or negative for any value of concentration higher or lower than the inflection point value.

Finally, as there is a discrepancy between the sample countries and their socio-economic and financial development, we will also study whether these relationships differ once we split the dataset into two subcategories, namely: (i) emerging and developing economies; and (ii) corrupted and less–corrupted countries.

To test this claim, we introduce a dummy variable that takes the value of 1 for developing economies/corrupted countries and 0 for emerging economies/less corrupted ones. Hence, we modify *Eq. 1* by introducing interaction terms between the CON and developing economies (DEV_j)/corrupted countries (COR_j). Introducing the interaction term between CON and DEV/COR dummy would account for a potential difference in the concentration–growth relationship between developing and emerging economies on one side and corrupted and less corrupted OIC countries on the other. A similar approach has been taken by Deidda & Fattouh (2005), Fernández *et al.* (2010), and Abuzayed & Al–Fayoumi (2016). We get the following models:

$$\mathrm{Gpc}_{i,t} = \alpha \mathrm{Gpc}_{i,t-1} + \beta_1 \mathrm{CON}_{i,t} + \beta_2 \mathrm{DEV}_j + \beta_3 (\mathrm{CON}_{i,t} \times \mathrm{DEV}_j) + \delta \mathrm{B}_{i,t} + \theta \mathrm{C}_{i,t} + \nu_i + \varepsilon_{i.t} \quad (5)$$

where *j* refers to emerging and developing economies, 0 for emerging and 1 for developing economy.

$$\mathrm{Gpc}_{i,t} = \alpha \mathrm{Gpc}_{i,t-1} + \beta_1 \mathrm{CON}_{i,t} + \beta_2 \mathrm{COR}_j + \beta_3 (\mathrm{CON}_{i,t} \times \mathrm{COR}_j) + \delta \mathrm{B}_{i,t} + \theta \mathrm{C}_{i,t} + \nu_i + \varepsilon_{i.t} \quad (6)$$

where *j* refers to corrupted and less–corrupted country.

Thus, in both cases, when the dummy variable (DEV or COR) is equal to 0, the marginal effect of bank concentration on economic growth would be:

$$\frac{\partial \mathrm{Gpc}}{\partial \mathrm{CON}} = \beta_1 \quad (7)$$

In other words, the sign of β_1 indicates the sign of the bank concentration-economic growth relationship for emerging/less corrupted economies. On the other hand, when the dummy variable (DEV or COR) is equal to 1, the marginal effect equation would be:

$$\frac{\partial \mathrm{Gpc}}{\partial \mathrm{CON}} = \beta_1 + \beta_3 \quad (8)$$

In short, the significance or insignificance of $\beta_1+\beta_3$ will determine whether there is a relationship between bank concentration and economic growth for developing economies/corrupted countries. Finally, by comparing β_1 with $\beta_1+\beta_3$ that are representing the marginal effect for emerging/corrupted and developing/less corrupted economies respectively, we can find out the difference between both types of income-and corruption-level countries in terms of a concentration-growth relationship.

3.4.2 Estimation Method

To date, various methods have been developed and introduced to measure bank concentration-growth relationships. Having in mind the fact that we are dealing with a dynamic panel dataset with a large number of cross-sections (*N*) and a small number of time periods (*T*), and following the existing literature on the topic, we will employ the generalized method of moments (GMM) estimators in our analysis.

The initial GMM method was formalized by Hansen (1982), subsequently developed by Holtz–Eakin, Newey, & Rosen (1988), Arellano & Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) and Bond, Hoeffler, & Temple (2001) and became known in the literature as difference GMM and system GMM estimators.

Both GMM estimators address the bias problems encountered by the OLS method and were developed for dynamic panel data models with many cross-section units (***N***) and a small number of time periods (***T***). They allow for the endogeneity of regressors (meaning that one or more of the regressors can be correlated with the error term), fixed effects, heteroskedasticity and autocorrelation within individuals. They can take care of unobserved country-specific effects (Roodman, 2009a).

Both estimators fit our model using linear GMM. The difference GMM, also known as Arellano–Bond estimator, was operationalized by Arellano & Bond (1991) whereby the estimation is proceeded by transforming all regressors, usually by differencing, in order to eliminate the fixed effect (Roodman, 2009b). However, this estimator may lead to poor results and large sample bias. Hence, to address this issue, Arellano & Bover (1995) and Blundell & Bond (1998) developed the *system GMM* which combines in a system the regression in differences with the regression in levels, i.e. it combines two equations (the original and the transformed one) in a system. In other words, "where lagged variables in levels instrument the differenced equation, lagged differences now instrument levels" (Roodman, 2009b, p. 138). This can improve efficiency and allows the introduction of more instruments (Roodman, 2009a).[8] Consequently, the system GMM method is much more consistent, asymptotically normally distributed, and efficient in estimating the coefficients of the model and in solving the problems of endogeneity, heteroscedasticity, and autocorrelation (Arellano & Bover, 1995; Hsiao, 2007).

The consistency of the GMM estimator relies on two hypotheses. First, the assumption on validity (exogenous) of the instruments used. Second, the assumption that the differenced error terms do not exhibit second– or higher-order serial correlation. In order to ensure the GMM estimation validity and test the above hypotheses, we will run two specification tests suggested by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998).

The first hypothesis, i.e. the validity of instruments, is tested using Sargan and Hansen test of over-identifying restrictions. It tests the overall validity of the instruments by analysing the sample analogy of the moment conditions used in the estimation procedure. The null hypothesis is that there is no correlation between the residuals and the instrumental variables (Beck & Levine,

[8] For detailed discussions about the GMM methods, see Roodman (2009a, 2009b) and Zsohar (2012), among others.

2004). The second hypothesis, i.e. no second-order serial correlation, is tested using Arellano–Bond tests for first-order autocorrelation (AR1) and second-order autocorrelation (AR2). Failure to reject the null hypothesises of both tests gives support to our model (Beck & Levine, 2004; Boyd et al., 2001).

To sum up, dynamic panel techniques, such as GMM methods, fulfils the requirements of our proposed study since we have a relatively low number of years and a large number of cross-sections per year, i.e. unbalanced panel. However, due to the structure of our dataset, overall superiority of the system GMM and for the consistency of our interpretations, we will use the system GMM for all models in the text.

4. Empirical Results and Discussion

To get our results, we employ GMM for reasons explained earlier. We use the STATA software version 14.2 and Roodman's (2009) *xtabond2* command due to its more flexible features over the built-in command. Given the models, we treat all explanatory variables to be weakly exogenous. Furthermore, in all our models, we use the year dummies (2000-2015) to control for potential time shocks not captured in our specifications. Nevertheless, due to the lack of informative content of these variables and space constraints, we opt not to report them in our tables.

4.1 Main Results

4.1.1. Baseline Results

Table 7 provides estimation results of equations (*Eq. 1*) using the two-step robust system GMM estimation methods. More specifically, this table presents the effect of bank market structure and market power, measured by concentration ratio of top 3 banks (CR3) and Lerner index (LI) respectively, on economic growth measured by the real per capita GDP (Gpc). While doing so, we use sets of banks–specific and country-specific variables discussed earlier.[9]

Furthermore, throughout this study, we will use two proxies for financial development, namely private credit to GDP ratio (FIN_p) and liquid liabilities to GDP ratio (FIN_l). Hence, the results in each panel of Table 7 are organized as follows: (i) Models (1)–(3) and (7)–(9) are using FIN_p; and (ii) Models (4)–(6) and (10)–(12) are using FIN_l for CR3 and LI Models respectively.

Note that Models (1), (4), (7), and (10) report results using only country-specific control variables. Models (2), (5), (8), and (11), on the other hand, provide estimation results using both banks- and country-specific control variables. Finally, under the Models (3), (6), (9) and (12) we consider the global financial crisis (C) and inflation (INF) to investigate their possible effects and significance on the economic growth. This format will be applied throughout all regression results tables where applicable.[10]

[9] Initially, we started with all control variables, then, the insignificant ones are excluded gradually (one by one). These initial results using all control variables, however, are nor reported.

[10] After running regressions using several models applicable in our studies, it turns out that the financial crisis is insignificant in most cases. Hence, for brevity of results interpretation, we excluded this control variable from other models.

Diagnostic statistics, reported at the bottom of every table, imply adequacy of GMM estimations. More specifically, the autoregressive coefficients indicate significant persistence required for using GMM. Furthermore, the autocorrelation tests of the first–differenced residuals suggest the presence of autocorrelation of order 1 (AR1) in all cases but fail to reject the null of no autocorrelation of order 2 (AR2). These results indicate that the residuals in *Eq. 1* are free from the autocorrelation problem in all models. Finally, we use the Hansen's *J* test to test for the relevance and validity of the instruments used. Accordingly, the Hansen test statistics confirm the validity of instruments used in our estimation models.

Table 7: Concentration – Growth Relationship: Linear Model – Baseline Results

Variables	Panel A - CR3						Panel B - LI					
	FIN_p			FIN_l			FIN_p			FIN_l		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
lnGpc $_{t-1}$	0.984***	0.939***	0.946***	0.978***	0.931***	0.942***	1.036***	1.113***	1.063***	1.098***	0.868***	0.893***
	[0.009]	[0.021]	[0.011]	[0.007]	[0.023]	[0.013]	[0.024]	[0.059]	[0.065]	[0.051]	[0.133]	[0.129]
CR3	-0.056***	-0.090**	-0.086***	-0.065***	-0.094*	-0.087**						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]						
LI							-0.152**	-0.093	-0.000	-0.337*	0.084	0.150
							[0.070]	[0.125]	[0.022]	[0.201]	[0.202]	[0.272]
lnFIN_p	-0.002	-0.010	-0.003				-0.044**	-0.064**	-0.070***			
	[0.008]	[0.012]	[0.014]				[0.022]	[0.031]	[0.023]			
lnFIN_l				-0.001	-0.035*	-0.033*				-0.129*	-0.021	-0.028
				[0.009]	[0.018]	[0.018]				[0.070]	[0.055]	[0.074]
lnGCF	0.031**	0.027	0.040	0.030**	0.027	0.027	0.023*	0.063*	0.032**	0.034	0.032	0.028
	[0.012]	[0.025]	[0.026]	[0.015]	[0.027]	[0.026]	[0.013]	[0.036]	[0.016]	[0.033]	[0.081]	[0.098]
lnTO	0.029**	0.067**	0.052**	0.040***	0.081**	0.069**	-0.019	-0.018	-0.011	-0.021	0.109	0.104
	[0.013]	[0.027]	[0.024]	[0.014]	[0.033]	[0.028]	[0.020]	[0.048]	[0.021]	[0.038]	[0.115]	[0.132]
lnGS	-0.025***	-0.022	-0.012	-0.025**	-0.021	-0.001	0.006	-0.023	-0.049**	-0.019	-0.029	-0.022
	[0.009]	[0.028]	[0.023]	[0.010]	[0.028]	[0.019]	[0.017]	[0.052]	[0.025]	[0.047]	[0.071]	[0.095]
lnBNI		-0.037**	-0.022		-0.055**	-0.045*		0.118*	0.016		-0.137	-0.110
		[0.018]	[0.020]		[0.024]	[0.024]		[0.065]	[0.013]		[0.137]	[0.146]
lnBCI		-0.112**	-0.092***		-0.126**	-0.096***		0.186	-0.010		-0.188	-0.120
		[0.056]	[0.032]		[0.062]	[0.035]		[0.149]	[0.010]		[0.226]	[0.203]
lnBNIM		-0.041***	-0.038***		-0.062***	-0.057***		0.067	-0.008**		-0.113	-0.102
		[0.013]	[0.014]		[0.019]	[0.015]		[0.047]	[0.004]		[0.125]	[0.140]
lnINF			0.009***			0.008***			0.001			0.008
			[0.002]			[0.003]			[0.001]			[0.011]
C			-0.009			-0.008			-0.002			-0.009
			[0.006]			[0.005]			[0.003]			[0.015]
Constant	0.033	0.925**	0.683***	0.043	1.177**	0.896***	-0.086	-1.957	-0.184	-0.134	2.010	1.434
	[0.036]	[0.396]	[0.252]	[0.038]	[0.492]	[0.306]	[0.062]	[1.215]	[0.506]	[0.170]	[2.229]	[2.165]
Observations	548	514	463	548	514	463	461	461	422	461	461	422
No. of instruments	34	35	37	34	35	37	10	21	22	18	15	17
No. of groups	39	39	39	39	39	39	37	37	37	37	37	37
Arellano-Bond: AR (1)	0.013	0.001	0.001	0.011	0.001	0.001	0.014	0.050	0.027	0.041	0.053	0.048
Arellano-Bond: AR (2)	0.209	0.219	0.220	0.213	0.120	0.111	0.173	0.535	0.114	0.488	0.106	0.114
Hansen test (p-val)	0.247	0.566	0.826	0.288	0.683	0.906	0.108	0.788	0.177	0.357	0.613	0.829

Notes: *(i) Standard errors in brackets, (ii) * p<0.1, ** p<0.05, *** p<0.01.*

lnGpc is the natural log of the real GDP per capita. CR3 is the 3-bank concentration ratio (due to low values; we multiplied the coefficients by 100). LI is the Lerner index. lnFIN_p is the natural log of the ratio of private credit to GDP. lnFIN_l is the natural log of the ratio of liquid liabilities to GDP. lnGCF is the natural log of the gross capital formation. lnTO is the natural log of trade openness. lnGS is the natural log of the government size. lnBNI is the natural log of the bank noninterest income to total income ratio. lnBCI is the natural log of the bank cost to income ratio. lnBNIM is the natural log of the bank net interest margin. lnINF is the natural log of inflation. C is the crisis dummy variable.

Bank market structure, as measured by CR3 in Table 7, is found to be negatively significant in all estimations. The same relationship is evidenced when using LI as the primary independent variable, but only in two models, Model (7) and Model (10). Obviously, the results indicate a negative relationship between bank concentration and real per capita GDP (Gpc), regardless of whether we use market structure (CR3) or market power (LI) measure as proxies for bank concentration. For instance, Model (1) suggests that *ceteris paribus*, the impact of one standard deviation increase in bank concentration (CR3) decreases real per capita GDP by about 1.8%. Similarly, Model (10) suggests that *ceteris paribus*, the impact of one standard deviation increase in bank market power (LI) decreases real per capita GDP by about 4%.

The findings support the competitive banking structure view and are consistent with the results found by Black & Strahan, (2002), Beck *et al.* (2003), Carlin & Mayer (2003), Deidda and Fattouh (2005), Cetorelli & Strahan (2006), Fernández *et al.* (2010), Ferreira (2012), Ghasemi & Abdolshah (2014), Abuzayed & Al–Fayoumi (2016) and Diallo and Koch (2017). The results, however, are in contrast to Petersen and Rajan (1995), Maudos & de Guevara (2006), and Abuzayed & Al–Fayoumi (2016), among others, who found a positive relationship between bank concentration and economic growth.

As for the control variables, the results are somehow mixed. By looking at the country-specific or macroeconomic control variables, trade openness (TO) shows a positively significant impact on Gpc in all models under Panel A, while gross capital formation (GCF) and government size (GS) are positively and negatively significant in Models (1) and (4), respectively. The findings are in line with existing literature that shows the negative impact of a large public sector on economic growth (Baklouti & Boujelbene, 2016; Nyasha & Odhiambo, 2019; Sheehey, 1993). In other words, the impact of GS depends on the relative size of the public sector and the level of Gpc. Given the fact that the majority of OIC countries are overburdened with large public sectors that are, in most cases, ineffective and corrupt, finding a negative relationship is not a surprise.

In Panel B, however, where LI is used as a proxy for bank concentration GCF is the only control variable positively significant in Models (7–9). For instance, an increase of 1% in GCF under Model (8) would increase Gpc by 0.06%.

Similar results are found in the case of bank-specific control variables. Almost all variables are significant, indicating a negative impact on Gpc, at least when CR3 is used as a proxy for bank market structure (Panel A). Taking Model (2) as an illustration, the impact of 1% increase in bank noninterest income (BNI), bank cost to income ratio (BCI), and bank net interest margin (BNIM) would decrease Gpc by about 0.04%, 0.11% and 0.04%, respectively. In Panel B, however, only BNI is significant, with rather a positive impact on Gpc. In addition, the results indicate a positive effect of inflation (INF) on Gpc in all four Models, but the coefficients are significant in only three models, Models (3), (6), and (9). Contrary to that, crisis (C) is significant only in Model (9) indicating a negative impact on Gpc.

Finally, since we are interested in financial development as well, it is worth noting that financial development proxies, FIN_p and FIN_l, have significant adverse effects on real per capita GDP (Gpc) in five cases. Although this might be counterintuitive, these results are in line with findings reported by Shen and Lee (2006), Bezemer, Grydaki, and Zhang (2014), Samargandi, Fidrmuc, and Ghosh (2015) and Benczúr, Karagiannis, and Kvedaras (2019). It seems that the composition of credit has changed over the years and the results are negative since most of the credit goes to financial assets, thus not contributing to the growth. Similarly, Naceur et al. (2017) found that thresholds mark the finance–growth relationship, and it depends on income level, policy regime, institutional quality, and region of a given country.

To sum up, these baseline results are preliminary as there might be some other conditions that might influence the bank concentration-economic growth relationship. This may include non-linearity, income level, and corruption level to which we now turn.

Table 8: Concentration – Growth Relationship: Non–Linear Model

Variables	Panel A - CR3						Panel B - LI					
	FIN_p			FIN_l			FIN_p			FIN_l		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
lnGpc $_{t-1}$	0.984***	0.941***	0.956***	0.978***	0.933***	0.944***	1.036***	1.192***	1.022***	1.090***	0.832***	0.866***
	[0.008]	[0.021]	[0.013]	[0.007]	[0.020]	[0.013]	[0.028]	[0.104]	[0.066]	[0.046]	[0.163]	[0.104]
CR3	0.201*	0.063	0.023	0.196	0.045	-0.025						
	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]						
CR3SQR	-0.001**	-0.001	-0.001	-0.002**	-0.001	-0.000						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
LI							0.404*	1.051*	0.272	0.370	-0.236	-0.177
							[0.209]	[0.607]	[0.285]	[0.242]	[0.529]	[0.377]
LISQR							-0.816*	-1.932*	-0.478	-1.056*	0.556	0.457
							[0.433]	[1.049]	[0.515]	[0.573]	[1.082]	[0.808]
lnFIN_p	-0.002	-0.011	-0.003				-0.039	-0.106*	-0.018			
	[0.007]	[0.012]	[0.011]				[0.026]	[0.058]	[0.034]			
lnFIN_l				-0.002	-0.035**	-0.031*				-0.121**	-0.022	-0.010
				[0.008]	[0.017]	[0.017]				[0.059]	[0.050]	[0.038]
lnGCF	0.029**	0.023	0.025	0.027**	0.024	0.027	0.018	0.034	0.025	-0.006	0.025	0.009
	[0.012]	[0.025]	[0.021]	[0.013]	[0.027]	[0.028]	[0.016]	[0.057]	[0.019]	[0.032]	[0.072]	[0.053]
lnTO	0.031**	0.069**	0.044*	0.040***	0.081**	0.068**	-0.002	-0.028	-0.002	-0.013	0.139	0.099
	[0.013]	[0.030]	[0.023]	[0.013]	[0.032]	[0.028]	[0.023]	[0.077]	[0.029]	[0.042]	[0.132]	[0.096]
lnGS	-0.030***	-0.023	-0.018	-0.029***	-0.023	-0.004	-0.016	0.029	-0.004	-0.016	-0.052	-0.041
	[0.010]	[0.028]	[0.019]	[0.011]	[0.025]	[0.018]	[0.026]	[0.089]	[0.038]	[0.045]	[0.064]	[0.058]
lnBNI		-0.037**	-0.021		-0.055**	-0.042*		0.176	0.010		-0.174	-0.130
		[0.018]	[0.017]		[0.022]	[0.024]		[0.112]	[0.057]		[0.165]	[0.118]
lnBCI		-0.105**	-0.075**		-0.119**	-0.090***		0.204	0.027		-0.256	-0.208
		[0.051]	[0.029]		[0.052]	[0.032]		[0.160]	[0.073]		[0.271]	[0.148]
lnBNIM		-0.040***	-0.032**		-0.060***	-0.054***		0.084	0.005		-0.146	-0.137
		[0.014]	[0.015]		[0.016]	[0.014]		[0.060]	[0.038]		[0.145]	[0.122]
lnINF			0.008***			0.008***			-0.000			0.015
			[0.003]			[0.003]			[0.007]			[0.011]
C			-0.007			-0.008			-0.003			-0.009
			[0.005]			[0.005]			[0.008]			[0.011]
Constant	-0.030	0.843**	0.588***	-0.018	1.099***	0.827***	-0.178	-2.889*	-0.334	-0.116	2.741	2.231
	[0.041]	[0.348]	[0.214]	[0.043]	[0.397]	[0.266]	[0.146]	[1.600]	[0.926]	[0.215]	[2.784]	[1.762]
Observations	548	514	463	548	514	463	461	461	422	461	461	422
No. of instruments	35	36	38	35	36	38	21	19	21	15	15	16
No. of groups	39	39	39	39	39	39	37	37	37	37	37	37
Arellano-Bond: AR(1)	0.009	0.001	0.001	0.008	0.001	0.001	0.006	0.099	0.021	0.036	0.084	0.089
Arellano-Bond: AR(2)	0.212	0.211	0.212	0.215	0.113	0.114	0.131	0.540	0.100	0.494	0.143	0.148
Hansen test (p-val)	0.294	0.529	0.730	0.327	0.686	0.891	0.101	0.464	0.102	0.120	0.371	0.429

Notes: *(i) Standard errors in brackets, (ii) * p<0.1, ** p<0.05, *** p<0.01.*
lnGpc is the natural log of the real GDP per capita. CR3 is the 3-bank concentration ratio (due to low values; we multiplied the coefficients by 100). CR3SQR is the square term of CR3 (multiplied by 100). LI is the Lerner index. LISQR is the square term of LI. lnFIN_p is the natural log of the ratio of private credit to GDP. lnFIN_l is the natural log of the ratio of liquid liabilities to GDP. lnGCF is the natural log of the gross capital formation. lnTO is the natural log of trade openness. lnGS is the natural log of the government size. lnBNI is the natural log of the bank noninterest income to total income ratio. lnBCI is the natural log of the bank cost to income ratio. lnBNIM is the natural log of the bank net interest margin. lnINF is the natural log of inflation. C is the crisis dummy variable.

4.1.2. Non–Linear Bank Market Structure & Economic Growth Relationships

By investigating non–linearity of this relationship, we are simply testing whether the effect of bank concentration on economic growth depends on its degree/level. Looking from a bank's perspective, experiencing some sort of bank power and/or concentration has its advantages and disadvantages as well. On one side, a bank may become more careful in credit analysis and investment opportunities, and at the same time as its power increases its ability to cope with losses improves. On the other hand, as its market power increases, it may induce bank's managers to take on riskier projects, thus increasing its probability of default and bad loans.

Our baseline model presented in the previous section is modified by including a quadratic term of bank market structure, namely CR3SQR and LISQR, as explained in the *Data and Methodology* chapter. Table 8 represents various estimations of a non–linear model using CR3 and LI as market structure measures, respectively.

Diagnostic statistics imply the adequacy of GMM estimations and confirm the validity of instruments used in our estimation models. With the addition of quadratic terms, CR3SQR and LISQR, most linear coefficients of the bank market structure turn out to be insignificant. However, the results in this table show some evidence that there is a non-linear relationship between the bank market structure and economic growth. This is especially true for Model (1) using CR3 and Models (7–8) using LI. In these cases, the results indicate the existence of a threshold and that there is an "inverted U–shaped" relationship. These findings are similar to those reported by De Guevara and Maudos (2011).

Taking into consideration Model (1), we find that there is an inverted U-shaped relationship between CR3 and Gpc. The cut-off point is 53.68, indicating that countries with CR3 below 53.68 have a positive impact of CR3 on Gpc, while in countries with CR3 above 53.68 this impact is negative. In general, however, most countries (80% of the data) lie above this cut-off point, indicating that the bank concentration-economic growth relationship is significantly negative. Similarly, the results obtained for LI in Model (7) show that the cut-off point is 0.247. Countries with LI below this cut-off point are experiencing a positive impact of LI on Gpc, while those above it show evidence of a negative impact of LI on Gpc. It is found, however, that 70% of data are above the cut-off point demonstrating a significant and negative relationship as well.

Finally, financial development proxies indicate a negative impact on economic growth, but their significance is confirmed only in four cases. Similar results for control variables, including inflation, are found in Panel A, where CR3 is used, but this is not the case when LI is used in Panel B.

All in all, we can conclude that at low levels of concentration, an increase in bank concertation increases growth. However, when a banking sector becomes more and more concentrated, the negative impact is coming in, and it reduces growth. Given that the concentration measures in many of the sample countries are above the threshold value, it means that the bank concentration is primarily decreasing economic growth within the sample.

4.1.3. Income Levels, Bank Market Structure & Economic Growth Relationships

The discussion so far focused on the general equations of the baseline and non–linear models, forcing the effect of bank concentration on economic growth to be identical even though a country might be classified as a developing or emerging economy. This is to say that estimations in Table 7 based on our original *Eq. 1* and Table 8 based on our original *Eq. 3* do not address whether this relationship depends on a country's income level. As part of our research objectives, we want to investigate whether the effect of bank concentration on economic growth is significantly different for developing economies in this subsection and for corrupted countries in the following one.

Table 9: Concentration – Growth Relationship – Developing Economies

Variables	Panel A - CR3				Panel B - LI			
	FIN_p		FIN_l		FIN_p		FIN_l	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnGpc $_{t-1}$	0.921***	0.858***	0.876***	0.884***	0.952***	0.812***	1.067***	1.034***
	[0.017]	[0.049]	[0.038]	[0.032]	[0.025]	[0.121]	[0.152]	[0.077]
CR3	0.003	0.327	-0.040	0.088				
	[0.001]	[0.003]	[0.001]	[0.003]				
CR3SQR		-0.002		-0.001				
		[0.000]		[0.000]				
LI					0.117	0.130	0.045	-0.270
					[0.093]	[0.122]	[0.083]	[0.542]
LISQR						-0.224		0.002
						[0.159]		[0.630]
DEV	-0.077	-0.087	-0.101	-0.086	-0.077	-0.562	0.141	0.015
	[0.063]	[0.101]	[0.076]	[0.090]	[0.053]	[0.454]	[0.374]	[0.123]
CR3xDEV	-0.001*	-0.003***	-0.002***	-0.002***				
	[0.001]	[0.001]	[0.001]	[0.001]				
LIxDEV					-0.069	0.005	-0.084	0.213
					[0.093]	[0.065]	[0.126]	[0.269]
lnFIN_p	0.021	0.040*			0.016	0.049		
	[0.014]	[0.024]			[0.019]	[0.045]		
lnFIN_l			-0.003	-0.010			-0.075	-0.046
			[0.023]	[0.020]			[0.077]	[0.046]
lnGCF	0.003	0.014	0.017	0.024	0.022	-0.010	0.013	0.031
	[0.016]	[0.034]	[0.030]	[0.028]	[0.025]	[0.025]	[0.017]	[0.046]
lnTO	0.017	0.014	0.047*	0.037	0.008	0.055***	0.065**	0.041
	[0.012]	[0.024]	[0.024]	[0.023]	[0.022]	[0.021]	[0.031]	[0.040]
lnGS	-0.043**	-0.074*	-0.060**	-0.067**	-0.040*	-0.042	0.025	-0.051
	[0.020]	[0.040]	[0.029]	[0.026]	[0.024]	[0.048]	[0.040]	[0.059]
Constant	0.708***	1.129**	1.085***	1.025***	0.373*	1.561	-0.694	-0.185
	[0.176]	[0.476]	[0.324]	[0.334]	[0.218]	[1.155]	[1.348]	[0.610]
$\beta_1 + \beta_3$	-0.001***	0.000	-0.003***	-0.001	0.048	0.135	-0.038	-0.058
	[0.000]	[0.003]	[0.001]	[0.003]	[0.059]	[0.086]	[0.065]	[0.388]
Observations	548	548	548	548	461	461	461	461
No. of instruments	36	19	16	20	34	19	13	17
No. of groups	39	39	39	39	37	37	37	37
Arellano-Bond: AR (1)	0.007	0.004	0.002	0.001	0.014	0.034	0.020	0.019
Arellano-Bond: AR (2)	0.228	0.245	0.239	0.234	0.030	0.112	0.110	0.146
Hansen test (p-val)	0.357	0.209	0.238	0.228	0.236	0.070	0.323	0.624

Notes: *(i) Standard errors in brackets, (ii) * p<0.1, ** p<0.05, *** p<0.01.*
lnGpc is the natural log of the real GDP per capita. CR3 is the 3-bank concentration ratio (due to low values; we multiplied the coefficients by 100). CR3SQR is the square term of CR3 (multiplied by 100). LI is the Lerner index. LISQR is the square term of LI. DEV is the dummy variable representing a developing economy. CR3xDEV is the interaction term between CR3 and DEV. LIxDEV is the interaction term between LI and DEV. lnFIN_p is the natural log of the ratio of private credit to GDP. lnFIN_l is the natural log of the ratio of liquid liabilities to GDP. lnGCF is the natural log of the gross capital formation. lnTO is the natural log of trade openness. lnGS is the natural log of the government size.

In order to investigate this empirically, we introduce a dummy variable DEV that takes a value of 1 if a country is classified as a developing economy and 0 if it is classified as an emerging economy based on the World Bank classification[11] Further, we interact this dummy variable

[11] Note, that in case of interaction models, we are using only country-specific control variables. Furthermore, in case of non–linear models where we have CR3 and CR3SQR in Panel A and LI and LISQR in Panel B, we may interact with the developing economies dummy (DEV) each one of them or only one. As per preliminary testing results (not

with each measure of bank market structure, namely CR3 and LI. Hence, we get CR3xDEV and LIxDEV as interaction terms as presented in *Eq. 5* (baseline model) and *Eq. 8* (non-linear model) in the previous subsection. This is done to allow the relationship between CR3 and Gpc and similarly, the relationship between LI and Gpc to be different for developing and emerging economies. Table 9 presents the results for both baseline and non–linear models.

Diagnostic statistics imply adequacy of GMM estimations and confirm the validity of instruments used in our estimation models except for Model (5) where the autocorrelation tests of residuals suggest the presence of autocorrelation of order 2 (AR2), indicating the autocorrelation problem.

Coefficients of the market structure and the market power are insignificant throughout. However, the interaction term between concentration and developing economies is negatively significant. In other words, the impact of the market structure and the market power are not significant for emerging economies, but they bring a negative impact on growth for developing economies.

This has been pointed out by Brambor *et al.* (2006). He says that when it comes to interaction terms models, the coefficient CR3/LI only captures the effect of CR3/LI on Gpc when DEV is zero. Similarly, it should be evident that the coefficient on DEV only captures the effect of DEV on Gpc when CR3/LI is zero. Thus, the sign of the interaction term can be interpreted when the coefficients are jointly significant, even if the interaction term coefficient alone is found to be insignificant—in other words, testing whether CR3 + CR3xDEV = 0 is more crucial than looking at the significance/insignificance of the interaction term itself. [12] In particular, in emerging economies, the bank concentration has no impact on Gpc, while it has a negative impact on Gpc in developing economies, based on results in Table 9. In other words, this interaction model asserts that the effect of a change in CR3 on Gpc depends on the value of the conditioning variable DEV. Taking Model (3) as an example, given one standard deviation increase in CR3 it would decrease Gpc by approximately 5.4% if a country belongs to the developing economies group, while it will have no impact if a country belongs to the emerging economies group. [13]

4.1.4. Corruption, Bank Market Structure & Economic Growth Relationships

Finally, as it was briefly mentioned in the previous subsection, we want to investigate whether the impact of the bank concentration on economic growth yields to same results for countries that are classified as corrupted or less–corrupted or it would yield to relatively similar results. The approach is like the previous model, except that we use control of corruption (COR) variable. Similarly, we interact with this COR variable with each measure of bank market structure, namely CR3 and LI. Hence, we get CR3xCOR and LIxCOR as interaction terms.

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reported here), when we include interaction terms for both, linear and non–linear terms, the results show insignificance of all interaction terms and even insignificance of bank concentration terms. Hence, we conclude that it is better to interact only CR3 and LI as presented in Table 9.

12 Testing joint significance of CR3 + CR3xDEV and/or LI + LIxDEV is presented in the table as $\beta_1 + \beta_3 = 0$.

13 To explain this issue further and to be more precise, let us assume that CR3 coefficient in Model (3) is significant. In that case, the marginal effect for high-income countries is $\partial Gpc / \partial CR3 = \beta_1 = -0.0003975$, while the marginal effect for low-income countries is $\partial Gpc / \partial CR3 = \beta_1 + \beta_3 = -0.0003975 - 0.0023584 = -0.0027559 \approx -0.003$. This suggests that an increase in CR3 for one standard deviation would cause a negative change on Gpc by approximately 0.7% for high-income countries, while it would cause a higher negative change by 4.9% if a country belongs to low-income countries group.

This is done to allow the relationship between CR3 and Gpc and similarly, the relationship between LI and Gpc to be different for corrupted and less–corrupted countries. Table 10 presents the results for these relationships.

Table 10: Concentration – Growth Relationship – Corrupted Countries

Variables	Panel A - CR3				Panel B - LI			
	FIN_p		FIN_l		FIN_p		FIN_l	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnGpc $_{t-1}$	0.921***	0.858***	0.876***	0.884***	0.952***	0.812***	1.067***	1.034***
	[0.017]	[0.049]	[0.038]	[0.032]	[0.025]	[0.121]	[0.152]	[0.077]
CR3	0.003	0.327	-0.040	0.088				
	[0.001]	[0.003]	[0.001]	[0.003]				
CR3SQR		-0.002		-0.001				
		[0.000]		[0.000]				
LI					0.117	0.130	0.045	-0.270
					[0.093]	[0.122]	[0.083]	[0.542]
LISQR						-0.224		0.002
						[0.159]		[0.630]
DEV	-0.077	-0.087	-0.101	-0.086	-0.077	-0.562	0.141	0.015
	[0.063]	[0.101]	[0.076]	[0.090]	[0.053]	[0.454]	[0.374]	[0.123]
CR3xDEV	-0.001*	-0.003***	-0.002***	-0.002***				
	[0.001]	[0.001]	[0.001]	[0.001]				
LIxDEV					-0.069	0.005	-0.084	0.213
					[0.093]	[0.065]	[0.126]	[0.269]
lnFIN_p	0.021	0.040*			0.016	0.049		
	[0.014]	[0.024]			[0.019]	[0.045]		
lnFIN_l			-0.003	-0.010			-0.075	-0.046
			[0.023]	[0.020]			[0.077]	[0.046]
lnGCF	0.003	0.014	0.017	0.024	0.022	-0.010	0.013	0.031
	[0.016]	[0.034]	[0.030]	[0.028]	[0.025]	[0.025]	[0.017]	[0.046]
lnTO	0.017	0.014	0.047*	0.037	0.008	0.055***	0.065**	0.041
	[0.012]	[0.024]	[0.024]	[0.023]	[0.022]	[0.021]	[0.031]	[0.040]
lnGS	-0.043**	-0.074*	-0.060**	-0.067**	-0.040*	-0.042	0.025	-0.051
	[0.020]	[0.040]	[0.029]	[0.026]	[0.024]	[0.048]	[0.040]	[0.059]
Constant	0.708***	1.129**	1.085***	1.025***	0.373*	1.561	-0.694	-0.185
	[0.176]	[0.476]	[0.324]	[0.334]	[0.218]	[1.155]	[1.348]	[0.610]
$\beta_1 + \beta_3$	-0.001***	0.000	-0.003***	-0.001	0.048	0.135	-0.038	-0.058
	[0.000]	[0.003]	[0.001]	[0.003]	[0.059]	[0.086]	[0.065]	[0.388]
Observations	548	548	548	548	461	461	461	461
No. of instruments	36	19	16	20	34	19	13	17
No. of groups	39	39	39	39	37	37	37	37
Arellano-Bond: AR(1)	0.007	0.004	0.002	0.001	0.014	0.034	0.020	0.019
Arellano-Bond: AR(2)	0.228	0.245	0.239	0.234	0.030	0.112	0.110	0.146
Hansen test (p-val)	0.357	0.209	0.238	0.228	0.236	0.070	0.323	0.624

Notes: *(i) Standard errors in brackets, (ii) * p<0.1, ** p<0.05, *** p<0.01.*
lnGpc is the natural log of the real GDP per capita. CR3 is the 3-bank concentration ratio (due to low values; we multiplied the coefficients by 100). CR3SQR is the square term of CR3 (multiplied by 100). LI is the Lerner index. LISQR is the square term of LI. DEV is the dummy variable representing a developing economy. CR3xDEV is the interaction term between CR3 and DEV. LIxDEV is the interaction term between LI and DEV. lnFIN_p is the natural log of the ratio of private credit to GDP. lnFIN_l is the natural log of the ratio of liquid liabilities to GDP. lnGCF is the natural log of the gross capital formation. lnTO is the natural log of trade openness. lnGS is the natural log of the government size.

Based on the results presented in Table 10, diagnostic statistics imply the adequacy of GMM estimations and confirm the validity of instruments used in our estimation models. Most baseline and non-linear coefficients of CR3 and LI are significant. However, corruption (COR) coefficients and their interaction with bank market structure measures (CR3xCOR & LIxCOR) coefficients are all individually insignificant. Nevertheless, the joint significance tests confirm the validity of interaction terms introduction in non-linear Models (2), (4) and (6) in which the interaction terms are insignificant on their own. Thus, in these cases, we can interpret signs of the interaction terms' coefficients which are positive.

For illustration purposes, we will take a few examples. Given that in Model (2) $\beta_1+\beta_3$ = 0.003, we will multiply this number with the lowest, the mean, and the highest corruption value in our dataset. Hence, the lowest control for corruption value was recorded in Afghanistan in 2008, and it was -1.64 indicating the highest degree of corruption. When multiplied by 0.003 we get -0.00492, indicating a decrease in Gpc by about 0.5%. Next, the mean corruption value for our sample is -0.60, and after multiplying it with 0.003, we get -0.0018, showing that on average Gpc would decrease by 0.2%. Finally, the highest value for the control of corruption, i.e. the least corrupted country was Pakistan in 2009, and it was 1.57. In this case, we see that there will be an increase in Gpc by 0.5%.

Overall, the table confirms the significance of the market structure measure of the bank concentration and non–linearity of its relationship with economic growth. Also, joint significance tests suggest that the effect of CR3 and LI on Gpc depends on the level of corruption in these three models.

4.2. Robustness Checks

This section highlights the main results of robustness tests following the same format that we had in the previous subsections. Here, however, we would like to make a few notes. First, in this section, we will report results using three additional measures of the bank concentration. Two of them are the market structure measures – the concentration ratio of the top 5 banks (CR5) and the Herfindahl-Hirschman Index (HHI) – and the third one is the market power measure – the Boone indicator (BI) – as discussed earlier. Second, we will report data using only private credit to GDP ratio (FIN_p) as a proxy for financial development.

4.2.1 Baseline and Non-Linear Models

The baseline and non-linear models for economic growth and bank concentration relationships are presented in Table 11. We will start first with baseline (linear) models (Models 1-2 and 5-6 for CR5 and BI respectively). The diagnostic tests confirm the validity of the instruments used and the adequacy of GMM estimation. The results show that the coefficients for the market structure measure (CR5), although negative, are all insignificant. In contrast, the market power measure (BI) coefficients are negative but significant only in the Model (5). It seems that the impact of the bank market structure on economic growth is not significant, although we found significance between CR3 and Gpc in Table 7. The results, however, show some evidence of the bank market power (BI) impact on economic growth, similar to the findings of Table 7. Interestingly, the impact of financial development is positive, but insignificant in all models. Finally, when it comes to the control variables, the results conform to the findings in Table 7 when it comes to their significance and signs.

When it comes to non-linear models (Models 3-4 and 7-8 for CR5 and BI respectively), we found some evidence earlier about non-linear, the inverted U–shaped, the relationship between bank concentration measures on one side and economic growth on the other (see Table 8). However, using our robustness models, the only non-linear relationship is found in the Model (8) of Table 11 where coefficients for BI and its square term (BISQR) are both significant and positive, contrary to the earlier findings. Based on these results, it seems that an increase in BI increases Gpc, and after it reaches the inflection point (-0.044), it intensifies its positive impact on Gpc significantly. When it comes to financial development proxy and other control variables, then robustness tests indicate similar findings as in the case of linear models reported earlier.

4.2.2 Income and Corruption Level Models

Table 12 reports robustness tests for developing economies (Models 1-2 for CR5 and 5-6 for BI) and corrupted countries (economies (Models 3-4 for CR5 and 7-8 for BI). When it comes to developing countries' models, the results show a positive and significant impact of CR5 only. At the same time, all other linear and non-linear terms for bank market structure/power measures are insignificant. In line with the main results, the interaction terms are significant in Models (1) and (2), but the joint significance test is confirmed only in Model (1). Hence, as with the main results, we find limited evidence that the impact of bank market structure on economic growth differs statistically with a country's income level. In other words, we find some evidence that bank concentration hurts economic growth only in low-income countries. Finally, the results in Table 12 show no evidence of financial development impact on economic growth whatsoever. The same applies to the majority of control variables except for GS that exhibits a negative impact on Gpc – the results that are in line with our main findings.

Table 11: Robustness Checks for Linear and Non-Linear Models

Variables	CR5				BI			
	Linear		Non-Linear		Linear		Non-Linear	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnGpc$_{t-1}$	0.960***	0.919***	0.962***	0.885***	0.988***	0.928***	0.987***	0.922***
	[0.012]	[0.027]	[0.012]	[0.046]	[0.010]	[0.015]	[0.010]	[0.014]
CR5	-0.022	-0.112	-0.003	-0.004				
	[0.000]	[0.001]	[0.004]	[0.008]				
CR5SQR			0.002	0.002				
			[0.000]	[0.000]				
BI					-0.123*	-0.072	-0.065	0.572*
					[0.065]	[0.156]	[0.145]	[0.331]
BISQR							0.549	6.426**
							[1.022]	[2.888]
lnFIN_p	0.014	0.000	0.012	0.002	0.003	0.010	0.004	0.013
	[0.009]	[0.018]	[0.010]	[0.028]	[0.011]	[0.015]	[0.011]	[0.016]
lnGCF	0.023	0.030	0.021	0.019	0.036***	0.047*	0.036***	0.046
	[0.016]	[0.034]	[0.013]	[0.046]	[0.013]	[0.028]	[0.013]	[0.030]
lnTO	0.061***	0.082***	0.060***	0.119*	0.017	0.048*	0.017	0.050*
	[0.020]	[0.030]	[0.018]	[0.061]	[0.010]	[0.028]	[0.011]	[0.027]
lnGS	-0.031	-0.016	-0.023	-0.008	-0.025**	-0.034	-0.023**	-0.026
	[0.027]	[0.032]	[0.019]	[0.055]	[0.012]	[0.025]	[0.011]	[0.031]
lnBNI		-0.043**		-0.058		-0.041		-0.050*
		[0.021]		[0.043]		[0.025]		[0.027]
lnBCI		-0.104**		-0.138*		-0.130***		-0.147***
		[0.049]		[0.073]		[0.038]		[0.037]
lnBNIM		-0.047**		-0.069*		-0.046***		-0.053***
		[0.022]		[0.040]		[0.016]		[0.018]
lnINF		0.009*		0.015*		0.010***		0.009***
		[0.005]		[0.008]		[0.003]		[0.003]
C		-0.012		-0.007		-0.008		-0.008
		[0.008]		[0.011]		[0.007]		[0.008]
Constant	0.064	0.974**	0.167	1.411*	-0.018	0.995***	-0.018	1.116***
	[0.094]	[0.403]	[0.153]	[0.756]	[0.050]	[0.319]	[0.044]	[0.321]
Observations	472	400	472	400	521	467	521	467
No. of instruments	34	20	35	20	32	37	33	38
No. of groups	36	36	36	36	39	39	39	39
Arellano-Bond: AR(1)	0.009	0.006	0.010	0.005	0.001	0.001	0.001	0.000
Arellano-Bond: AR(2)	0.318	0.345	0.280	0.258	0.197	0.153	0.194	0.126
Hansen test (p-val)	0.514	0.705	0.531	0.732	0.220	0.641	0.286	0.770

*Notes: (i) Standard errors in brackets, (ii) * p<0.1, ** p<0.05, *** p<0.01.*
lnGpc is the natural log of the real GDP per capita. σ is the income volatility. CR5 is the 5-bank concentration ratio. CR5SQR is the square term of CR5 (multiplied by 100). BI is the Boone indicator. BISQR is the square term of BI. lnFIN_p is the natural log of the ratio of private credit to GDP. lnFIN_l is the natural log of the ratio of liquid liabilities to GDP. lnGCF is the natural log of the gross capital formation. lnTO is the natural log of trade openness. lnGS is the natural log of the government size. lnBNI is the natural log of the bank noninterest income to total income ratio. lnBCI is the natural log of the bank cost to income ratio. lnBNIM is the natural log of the bank net interest margin. lnINF is the natural log of inflation. C is the crisis dummy variable.

Table 12: Robustness Checks for Developing Economies & Corruption Level Models

Variables	CR5				BI			
	Developing		Corruption		Developing		Corruption	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnGpc$_{t-1}$	0.884***	0.899***	0.952***	0.952***	0.919***	0.923***	0.863***	0.877***
	[0.036]	[0.041]	[0.019]	[0.018]	[0.020]	[0.024]	[0.111]	[0.061]
CR5	0.002**	-0.005	-0.027	-0.345				
	[0.001]	[0.008]	[0.000]	[0.004]				
CR5SQR		0.004		0.002				
		[0.000]		[0.000]				
BI					0.220	0.360	0.048	0.064
					[0.199]	[0.238]	[0.419]	[0.510]
BISQR						1.554		-0.095
						[2.329]		[3.794]
DEV	0.121	0.089			-0.191***	-0.184***		
	[0.102]	[0.103]			[0.053]	[0.060]		
CR5xDEV	-0.004***	-0.003**						
	[0.001]	[0.002]						
BIxDEV					-0.408	-0.362		
					[0.311]	[0.311]		
COR			0.037	0.032			0.092	0.083
			[0.048]	[0.045]			[0.075]	[0.053]
CR5xCOR			-0.015	-0.008				
			[0.001]	[0.001]				
BIxCOR							-0.073	0.027
							[0.491]	[0.340]
lnFIN_p	0.035	0.021	0.015	0.014	0.026	0.028	0.053	0.057*
	[0.024]	[0.030]	[0.011]	[0.011]	[0.016]	[0.020]	[0.058]	[0.033]
lnGCF	0.035	0.034	0.022	0.024	0.022	0.026	0.105	0.050
	[0.030]	[0.041]	[0.020]	[0.020]	[0.027]	[0.031]	[0.095]	[0.070]
lnTO	0.011	0.015	0.075**	0.074**	0.005	-0.003	0.167	0.148
	[0.020]	[0.029]	[0.032]	[0.029]	[0.019]	[0.021]	[0.130]	[0.096]
lnGS	-0.102**	-0.100**	-0.033	-0.034	-0.065*	-0.059*	-0.097	-0.081
	[0.045]	[0.046]	[0.034]	[0.034]	[0.034]	[0.033]	[0.069]	[0.061]
Constant	0.882***	1.068**	0.100	0.220	0.765***	0.730***	0.196	0.286
	[0.331]	[0.482]	[0.107]	[0.182]	[0.241]	[0.253]	[0.344]	[0.325]
$\beta_1 + \beta_3$	-0.002**	-0.008	-0.000	-0.004	-0.188	-0.002	-0.024	0.091
	[0.001]	[0.008]	[0.001]	[0.004]	[0.200]	[0.321]	[0.739]	[0.657]
Observations	472	472	444	444	521	521	486	486
No. of instruments	20	19	35	36	34	35	14	13
No. of groups	36	36	36	36	39	39	39	39
Arellano-Bond: AR(1)	0.012	0.015	0.013	0.015	0.002	0.002	0.039	0.011
Arellano-Bond: AR(2)	0.579	0.464	0.188	0.164	0.203	0.203	0.108	0.115
Hansen test (p-val)	0.312	0.239	0.491	0.499	0.361	0.284	0.270	0.409

Notes: *(i) Standard errors in brackets, (ii) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.*
lnGpc is the natural log of the real GDP per capita. σ is the income volatility. CR5 is the 5-bank concentration ratio (multiplied by 100). CR5SQR is the square term of CR5 (multiplied by 100). BI is the Boone indicator. BISQR is the square term of BI. DEV is the dummy variable representing developing economies. CR3xDEEV is the interaction term between CR3 and DEV. BIxDEV is the interaction term between BI and DEV. COR is a variable representing a corrupted country. CR5xCOR is the interaction term between CR5 and COR (multiplied by 100). BIxCOR is the interaction term between BI and COR. lnFIN_p is the natural log of the ratio of private credit to GDP. lnFIN_l is the natural log of the ratio of liquid liabilities to GDP. lnGCF is the natural log of the gross capital formation. lnTO is the natural log of trade openness. lnGS is the natural log of the government size.

After low-income countries analysis, we come to the robustness checks and analysis of corrupted–countries model's whereby Models 3-4 and 7-8 of Table 12 report findings for these models using CR5 and BI, respectively. All models are correctly specified as can be seen from diagnostic statistics tests. Results indicate no significance whatsoever for most of the coefficients. All bank market structure/power coefficients, both linear and non–linear terms, are insignificant. This is contrary to the findings previously reported in Table 10, where both linear and non-linear terms are found to be significant. Similarly, corruption (COR) and all interaction terms coefficients are also insignificant. This is further validated by the insignificance of joint significance tests of all models.

5. Conclusion

The present study was designed to determine the effect of bank concentration on economic growth in OIC countries. These findings suggest that in general bank concentration has a mostly negative impact on economic growth. Furthermore, the results show a positive impact of bank concentration on growth at a low level of concentration. However, this positive impact has its limits and becomes negative for the majority of OIC countries due to the high level of bank concentration. Although counterintuitive, the impact of financial development on economic growth is found to be negative using our main independent variables. It was also shown that the impact of bank concentration on economic growth depends on the country's income level.

Nevertheless, it seems that this relationship is not affected by the country's corruption level. Finally, our robustness tests show little support for our findings. In the case of financial development, the robustness tests indicate the opposite, i.e. the positive impact on economic growth.

These findings provide practical implications for all stakeholders. First, the negative impact of bank concentration on economic growth can be decreased by increasing competition in the market. One way would be to open up the market for new entrants in the banking sector. Second, the relationship is non-linear, and the negative impact of the bank market power is dominating. Therefore, the policymakers and regulators need to keep the bank market power levels as low as possible and improve other aspects of socio-economic life. Third, improving overall socio-economic conditions, combined with specific controls of bank concentration, are among the steps that should be taken by policymakers and regulators of developing- and emerging economies within OIC countries. Fourth, it seems that improving overall financial development may be an ineffective policy for improving the economic conditions of OIC countries. Instead, the policymakers should focus directly on curbing bank concentration if they want to achieve better economic growth rates. Fifth, using a single measure could be very misleading, and hence it is up to regulators to consider as many measures as possible. Central banks and other regulators should observe bank-level and market-level data regularly to be able to take precautionary measures toward banks that are gaining higher market power. This could bring about more growth and overall stability to the economies of OIC countries. In short, there is a need for a *case–by–case* approach by regulators and policymakers as *one–size–fits–all* may not be the best solution in this scenario.

This study, as is the case with any other studies, comes with several limitations. At the same time, these limitations are also potential areas for further research on the topic and additional investigations. First, we used the real per capita GDP as a proxy for economic growth. It would be worthwhile investigating whether the data will reveal the same results if alternative proxies are used. For example, we could use annual growth rates of GDP instead of GDP per capita. Alternatively, we could also use the growth rates of various industry sectors and bank-level data instead of aggregates. Second, although we included a few bank-specific and country-specific control variables, alternative proxies could produce better and/or more reliable results on the topic. For example, collecting data on the interest rate that largely were not available for our sample, or alternative measures of bank efficiency and profitability can bring about more relevant information to the results.

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A NETWORK ANALYSIS OF THE ASIA-PACIFIC AND OTHER DEVELOPED STOCK MARKETS: PRE AND POST GLOBAL FINANCIAL CRISIS

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Abstract

The paper examines the volatility spillover and connectedness between Asia-Pacific, US, UK, and eurozone stock markets. A spillover index is built using forecast error variance decomposition in a vector autoregression framework and the spillover index is used to build network diagrams. It shows evidence of how the increase in risk transfer (volatility spillover) between the markets led to the global financial crisis and of the higher level of connectedness since. The time variations in spillover are aligned with recognizable international events. Network diagrams show the direction and strength of the connectedness. The Chinese market appears to be the most insulated, while the South Korean, Hong Kong, and Singapore stock markets dominate in terms of risk transfer. The US, UK, EU, Singapore and Hong Kong are the top five volatility spillover recipient markets, both during pre and post global financial crisis periods. We find the market size to be irrelevant in the determination of the level of connectedness, whereas the role of geographical proximity cannot be ruled out. The findings are relevant to multinational investment strategies and in understanding the relative risk of investment in the Asia-Pacific region.

Keywords: Connectedness; European Debt Crisis; Global Financial Crisis; Network Diagrams Volatility Spillover Index.

1. Introduction

One of the questions at the centre of contemporary financial research is how markets influence each other. Connectedness in terms of risk and return has been a popular research topic, since news that affects one country's stock prices can potentially change the fundamentals of another country, causing fluctuations in its stock prices. Consequently, intermarket connectedness not only affects the decisions of individual agents (e.g., portfolio management) but also contributes to systemic risk. The impact of market connectedness was evident during the 2008 global financial crisis and the European debt crisis (EDC). Under the wake-up call hypothesis, a financial shock or crisis in one financial market acts as a wake-up call to investors in another market, and these investors then reassess and acquire information about local market fundamentals (Forbes, 2012). Such reappraisals of risk spread the crisis from one market to another. Understanding the directional connectedness and network strength of financial markets influences the portfolio management decisions of international funds. The value of such knowledge is becoming increasingly critical in portfolio management, since there is increasing regulatory and fundamental convergence across financial markets, driving out the diversification potential for investors (Forbes & Rigobon, 2002; Markwat et al., 2009; Aloui et al., 2011). Estimation of the strength of the network of markets helps policymakers understand the spillover of a crisis in the event of a trigger in one country. A comprehensive network-based study of multiple markets can discern the risk involved in investing in that country in times of impending crisis.

The present study uses a generalized vector autoregression (VAR) methodology and the variance decomposition matrix of Diebold and Yilmaz (2012, 2014, 2016) to understand the directional connectedness of markets. Diebold and Yilmaz's methodology measures the volatility spillover between the countries, and it does not distinguish between contagion and interdependence. This feature is useful when a policymaker wants to know what country (or group of countries) is more vulnerable to the volatility spillover from another country. We show network diagrams indicating the relative strength and direction of spillover between countries. The findings are relevant to multinational investment strategies and help in understanding the relative risk of investment in strategically important groups of markets.

Since most of the decision areas affected by market connectedness are related to risk management, this study looks at the network from a volatility spillover or risk transfer perspective. It examines the network dynamics of a group of stock markets from the Asia-Pacific region, along with the US, UK, and eurozone markets, during the period from 2000 to 2019. We examine the degree of volatility spillover between the US, UK, EU, and Asia-Pacific markets and how likely the Asia-Pacific markets are to be affected by an emerging crisis in the developed markets. The 2008 global financial crisis is in the middle of the period of study, and we assess how network strength changed, leading to the crisis, and its status after the crisis. We also examine the time-varying volatility spillover levels during the entire period covering the European debt crisis. Related questions undertaken in our study concerned the spillover bursts during crisis periods, the importance of market size in volatility spillover across markets and whether geographical proximity plays a role in risk transfer (Rejeb & Boughrara, 2015). The importance of the present study lies in unearthing the relative risk of investment in Asia-Pacific stock markets and identifying the Asia-Pacific markets that have higher/lower directional spillover and higher/lower risk in case of an impending crisis.

The Asia-Pacific region represents a group of emerging and developed financial markets with established financial instruments, regulatory and legal frameworks, market infrastructure, and a critical mass of market participants. In the Asia-Pacific region, most of the stock markets are in open economies (e.g., Hong Kong, Taiwan, Shanghai, and Korea), which rely very much on external trade, their largest markets being the United States, the United Kingdom, and the European Union (EU). It is possible that their individual comovement with the US and EU markets causes connectedness between these Asia-Pacific stock markets, US and EU markets. The study would thus be incomplete if EU and US market data were not a part of the sample.

The remainder of the paper is organized as follows. Section 2 briefly reviews the literature. Section 3 describes the data, followed by an elaboration of the methodology. Section 4 presents data analysis, results, and findings. Section 5 concludes the paper.

2. Literature Review

The terms connectedness, contagion, and spillover are widely used in financial market research. While Engle et al. (1990) focused on causality in the variance between markets for volatility spillover, Forbes and Rigobon (2002) used contagion to understand the cross-market linkages after a shock. While all of the terms indicate the transmission of shocks unexplained by fundamentals or comovement, Billio and Pelizzon (2003) provide a concise discussion of the terms, their measurements, along with restrictions on their definitions. Research on volatility spillover possibly originated in response to the October 1987 crisis in the United States that spread across markets. Researchers have provided evidence that the volatility of one country leads to fluctuations in prices in other countries. The source and destination can be developed or emerging nations.

Volatility spillover is explained by information transmission theory (Ross, 1989), which in turn helps us in deciphering how price and volatility affect information flow and the efficiency of the stock markets. While explaining similar time-varying volatility across international stock markets, Engle and Susmel (1993) argued for the presence of regional factors with time-varying variance. Longin and

Solnik (1995) noted that the conditional correlation between the monthly returns of international stock markets is not constant, it had increased between 1960 and 1990, and it is higher when the stock markets experience high volatility. Other inspiring works on contagion and volatility spillover include those of Kearney (2000), Ling and McAleer (2003), Cappiello et al. (2006), Diebold and Yilmaz (2009, 2012, 2014, 2016), Silvennoinen and Terasvirta (2009), Conrad and Karanasos (2010), and Bauwens et al. (2013) and references therein. Anastasopoulos (2018) showed that both the Greek debt crisis and the effects of the yuan devaluation produced contagion effects.

The preferred methodology of early researchers involved variations of the generalized autoregressive conditional heteroskedasticity (GARCH) model. Alper and Yilmaz (2004) evidenced volatility spillover from countries with active financial centres to the Istanbul Stock Exchange during the Asian financial crisis. Supporting the use of the MGARCH model for spillover studies, Bauwens et al. (2006) noted the model's efficiency in capturing transmission through a conditional variance or conditional covariance, while Allen et al. (2013) calculated conditional correlations and spillover using multivariate GARCH to capture the spillover effects from China to different markets in the Pacific Basin area during the financial crisis from 2007 to 2008. Using the asymmetric multivariate GARCH model proposed by Engle and Kroner (1995) and extended by Kroner and Ng (1998), Li and Giles (2015) evidenced unidirectional shock and volatility spillover from the US market to China, India, Japan, Malaysia, Indonesia, the Philippines, and Thailand in general, but a more robust, bidirectional relationship during the Asian financial crisis. Hemche et al. (2016) used a DCC-MGARCH model to show that the correlation between the US and other developed and emerging markets increased during the subprime crisis and the European sovereign debt crisis in 2009-10.

In parallel to studies using the GARCH methodology to study connectedness, Gallo & Otranto, (2008) used regime-switching volatility, spillover models. Dungey and Gadjurel (2014) relied on a latent factor model to detect and measure the extent of contagion effects from the United States to other developed and emerging nations that explains a large portion of the variance in both these markets. Nomikos and Salvador (2014) studied volatility transmission patterns by using a Markov bivariate BEKK model, while Otranto (2015) observed spillover between the United States, Japan, the eurozone, and Hong Kong using a multiplicative error model that decomposes part of the mean volatility into a spillover-measuring component that can be appropriately studied and interpreted. Using variance decompositions from VAR, Guimarães-Filho, and Hong (2016) examined the time-varying characteristics of their measure and the connectedness between China's equity markets and other major equity markets. They found significant spillover from China to both developed and emerging markets. However, BenSaïda et al. (2018) noted that the above-mentioned studies focus on two countries at a time (bivariate) and hence lack multi-country connectedness dynamics. The authors used a Markov switching VAR model to show that spillover increases during crises.

The majority of prior research in spillover and connectedness has applied multivariate GARCH, regime-switching, and stochastic volatility models. However, the finance community has noted a departure from the inclination to use these methods, with Diebold and Yilmaz (2009) providing an index measure of returns and volatility spillover based on forecast error variance decomposition within a VAR framework. Using this methodology, Diebold and Yilmaz (2011) evidenced widely varied levels of spillover in both risk and returns between Argentina, Brazil, Chile, Mexico, and the United States, while Yilmaz (2010) evidenced return and volatility spillover among major Asian countries. Diebold and Yilmaz (2012) upgraded their 2009 method, making the error variance decomposition order invariant and using this newer model to provide evidence of limited cross-market spillover between US stocks, bonds, foreign exchanges, and commodity markets until the subprime crisis, and a significant increase in volatility after the collapse of Lehman Brothers. Tsai (2014) used Diebold and Yilmaz's (2012) approach to show that information transmission between five developed stock markets - the United States, the United Kingdom, Japan, France, and Germany - increased significantly after 1998, with the US stock market showing positive net spillover before 1997, during the dot-com bubble, and during the subprime crisis. Building connectedness measures from this variance decomposition, Diebold and Yilmaz (2016) evidenced unidirectional spillover from the United States to Europe from 2007 to 2008. However, they showed that this connectedness became bidirectional starting in late 2008. The authors also reported that, as the condition of financial institutions in Europe dwindled, spillover from European to US financial institutions increased in June 2011. Demirer et al. (2018) reported that banking stock connectedness increases during crises, with cross-country linkages providing more fluctuations than within-country bank linkages. Caloia et al. (2018) built on Diebold and Yilmaz's (2012) model. They used a multivariate extension of the heterogeneous autoregressive model to show asymmetric risk transmission between Germany, France, the Netherlands, Italy, and Spain. Baruník et al. (2016) modified the Diebold–Yilmaz (2012) model to consider and differentiate between volatilities from positive and negative changes in prices. They then reported that connectedness across sectors is asymmetric and of different strengths. Xu et al. (2018) used a multiplicative error model based on that of Diebold and Yilmaz (2009) to report high interdependency across equity markets in terms of volatility and illiquidity, with increased interdependency increased during the global financial crisis.

Complex network diagrams are used to characterize the structure of the linkages in a financial system. Nobi et al. (2014) showed structural changes in a network diagram of the correlations between stock market prices and attributed them to the global crisis, while Zhao et al. (2016) provided for the dynamic evolution of stock markets in crises. Wang et al. (2018) proposed a correlation-based network to analyse the correlation structure and evolution of world stock markets. They argued that the connectedness between two stock markets is significantly affected by other markets and that, during the subprime crisis, the stock markets were highly correlated with the quick transmission of information. Bhattacharjee et al. (2019), using network theory, explored the connectedness of between 14 Asian capital markets and showed the influence of the 2008 financial crisis on the connectivity and clustering patterns in the network of Asian indexes.

In the context of the Asia-Pacific markets, empirical work on the relationship between stock markets have provided varied evidence. Asia Pacific region has some of the most important equity markets in the world, both in terms of market capitalization and traded volume (Ferris et al. 2007). However, the role of the US equity market as a source of volatility Spillover or a volatility contributor to Asia Pacific markets has been demonstrated in Liu and Pan (1997), Alaganar and Bhar (2002), Cheng and Glascock (2006) and Kolluri et al. (2014). Johnson and Soenen (2002) advocate a substantial degree of interaction between the Japanese stock market and those in New Zealand, Hong Kong, China and Australia. They concluded that rising export and FDI flow from Japan are the key contributors to this relation. Alaganar and Bhar (2002) reveal that fluctuations in US equities have a significant effect on both the return and the volatility of the Australian equity market. There have been varying reports of the integration of the Chinese stock market with other markets. Johansson and Ljungwall (2009) illustrate that the Chinese stock market volatility has had a short-term effect due to Spillover from Hong Kong and Taiwan, while Mitra and Iyer (2016) demonstrate that the Chinese stock market is the least integrated share market in the Asia Pacific. Abidin et al. (2014) advocated the connectedness between the Chinese, Australian, Hong Kong and New Zealand stock markets, while stressing on the emerging connectedness between Australia and the Chinese equity markets. Spillover effects from China on different Asia Pacific markets are recorded by Allen et al. (2013) and Ahmed and Huo (2019), while Guimarães-Filho and Hong (2016) note that China has increasingly become a net "giver" of spillover volatility in the Asia Pacific region. Li and Giles (2015) and Bissoondoyal-Bheenick et al. (2018) have shown a one-way volatility spillover from the US market to China. Allen et al. (2017) studied the volatility spillover between Australia, China, Japan, Korea and the United States during 2004-2014. They noted that China (includes Hong Kong) and US markets have the greatest influence on the Australian market. Bissoondoyal-Bheenick et al. (2018) report an insignificant volatility spillover in selected sectors from the Australian to the Chinese stock markets. This study reassesses the importance of the Chinese stock market in terms of its connectedness with other markets.

The literature review summarizes and points towards changes in the magnitude and direction of the connectedness across markets. We augment the literature while building complex network diagrams within a quantifiable framework based on the work of Diebold and Yilmaz (2012) to show how connectedness changed as the markets approached the subprime crisis and to compare their connectedness during the pre- and post-subprime crisis periods. Given China's different market microstructure, we explore how China differs from its neighbours.

3. Data and Methodology

We consider the daily data from April 2000 to April 2019 on 11 stock market indexes from the Asia-Pacific region: All Ordinaries index (AORD) in Australia, Hang Seng index (HSI) in Hong Kong, Nikkei index (NIKKEI) in Japan, Straits Times Index (STI) in Singapore, SSE Composite Index (SSE) in China, NIFTY 50 index (NIFTY) in India, Jakarta Stock Exchange Composite index (JKSE) in Indonesia, Korea Composite index (KOSPI) in South Korea, Bursa Malaysia KLCI Index (KLSE) in Malaysia, Philippine Stock Exchange index (PSEI) in the Philippines and Taiwan Weighted index (TWII) in Taiwan. The data are obtained from the Thomson Reuters database. Lehman Brothers filed for bankruptcy on 15 September 2007. We consider this event like the announcement of the subprime crisis, and the date is considered for the sample split. Thus, the period from 03 April 2000 to 15 September 2007 is considered as pre subprime crisis period leading to the subprime crisis while 16 September 2007 to 03 April 2019 is considered as post subprime crisis period. Many countries with an open economy considered above (e.g., Hong Kong, Taiwan, Shanghai, and Korea) rely on external trade, especially with the United States and the eurozone. Their comovement can cause the spillover between these Asia-Pacific stock markets and US and EU markets. To gain a comprehensive and unified idea of the connectedness between these markets, we include the following stock market indexes in the study: the Dow Jones Industrial Average (DJI) for the United States, the Financial Times Stock Exchange (FTSE) 100 for the United Kingdom, and the EURO STOXX 50 Index for the eurozone. The returns from these markets are the logarithmic differences of the indexes. Following empirical literature (Diebold & Yilmaz, 2012, and references therein), the daily variance for market *i* on day *t* is estimated as $\tilde{\sigma}_{it}^2 = 0.361[\ln(M_{it}^{max}) - \ln(M_{it}^{min})]^2$, where M_{it}^{max} is the maximum (high) price in the market *i* on day *t* and M_{it}^{min} is the daily minimum (low) price. The estimate of the annualized daily volatility is $\hat{\sigma}_{it} = 100\sqrt{365 \times \tilde{\sigma}_{it}^2}$.

We develop the spillover index, as suggested by Diebold and Yilmaz (2014). This index is an improvement over their 2009 spillover index since it not only avoids the sensitivity of the forecast error variance decomposition on the ordering of the variables in the VAR framework but also considers correlated shocks. For each Asia-Pacific stock market *i,* we consider the forecast error variances to be from two sources—the fraction of H-step-ahead error variance in forecasting x_i that is due to shocks to x_i, for $i = 1, 2, \ldots, N$, and spillover as a fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, for $i, j = 1, 2, \ldots, N$, where $\forall j \neq i$. The spillover index is obtained as the sum of all the non-diagonal elements in the forecast error variance matrix.

We model Asia-Pacific stock market returns (or volatility) as a covariance stationary N-variable VAR(p) framework represented by $x_t = \sum_{i=1}^{p} \Phi_i x_{t-1} + \varepsilon_t$ where ε_t is a vector of independently and identically distributed disturbances with zero mean and covariance matrix $\sum$. As a tool for variance decomposition analysis, we represent the above VAR (p) framework in the moving average (MA) process as $x_t = \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-1}$, where Θ_i is the $N \times N$ matrix of MA coefficients that conforms to the following recursion: $\Theta_i = \Phi_1 \Theta_{i-1} + \Phi_2 \Theta_{i-2} + \ldots + \Phi_p \Theta_{i-p}$, with Θ_0 an $N \times N$ identity matrix and $\Theta_i = 0$ for $\forall i < 0$.

We next consider the variance decomposition, which allows us to deconstruct the forecast error variance of each variable into parts that are attributable to the various system shocks. Specifically, we look for the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall j \neq i$. We use directional spillover in the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) to obtain H-step-ahead forecast error variance decomposition as $\xi_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i'\Theta_h \sum e_j)^2}{\sum_{h=0}^{H-1}(e_i'\Theta_h \sum \Theta_h' e_i)}$, where the variance matrix for the error vector ε is denoted by Σ ; e_i is the selection vector, with one as the *i*th element, and zero otherwise; σ_{jj} is the standard deviation of the error term for the *j*th equation; and $\sum_{j=1}^{N}\xi_{ij}^{g}(H) \neq 1$. We then normalize each entry of the variance decomposition matrix by the row sum, as $\tilde{\xi}_{ij}^{g}(H) = \frac{\xi_{ij}^{g}(H)}{\sum_{j=1}^{N}\xi_{ij}^{g}(H)}$, and we maintain $\sum_{j=1}^{N}\tilde{\xi}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N}\tilde{\xi}_{ij}^{g}(H) = N$.

From the above variance decomposition, the total cross variation or total spillover index is calculated as $I^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\tilde{\xi}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\xi}_{ij}^{g}(H)} \times 100$. This total spillover index measures the contribution of the spillover of volatility shocks across Asia-Pacific stock markets, including the US and EU area, to the total forecast error variance.

The directional spillover received by market *i* from all the other markets *j*, assuming the normalized elements of the generalized variance decomposition matrix, is $I_{i\leftarrow\bullet}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\tilde{\xi}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\xi}_{ij}^{g}(H)} \times 100$. The directional volatility spillover transmitted from market *i* to all the other markets *j* is $I_{\bullet\leftarrow i}^{g}(H) = \frac{\sum_{j=1}^{N}\tilde{\xi}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\xi}_{ji}^{g}(H)} \times 100$. The difference between the total volatility shocks to and from all the other markets is the net volatility spillover, denoted by $I_{i}^{g}(H) = I_{.\leftarrow i}^{g}(H) - I_{i\leftarrow .}^{g}(H)$. Net volatility spillover helps us understand how much a stock market contributes to the volatility of other selected markets. The net pairwise volatility spillover between stock markets is, therefore $\xi_{ij}^{g}(H) = (\frac{\tilde{\xi}_{ji}^{g}(H) - \tilde{\xi}_{ij}^{g}(H)}{N}) \times 100$.

We develop a network diagram based on the spillover index to explore the connectedness between the chosen countries. Connectedness is central to all risk management practices worldwide and can help us in understanding how changes in the systemic risk of a single country multiply and affect global markets. Traditional methods used in connectivity studies employ correlation-based measures; these measures only pairwise association and are skewed toward linearity and Gaussian assumptions, restricting their acceptance in financial market contexts. The marginal expected shortfall method (Acharya et al., 2010), the conditional value at risk (CoVaR) method (Adrian & Brunnermeier, 2011), and the equicorrelation method (Engle & Kelly, 2012) have generated much interest, but, as Diebold and Yilmaz (2014) pointed out, these methods measure different things. There exists no unified framework of global or regional connectedness. Here we use the connectedness measurement proposed by Diebold and Yilmaz (2014), which is closely related both to modern network theory and defines a network by variance decomposition. Diebold and Yilmaz argued that these variance decomposition networks are more sophisticated than traditional networks and consider total directional connectedness. The total spillover $I^g(H)$ is the total connectedness or system-wide connectedness. In understanding connectedness and its better representation, we build network diagrams using system-wide connectedness and three previously calculated measures:

total directional connectedness from all other firms *j* to firm *i*: $I^g_{i\leftarrow\bullet}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\xi}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\xi}^g_{ij}(H)} \times 100$

total directional connectedness from firm *i* to all other firms *j*: $I^g_{\bullet\leftarrow i}(H) = \frac{\sum_{j=1}^{N} \tilde{\xi}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\xi}^g_{ji}(H)} \times 100$

net directional connectedness from market *i* to all other markets *j*: $I^g_i(H)$

Diebold and Yilmaz (2009) noted that the connectedness matrix converges quickly to a stable value when H increases, but it changes when H is tiny, especially if it is smaller than the order of the VAR.

Several events took place during our sample period that may have impacted the spillover. The spillover table possibly misses the time-varying nature of spillover and the impact of these events as it provides a useful average behaviour of spillover. Hence, we estimate the time-varying spillover of volatility over the full sample period using 150 days rolling data. The time-varying spillover plot is presented to capture the variation of volatility transmission over time, and it is connected with the economic events. Finally, we supplement the network diagrams of pre and post subprime crisis periods with the network diagrams for the periods of spillover bursts.

4. Data Analysis and Findings

The initial description (see Table 1.1) of the volatilities of the markets indicates that all the market volatilities are leptokurtic, and positively skewed in both the pre- and post-crisis periods. While all the countries showed changes in skewness and kurtosis between the pre- and post-crisis periods, the difference is minimal in the case of China. Table 1.2 shows that the mean returns are positive for all the chosen market indexes, except for the eurozone, Japan, and Taiwan. All the return series deviate from the Gaussian distribution, as evidenced by their skewness and kurtosis. The results of the augmented Dickey–Fuller test (ADF) show that the returns and volatilities of all the markets are stationary at the 1% level of significance.

4.1 Unconditional Patterns: The Full-Sample Volatility Spillover Table

The total spillover index values provided in Table 2 captures the spillover dynamics of the Asia-Pacific region. All the outcomes are based on second-order VAR with 10-step-ahead forecasts. We estimated initial VAR models with high order lags of the variables and finally selected the VAR (lag 2) model based on minimum information criteria as indicated by AIC.

Table 1.1: Descriptive Statistics: Daily Volatility

Markets	Period	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	ADF
Australia (AORD)	Pre	0.000039	0.00002	0.00183	0.000001	0.00008	11.73	206.63	-12.95*
	Post	0.000046	0.00003	0.00085	0	0.00006	5.92	59.4	-10.26*
	Combined	0.00005	0.00003	0.00236	0	0.0001	9.99	162.73	-10.66*
USA (DJI)	Pre	0.000091	0.00005	0.00262	0.000002	0.00014	6.88	95.55	-6.43*
	Post	0.000063	0.00003	0.00343	0.000002	0.00014	13.54	277.83	-10.22*
	Combined	0.0001	0.00004	0.004	0.000002	0.00021	8.99	118.79	-7.45*
Eurozone (EURO)	Pre	0.000157	0.00007	0.00327	0.000003	0.00026	4.83	37.18	-5.99*
	Post	0.000133	0.00007	0.00377	0.000001	0.00022	7.68	93.38	-10.42*
	Combined	0.00016	0.00008	0.00377	0.000001	0.00027	5.37	45.34	-9.43*
UK (FTSE100)	Pre	0.000107	0.00005	0.00213	0.000002	0.00018	5.36	45.22	-8.25*
	Post	0.000082	0.00004	0.00297	0.000002	0.00015	9.77	158.35	-11.5*
	Combined	0.00011	0.00005	0.00339	0.000002	0.00021	7.26	79.44	-8.20*
Hong Kong (HSI)	Pre	0.000093	0.00006	0.00153	0	0.00013	4.76	38.49	-9.73*
	Post	0.00007	0.00004	0.00164	0.000004	0.00011	7.59	85.05	-13.35*
	Combined	0.0001	0.00005	0.0055	0	0.00019	12.2	260.65	-6.92*
Indonesia (JKSE)	Pre	0.000114	0.00006	0.00286	0	0.00018	6.68	71.12	-12.32*
	Post	0.000075	0.00003	0.00327	0.000002	0.00016	10.26	164.6	-11.52*
	Combined	0.00011	0.00005	0.00583	0	0.00022	10.8	204.99	-11.56*
Malaysia (KLSE)	Pre	0.000056	0.00003	0.00182	0	0.0001	7.71	93.34	-15.30*
	Post	0.000021	0.00001	0.00064	0.000001	0.00004	8.72	110.37	-10.71*
	Combined	0.00004	0.00002	0.00182	0	0.00008	8.66	124.26	-11.45*
South Korea (KOSPI)	Pre	0.000171	0.0001	0.00275	0.000007	0.00023	4.06	27.99	-8.30*
	Post	0.000053	0.00003	0.00202	0	0.00011	9.42	135.62	-14.74*
	Combined	0.00013	0.00006	0.00906	0	0.00028	15.21	411.41	-13.61*
India (NIFTY)	Pre	0.000243	0.00011	0.01495	0.00001	0.00058	14.97	325.61	-18.82*
	Post	0.000075	0.00004	0.00125	0	0.00009	4.89	46.35	-13.56*
	Combined	0.00019	0.00008	0.01495	0	0.0005	16.44	397.57	-18.53*
Japan (NIKKEI)	Pre	0.000106	0.00007	0.00288	0.000003	0.00014	8.93	143.33	-11.17*
	Post	0.000084	0.00004	0.00684	0.000001	0.00027	16.68	362.21	-19.71*
	Combined	0.00011	0.00006	0.00684	0.000001	0.00026	13.67	267.44	-12.64*
Philippines (PSEI)	Pre	0.000076	0.00004	0.00324	0	0.00014	10.87	200.39	-30.50*
	Post	0.00006	0.00003	0.00115	0	0.0001	6.09	53.79	-9.61*
	Combined	0.00007	0.00004	0.00324	0	0.00013	9.44	171.1	-40.07*
China (SSE)	Pre	0.000179	0.00009	0.00373	0.000002	0.00029	5.04	41.2	-8.45*
	Post	0.000159	0.00007	0.00409	0.000005	0.00034	6.46	58.47	-6.80*
	Combined	0.00018	0.00008	0.00409	0.000002	0.00033	5.41	44.41	-6.32*
Singapore (STI)	Pre	0.000075	0.00004	0.00105	0	0.0001	3.73	24.38	-9.87*
	Post	0.000042	0.00002	0.00092	0	0.00006	5.73	53.88	-7.05*
	Combined	0.00008	0.00004	0.00545	0	0.00018	14.06	347.57	-8.20*
Taiwan (TWII)	Pre	0.000127	0.00007	0.00326	0.000003	0.00018	6.16	75.7	-8.98*
	Post	0.000046	0.00003	0.00173	0.000003	0.00008	10.36	169.56	-17.39*
	Combined	0.0001	0.00005	0.00326	0.000003	0.00016	6.59	83.12	-8.77*

* denotes rejection of the null hypothesis of the unit root at the 1% significance level. Pre denotes the period before the subprime crisis (01 April 2000 to 15 September 2007) and the descriptive statistics for the pre GFC period are presented in the same row. Post denotes the post subprime crisis period (16 September 2007 to 03 April 2029). Combined denotes the full period of study (01 April 2000 to 03 April 2019). Statistics in the same row are for the corresponding periods.

Table 1.2: Descriptive Statistics: Daily Returns

Market	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	ADF
Australia (AORD)	0.00022	0.00030	0.084832	-0.09230	0.01026	-0.39872	12.8921	-47.00*
USA (DJI)	0.000221	0.00040	0.058272	-0.07870	0.01087	-0.57986	9.6618	-49.00*
Eurozone (EURO)	-0.00012	0.00051	0.089338	-0.11392	0.01568	-0.3955	8.56014	-37.04*
UK (FTSE100)	4.17E-05	0.00033	0.101734	-0.07325	0.01216	0.019852	10.3116	-36.67*
Hong Kong (HSI)	0.00012	0.00059	0.146832	-0.14509	0.01680	-0.34002	13.7730	-50.75*
Indonesia (JKSE)	0.00080	0.00163	0.187637	-0.17673	0.01672	-0.80965	22.8371	-38.40*
Malaysia (KLSE)	0.00021	0.00046	0.073822	-0.11653	0.00988	-1.09353	19.7170	-44.63*
South Korea (KOSPI)	0.00034	0.00064	0.126791	-0.14382	0.01721	-0.4522	11.6533	-26.27*
India (NIFTY)	0.00063	0.00111	0.125554	-0.20883	0.01711	-1.19052	19.0043	-47.04*
Japan (NIKKEI)	-1.19E-05	0.00039	0.111885	-0.12477	0.01624	-0.6016	10.7191	-46.50*
Philippines (PSEI)	0.00053	0.00078	0.143117	-0.16296	0.01518	-0.06242	19.6259	-38.08*
China (SSE)	0.00018	0.00043	0.102257	-0.12435	0.01761	-0.33295	8.84843	-46.04*
Singapore (STI)	0.00015	0.00041	0.198372	-0.16108	0.01369	0.223601	32.5781	-48.46*
Taiwan (TWII)	-5.10E-05	0.00035	0.140371	-0.13497	0.01598	-0.65815	12.3305	-46.95*

* denotes rejection of the null hypothesis of the unit root at the 1% significance level.

The *ij*th entry in Table 2 is the estimated contribution to the forecast error variance of market *i* from innovations to market *j*. The off-diagonal column sums (labelled contributions to others) and row sums (labeled contributions from others) are the directional spillover to and from, respectively, and we can calculate the net volatility spillover as the difference between them. Additionally, the total volatility spillover index appears in the bottom right corner of the table. It is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum, including diagonals (or the row sum including diagonals), expressed as a percentage. In the volatility spillover table, the quantified ripple effects of the volatility shock in each country should be viewed as the input–output decomposition of the total volatility spillover index. Koutmos and Booth (1995) observed that national markets have grown more interdependent since the October 1987 crash, with a clear pattern emerging here as well: spillover both to and from others has increased considerably since the Lehman Brother collapse, whereas, in the case of Japan, the spillover is almost similar to that before the crisis. The to and from total spillover index values for the United States (DJI), the United Kingdom (FTSE), and the eurozone are higher than those of the other countries. Total spillover within the system consisting of the selected stock markets rose from 42.2% to 56.7% after the crisis, which is indicative of the higher level of integration among the stock markets.

The findings reveal that all the markets, except for Japan, are less susceptible to significant domestic volatility shocks in the pre-crisis period. The individual market analysis suggests that Japan and China differ from the other Asia-Pacific markets, as well as from the United States and the eurozone. China appears to be almost impregnable during the pre-crisis period, with 89.5% variation from its shocks and only 10.5% variation due to spillover from others, while the spillover from China to others has an index value of only 6.7. These values change significantly in the post-crisis world, where volatility spillover to China from others rises to 36.1%, and spillover from China to others increases to an index value of 37.6. During the entire period of study, the total spillover index value for China remained the same, at 14, for spillover both to and from others. For Japan, spillover from others is around 49% of its variation during both the pre- and post-crisis periods, suggesting the crisis had a minimal impact on Japan's stock market. In terms of spillover from Japan to others, the spillover index value is stable at 33.2 (pre-crisis) and 30.6 (post-crisis), indicating that Japan's contribution to global spillover did not change due to the crisis. Net directional volatility spillover before the crisis is highest from the US and eurozone stock markets to the others, and from the others to Australia. However, after the crisis, net directional volatility spillover is again highest from the US stock markets to the others, and from the others to the stock markets of the Philippines and Australia. Overall, net directional volatility spillover is greatest from the US stock market to the others, and from the others to Australia. Japan and Australia show consistent behavior regarding net volatility spillover during both the pre- and post-crisis periods.

Table 2: Directional spillover table

		DJI	FTSE	AORD	HIS	TWII	NIKKEI	STI	SSE	NIFTY	JKSE	KOSPI	KLSE	PSEI	EURO	From Others
DJI	Pre	45.9	16.39	2.44	1.99	3.7	2.16	2.68	0.2	0.1	0.89	3.27	0.98	0.14	19.17	54.1
	Post	35.07	14.08	4.21	3.51	4.61	2.4	6.03	3.03	3.3	2.35	7.87	1.69	0.18	11.68	64.9
	Combined	40.66	15.27	2.92	2.91	4.83	2.51	4.73	0.7	0.98	1.62	6.39	1.53	0.17	14.79	59.3
FTSE	Pre	16.44	38.9	3.75	2.4	3.16	2.63	3.79	0.03	0.12	0.75	1.75	1.07	0.21	24.99	61.1
	Post	16.2	30.17	4.08	3.51	4.39	2.2	6.3	2.57	2.99	2.96	6.79	1.86	0.48	15.48	69.8
	Combined	16.8	35.75	4.35	3.17	3.67	2.34	5.09	0.64	0.75	1.59	3.36	1.07	0.28	21.12	64.2
AORD	Pre	10.18	11.52	58.87	2.82	0.85	1.44	4.74	1.8	0.69	1.44	0.3	1.01	0.4	3.93	41.1
	Post	11.62	8.27	39.86	4.46	4.48	3.52	5.08	4.14	2.2	1.98	6.19	1.97	0.75	5.48	60.1
	Combined	10.76	11.63	53.97	4.08	0.95	1.67	4.74	2.91	0.59	1.4	0.44	0.35	0.43	6.11	46
HIS	Pre	3.97	5.85	1.38	50.66	5.74	3.57	9.49	0.21	2	2.2	6.19	6.07	0.26	2.41	49.3
	Post	6.27	4.94	3.14	36.41	6.91	2.91	9.15	7.1	4.54	3.66	7.84	3.24	1.07	2.81	63.6
	Combined	5.58	5.96	2.49	44.61	6.17	3.33	9.6	2.43	2.93	2.9	6.41	4.05	0.56	3	55.4
TWII	Pre	5.35	4.82	0.2	5.86	52.6	3.89	3.58	0.43	0.29	0.8	11.92	3.78	0.04	6.46	47.4
	Post	6.66	4.74	2.91	6.41	41.4	2.2	8.94	2.79	3.6	3.42	10.15	3.03	0.46	3.31	58.6
	Combined	6.31	3.9	0.23	5.21	46.7	3.35	5.89	0.28	2.35	1.79	15.26	4.82	0.16	3.73	53.3
NIKKEI	Pre	5.32	6.58	1.29	5.37	4.27	50.66	6.1	0.49	1.29	1.55	6.2	2.9	0.08	7.9	49.3
	Post	8.51	5.14	5.16	3.71	3.81	51.12	4.01	2.46	2.31	2.27	6.31	1.45	1.2	2.53	48.9
	Combined	7.17	5.61	1.87	4.38	4.98	51.52	4.95	0.19	1.89	1.88	7.79	2.75	0.54	4.48	48.5
STI	Pre	6.88	8.95	2.32	9.53	3.82	4.35	41.3	0.37	1.71	2.02	4.56	7.2	0.63	6.34	58.7
	Post	10.07	8.24	2.62	6.92	7.73	2.47	30.6	2.21	4.83	6.65	7.94	3.54	1.21	4.97	69.4
	Combined	9.24	8.54	2.1	7.93	6.19	3.29	35.3	1.26	3.46	4.34	6.8	5.26	0.92	5.4	64.7
SSE	Pre	0.08	0.04	2.74	0.63	0.34	0.76	0.54	89.46	0.27	0.46	2.28	0.38	0.82	1.19	10.5
	Post	3.75	2.7	2.38	9.9	3.04	1.1	2.18	63.89	1.54	1.83	3.18	2.51	0.18	1.83	36.1
	Combined	1.3	0.72	2.6	3.97	0.42	0.17	1.52	85.59	1.27	1.17	0.24	0.44	0.54	0.04	14.4
NIFTY	Pre	2.41	1.82	1.95	6.66	0.68	2.53	5.07	0.43	70.27	2.44	1.21	3.57	0.33	0.61	29.7
	Post	8.84	5.29	2.13	4.58	5.05	1.99	6.46	1.96	41.8	6.84	7.48	2.24	1.2	4.13	58.2
	Combined	5.54	2.62	0.9	4.69	3.73	2.41	6.17	1.52	54.88	4.65	6.55	4.35	0.78	1.22	45.1
JKSE	Pre	2.81	2.69	1.42	5.14	1.76	2.23	4.23	0.7	2.69	64.71	3.62	4.87	1.1	2.04	35.3
	Post	6.65	4.89	1.63	2.97	5.67	1.25	7.88	1.27	8.17	46.8	6.13	2.86	1.73	2.1	53.2
	Combined	5.23	3.79	1.1	3.88	3.87	1.76	6.53	1.04	5.64	54.31	5.46	4.03	1.46	1.89	45.7
KOSPI	Pre	4.95	3.5	0.19	6.77	9.69	4.72	5.73	0.29	0.43	1.69	54.15	3.8	0.12	3.98	45.8
	Post	10.11	5.9	3.45	5.91	7.4	3.23	7.69	2.52	5.16	4.09	37.55	2.32	0.63	4.05	62.4
	Combined	7.72	3.33	0.16	4.93	11.1	4.41	6.43	0.38	3.56	2.68	47.22	5.18	0.35	2.51	52.8
KLSE	Pre	2.41	3.17	0.93	7.81	2.92	1.58	6.93	0.13	1.79	2.64	2.88	64.3	0.78	1.74	35.7
	Post	4.85	3.37	2.23	5.34	5.34	2.46	5.88	3.6	3.31	4.71	4.01	51.94	1.09	1.86	48.1
	Combined	3.61	2.27	0.32	5.42	5.92	2.7	6.17	0.92	3.84	3.27	6.73	56.9	0.93	1.02	43.1
PSEI	Pre	1.16	1.19	0.99	0.59	0.99	0.18	2.02	1.42	0.51	1.6	0.22	2.15	85.92	1.05	14.1
	Post	3.78	1.82	2.07	2.5	1.64	3.48	3.61	1.44	3.06	5.51	3.23	2.89	64.01	0.95	36
	Combined	2.44	1.54	1.16	1.36	1.31	1.52	2.91	1.52	1.63	3.28	1.71	2.81	75.92	0.9	24.1
EURO	Pre	17.84	23.94	1.11	1.12	3.78	3.15	2.77	0.22	0.17	0.72	2.38	0.73	0.08	41.99	58
	Post	15.94	19.85	2.88	2.99	3.65	1.4	4.67	2.51	2.21	1.72	5.69	1.31	0.21	34.96	65
	Combined	17.35	23.53	2.35	2.13	3.55	2.14	3.55	0.16	0.35	1.02	2.92	0.55	0.1	40.31	59.7
TO Others	Pre	79.8	90.5	20.7	56.7	41.7	33.2	57.7	6.7	12	19.2	46.8	38.5	5	81.8	590.3
	Post	113.3	89.2	38.9	62.7	63.7	30.6	77.9	37.6	47.2	48	82.8	30.9	10.4	61.2	794.4
	Combined	99	88.7	22.5	54	56.8	31.6	68.3	14	29.2	31.6	70.1	37.2	7.2	66.2	676.4
TOTAL Spillover	Pre	125.7	129.4	79.5	107.4	94.3	83.9	99	96.2	82.3	83.9	100.9	102.8	90.9	123.8	42.20%
	Post	148.3	119.4	78.7	99.1	105	81.7	109	101.5	89	94.8	120.4	82.9	74.4	96.1	56.70%
	Combined	139.7	124.5	76.5	98.7	104	83.1	104	99.5	84.1	85.9	117.3	94.1	83.1	106.5	48.30%
Net Spillover	Pre	25.7	29.4	-20.4	7.4	-5.7	-16.1	-1	-3.8	-17.7	-16.1	1	2.8	-9.1	23.8	
	Post	48.4	19.4	-21.2	-0.9	5.1	-18.3	8.5	1.5	-11	-5.2	20.4	-17.2	-25.6	-3.8	
	Combined	39.7	24.5	-23.5	-1.4	3.5	-16.9	3.6	-0.4	-15.9	-14.1	17.3	-5.9	-16.9	6.5	

Note: Along each row in each period, the figures denote values of directional spillover index. Each value represents directional spillover from the different stock markets (j) (column heads) to the stock market (i) (represented in each row). The last column shows spillover received by each stock market (row under consideration) from all other stock markets. The "To Others" row represents spillover to all other stock markets. The total spillover row is obtained by vertical(column) summation of values of the same period. The values in each cell for net spillover is obtained as the difference between spillover "To Others" and spillover "From Others". Pre and Post denote the period before and after the subprime crisis respectively while Combined denotes the full period under study.

The total spillover of the system consisting of all the markets rise steadily and peaked during August–September 2008, just around the credit crisis. The peak persisted, indicating rising global market integration. Financial integration indicates the cohesion and comovement of financial markets and their ability to operate in similar directions, providing a cross-country dimension for each market's participants. The steady rise in spillover that led to the crisis suggests that financial integration can create conditions for higher volatility, by facilitating an abrupt reversal of capital flows, contagion, and the cross-border transmission of financial shocks. This increase in spillover is particularly salient when the institutional framework is not strong enough to identify and prevent adverse shocks. Policymakers might need to empirically validate whether the benefits of higher integration outweigh the risk of financial apocalypse. Obstfeld (1998) and Schmukler (2004) observed that crises and contagion are closely associated with the presence of asymmetric information and imperfect contract enforcement. Spillover started falling sharply around November 2012; it reached its low point in June 2013, when the Federal Reserve Board announced it was preparing to wind down its stimulus policies (initiated after the financial crisis) and the HSBC flash purchasing managers' index showed Chinese manufacturing activity had reached a nine-month low. These global events influenced the global markets, while investors were repricing their assets. However, most market regulators instituted central supervision and a robust institutional framework in the post-crisis period, and the shocks from these events did not increase the spillover. The low risk transfer was possibly due to improved institutional supervision and the learning curve effect. The findings support the wake-up call hypothesis, with the intriguing possibility of government policy mitigating contagion.

4.2 Network diagrams

Figures 1 to 3 show the connectedness diagrams of total spillover before and after the subprime crisis and another combining both periods, respectively.

Figure 1: Total directional connectedness to others (pre- subprime crisis period).

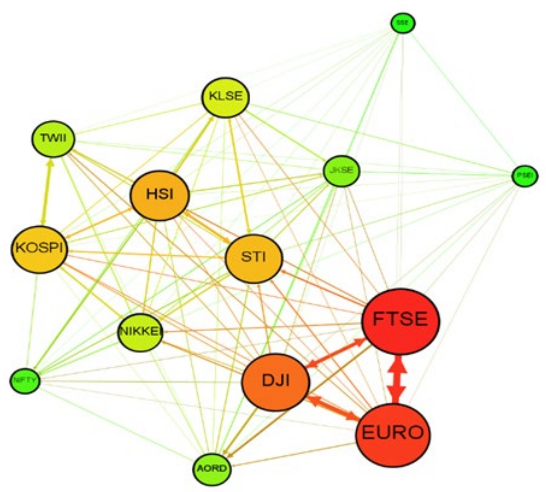
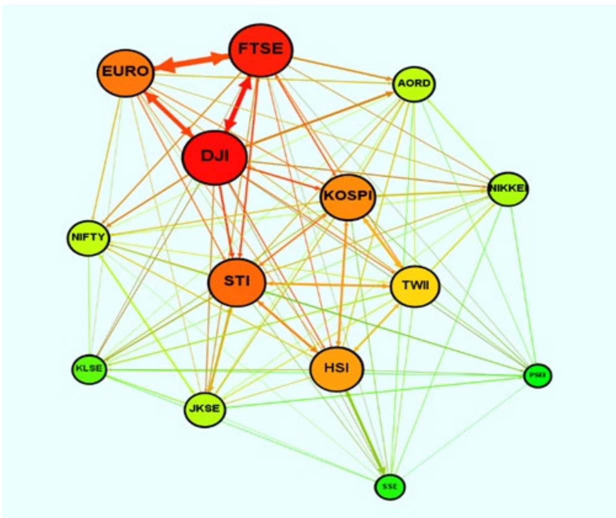
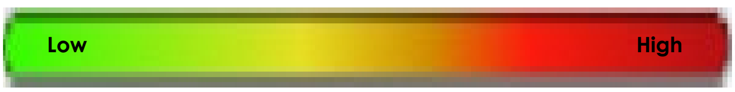


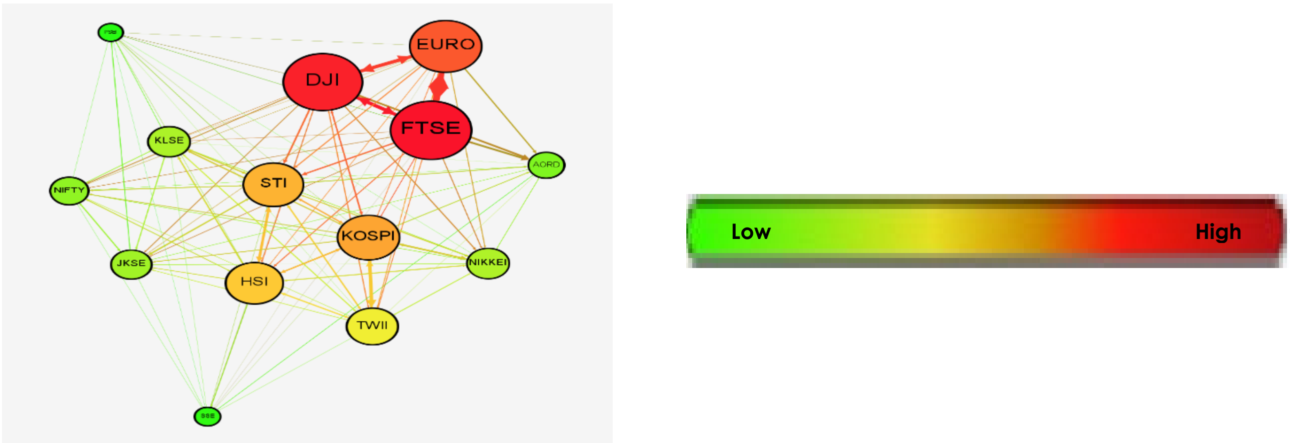
Figure 2: Total directional connectedness to others (Post- subprime crisis period)





Note: We use this node color code to indicate total directional connectedness to others, from weakest to strongest. The color and size of the nodes indicate their relative contribution to the network (smaller size denotes smaller contribution). The color and strength of the arrows indicate the network's strength. Pre and Post denotes the period before and after the subprime crisis respectively while Combined denotes the full period under study.

Figure 3: Total directional connectedness (during the entire period of the study)

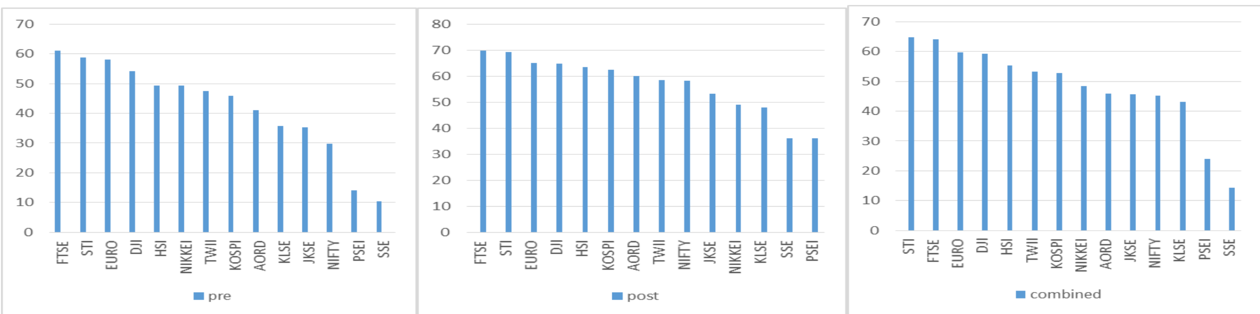


Note: We use this node color code to indicate total directional connectedness to others, from weakest to strongest. The color and size of the nodes indicate their relative contribution to the network (smaller size denotes smaller contribution). The color and strength of the arrows indicate the network's strength. Pre and Post denotes the period before and after the subprime crisis respectively while Combined denotes the full period under study.

In Figures 1 and 2, the connectedness between the chosen stock markets becomes stronger (more reddish circles) after the collapse of Lehman Brothers led the financial crisis around the world. Spillover from Hong Kong to China increases during the post-crisis period. The influence of the eurozone is reduced, and that of the United States has increased. However, China still differs in this context, since the SSE is still not highly networked, while other markets in the region are. The network diagrams revealing directional spillover show that China (SSE) stands separate, with the fewest connections. Congruent with the findings of Rejeb and Boughrara (2015), the diagrams suggest that geographical proximity is closely associated with connectedness. Total connectedness during the entire period (Figure 3) shows the connectedness between the Asia-Pacific stock markets and the US and eurozone markets, with China being the least connected to others.

The spillover from the system in Figure 4 clearly shows that the top five markets (i.e., the United Kingdom, Singapore, the Eurozone, the United States, and Hong Kong) that received spillover from others did not change between the pre- and post-crisis periods, even if we consider the entire period, although their relative positions change within the top five. Spillover to China and the Philippines from others was lowest during both the pre- and post-crisis periods, although the Chinese stock market (SSE) is much larger and more developed compared to that of the Philippines.

Figure 4: Spillover from the system



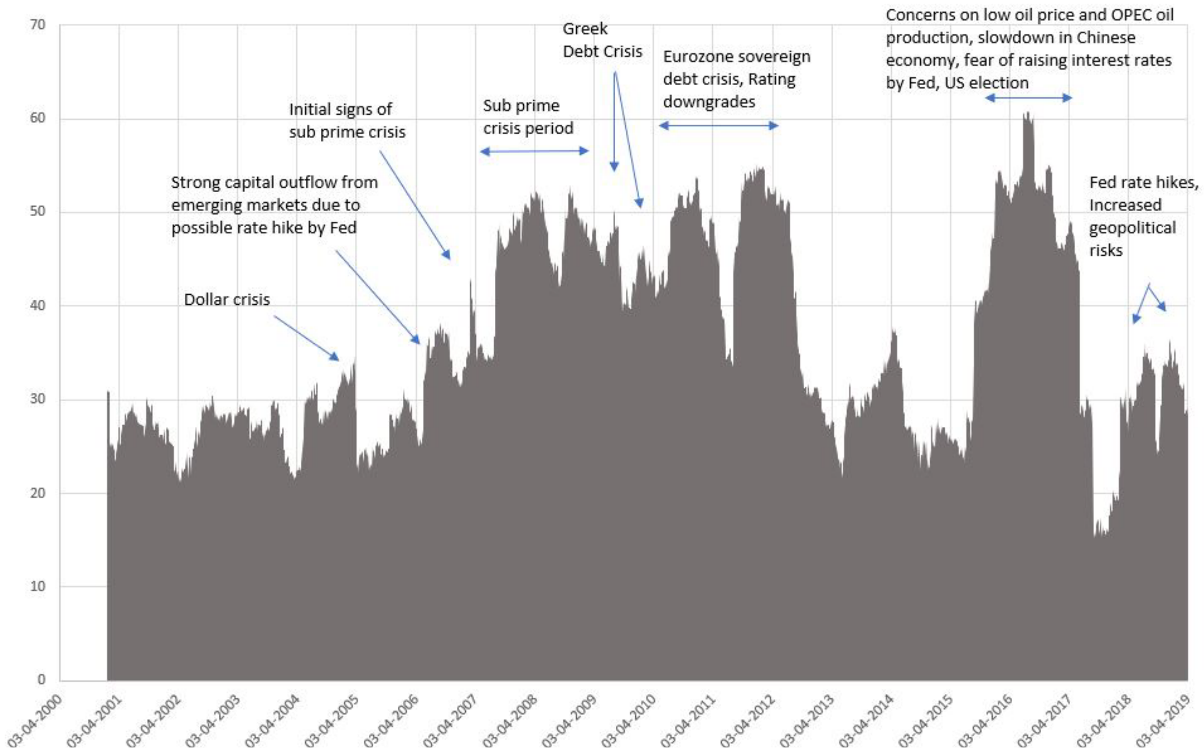
Note: This is a graphic representation of the data available in the last column of table 2 visualizing directional spillover from the system. The figure shows consecutively the equity market that receives the highest to lowest (left to right) spillover from others. Pre and Post denotes the period before and after the subprime crisis respectively while Combined denotes the full period under study.

These findings are in line with the observations of Zhou et al. (2012), Allen et al. (2013), and Jebran et al. (2017), where the impact of the global financial crisis on the Chinese stock market was minimal and did not affect its connectedness with others in the region. China was and continues to be less connected to other stock markets, presumably because of the restrictions on foreign capital flow into its stock market. Our results contradict the findings of Jebran et al. (2017), in the sense that we provide evidence of stronger bidirectional connectedness between the Chinese and Hong Kong stock markets after the crisis, whereas they argued for volatility spillover from Hong Kong to China.

4.3 Time Variation in Volatility Spillover

Figure 5 shows the time-varying spillover index plot, obtained using "to others" directional spillover index values, estimated using 150 days rolling window.

Figure 5: Time-varying Spillover Plot



Note: *The figure represents spillover index measuring contribution to other markets, obtained as a summation of variance decomposition of spillover contribution to others, estimated over a rolling period of 150 days.*

Figure 5 clearly shows the time-varying nature of volatility spillover and its peaks during crisis events. The figure also shows that the peaks are higher during the European debt crisis (EDC) than they were during the US subprime crisis or even before the US subprime crisis. The result is not surprising given that the European Union, along with the US, are the main markets for the Asia-Pacific economies and the majority of these economies depend heavily on these exports. While the US market was still recovering from the impact of the subprime crisis, the EDC led the Asia-Pacific markets to experience macroeconomic shocks owing to trade ties with crisis-hit countries. However, bursts during EDC in figure 5 also shows the presence of financial linkage between Asia-Pacific and EDC hit countries at least through equity markets.

The bursts in volatility spillover between Asia-Pacific markets have been observed during the following events:

1) Dollar crisis during March 2005 when policymakers of various Asia-Pacific nations like China, Japan, India and Korea showed intension of diversifying forex reserve.
2) The significant outflow of funds from emerging markets due to the Federal Reserve's rate hike signals in 2006.
3) Subprime crisis in the US in 2007 and 2008 that led to the collapse of Lehman Brothers, followed by a global financial crisis.
4) The Greek debt crisis and downgrading of Greek bank and government debt in 2009.
5) Eurozone sovereign debt crisis during 2010-2012.
6) Uncertainties and economic events in 2016 and 2017, such as low crude oil prices, indications of a downturn in the Chinese economy, expectations for a Fed rate hike, US election results and the confusion surrounding the US relationship with Russia, China and North Korea.
7) Concerns due to increased geopolitical risks caused by the US-China trade war beginning with imposing tariffs on each other's products, multiple rate hikes by Federal Reserve and uncertainties over Britain leaving the European Union.

As displayed in figure 5, there are three periods where we observe spillover bursts. We build the connectedness diagrams (figure 6, 7 and 8) for the three periods:

- *Subprime crisis period (February 2007 to December 2009):* The starting date coincides with the announcement made by Freddie Mac that it will no longer buy the riskiest subprime mortgages and mortgage-related securities. The period considered is till Dec 2009 when the US Treasury Department announces the removal of caps on the amount of preferred stock that the Treasury may purchase in Fannie Mae and Freddie Mac, besides Federal Reserve Bank declaring that it would offer interest-bearing term deposits to eligible institutions through an auction mechanism. The figure 6 shows that the US market is the most influential contributor to volatility spillover during the period compared to the other markets. The observation is not surprising as the US is the origination point of the subprime crisis.

- *European Debt Crisis period (December 2009 to Nov 2012)*: Fitch, S&P, Moody's downgraded Greece credit rating in December 2009 and that is the initial signal of the crisis in Europe. The period considered is till November 2012, when Eurozone nations and the IMF agreed to a revised aid deal for Greece, including lower interest rates on bailout loans and a debt-buyback. We find that the spillover (to others) initially reduces and then increases. Finta et al. (2019) observes similar spillover effect (decrease followed by increase) during EDC between the German stock market and the Greek, Italian, Portuguese and Spanish stock markets. During the period (figure 7), we find that the Australian stock market is the largest volatility spillover contributor to others, and the UK market follows next. While the UK is a European nation and as a member of the EU, is expected to witness the ripple effects of the EDC, the emergence of Australia as a leading contributor of volatility across the markets (as indicated by the red colored arrows) is expected to give newer insights in further studies.

- *Increased geopolitical risks and uncertainty (December 2015 – July 2017)*: The period witnessed many events that arguably led to the increase in spillover between Asia-pacific markets. U.S. Federal Reserve raised interest rates in Dec 2015 for the first time since before the global financial crisis. Throughout the period, the markets witnessed uncertainty and increased geopolitical risks from falling crude prices; slowdown and debt pile in China; US election and post-election uncertainties in the domestic US market and its external relationships with China, Russia and North Korea; and apprehensions about a further rate hike by US Federal Reserve that can alter the course of international capital flows. Australian stock market remained the leading contributor to the volatility spillover to the network during the time. The spillover between the Japanese, Singaporean, Malaysian and Indian stock markets is observed at a medium level. During this time, though, the US market is comparatively less connected. China and Hong Kong markets are least connected as shown by their network strength.

During all three periods, the Chinese equity market remains least connected with the other markets. The observation is in line with the earlier findings.

Connectedness during bursts in Spillover:

Figure 6: Subprime Crisis

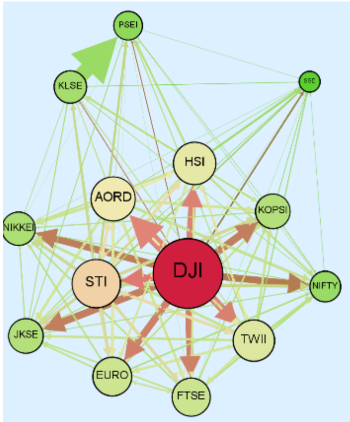


Figure 7: European Debt Crisis

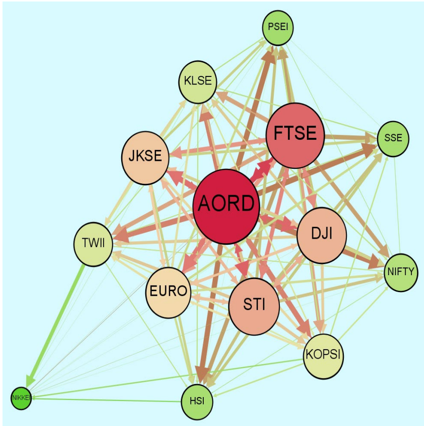
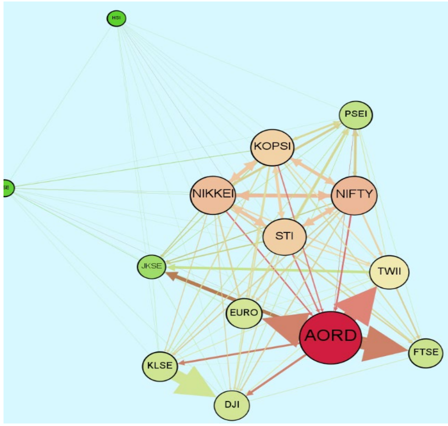


Figure 8: Geopolitical Uncertainty



We use this node color code to indicate total directional connectedness to others, from weakest to strongest. The color and size of the nodes indicate their relative contribution to the network (smaller size denotes smaller contribution, spillover increases as color changes from green to red).

During the three spillover burst periods, the relative contribution to the network varies across different markets. During the subprime crisis, the contribution of the US market was relatively much higher compared to any other market. During the European Debt Crisis, the Australian market emerged as the leading volatility spillover contributor to others, followed by the UK market. The emergence of the Australian market as a contributor to volatility spillover to other markets continued even after the EDC when the world markets witnesses increased uncertainty due to geopolitical situations. China remained least connected during all the periods.

5. Conclusion

The rationale behind international diversification is based on the expectation that most economic disturbances to be country specific, resulting in relatively low correlations between stock markets. If markets are connected, this would undermine much of the rationale for international diversification, because ignoring the connectedness can lead to poor portfolio diversification and an underestimation of risk. Except China, the US, UK, EU and the Asia-Pacific markets are reasonably connected between themselves, although the strength of their network varies over the period. The Chinese stock market had kept itself relatively insulated, even though it remained a volatile market throughout the study period. Of all the Asia-Pacific markets, those of South Korea (KOSPI), Hong Kong (HSI), and Singapore (STI) make the largest contribution to risk transfer. Market size does not determine the level of connectedness either, since it is clear that three big stock markets (in terms of volume), namely, Japan, China, and Australia, are less connected compared to the most connected countries. Geographical proximity seems to be a factor in increasing volatility spillover. These findings have significance for multinational portfolio management. Overall, while all the other stock markets are connected in terms of risk transfer (volatility spillover), the Chinese stock market experienced least volatility spillover from other markets. China's stringent financial market rules combined with the restrictions on non-Chinese participation in its stock markets could be the reason for the Chinese stock market's relative insulation.

The time variations in spillover show peaks and troughs, which may be aligned with readily recognizable international events. We also found overall network strength gradually increased, leading to the global financial crisis, symptomatic of the evolution of the subprime crisis into a global financial crisis. Interestingly, network strength seems to have increased since the crisis and has remained above its pre-crisis level. The transmission of volatility was higher during EDC and even after EDC than it was during the time of subprime crisis. This finding could be a sign of the integration of global standards of market regulation and the increased confidence level of transnational investment agents. However, it also indicates that shock to any one of these markets has the potential to spread to others very quickly and develop into a multi-country phenomenon. The network's strength always drastically fell after a stock market crash, indicating the disintegration of markets after a crash, which could be due to the withdrawal of investment from foreign markets. It is therefore possible that, whenever a major crash occurs, global investment firms will curtail their transnational activities, providing a window of opportunity for contrarians.

In the case of a new global crisis, some of these markets, such as South Korea, Hong Kong, and Singapore, are likely to be as badly hit as the Western markets. Future research could focus on dynamic hedging possibilities using an Asia-Pacific portfolio. On the policy front, the findings call for stronger supervision and regulations to mitigate the rising risks from market connectedness. Between highly connected markets, an adverse shock to one market has the potential to negatively impact the international fund flows to other markets, even if the other markets have strong fundamentals. This could trigger a financial crisis in other markets, one that is utterly unwarranted by those countries' fundamentals and policies. Stronger regulations should help in reducing the impact and in obtaining dedicated funds to stabilize the system. Financial market policies should encourage and improve the resilience of financial markets against shocks. However, this in itself requires more granular and timely information from market participants, and regulations on the capture of such data could help improve the flow of information and market monitoring.

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TIME-VARYING EQUITY PREMIUM FORECASTS BASED ON INDUSTRY INDEXES

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Abstract:

Various studies report that the ability of industry indexes to predict the broad market disappeared during the most recent years. I revisit this theme using more flexible switching models and imposing economically motivated constraints on the predictions. My results show that traditional constant coefficients linear models are unable to forecast the stock market over the period considered, but restricting the equity premium to be non-negative, five industries predict the market. I also show that the Markov-switching models exhibit a dismal performance, which is even worse than the ones from the constant coefficients model. Finally, I test a model with two regimes- recession and expansion- which are identified in real-time through the Arouba-Diebold-Scotti Business Conditions Index. Using this model, I find that 8 out of 33 industries can successfully forecast the market. Furthermore, a mean-variance investor who bases his decisions on it obtains sizeable utility gains, relative to another investor who uses, exclusively, the historical returns.

Keywords: Equity premium forecasts, Industry indexes, Regime switch, Portfolio choice

JEL classification: C58, G11, G17

1. Introduction

It is a known fact that investors' time and resources to process information is limited. Hong et al. (2007) draw on this issue to show that information flows slowly across industries, which implies that industry returns can predict the broad market returns. They find that 14 of 34 U.S. industry indexes returns possess the ability to predict the market over the period January 1946-December 2002. These results were contested by Tse (2015) and Ponka (2015), who argue that predictability disappears when the analysis is expanded to include the most recent years.

In this study, I revisit the theme of industry-based equity premium predictability. I aim to find if predictability disappeared, or if it has become time-varying in nature. To accomplish this goal, I consider both Markov switching models and a method that identifies recession states based on the observable Arouba-Diebold-Scotti (ADS) Business Conditions Index (see, Arouba et al. 2009), as in Sander (2018).

My contribution to the literature is twofold. First, I show that the ADS switching model uncovers the ability of several industries to predict the broad market, which is not apparent in the simple linear model. Second, I combine this method with economically motivated non-negativity restrictions on the equity premium and find a notorious improvement in forecasts during expansions.

My results reveal the ADS method markedly improves the equity premium forecasts relative to the simple linear and the Markov switching models. I find that 8 out of 32 industries can predict the market in the ADS model, and none in other ones. I also show that forecast combinations based on the ADS model generate positive out-of-sample R-squared and sizable utility gains for a mean-variance investor.

2. Literature Review

Several studies explore the slow diffusion of information across markets to forecast the equity premium. Hong et al. (2007) show that industry returns lead the market by up to two months. The statistical and economic out-of-sample performance of forecast combinations is analysed in Silva (2018), who finds that these combinations generate significant R-squared and sizable economic gains for a mean-variance investor. Using an updated version of Hong et al. (2008) database, Tse (2015) shows that industries do not lead the market, but the reverse causality holds for several industries. Probit models are used to forecast the direction of the US stock market, based on industry returns, in Ponka (2016). The author shows that these models outperform simple linear models and improve investment returns. Jacobsen et al. (2018) report that industrial metal returns lead the stock market, even after controlling for some other commonly used predictors. They also show that there is a direct relation between the stock market returns and past industrial metal returns during recessions, and an inverse one in expansionary periods.

The predictability of industry returns is addressed in Menzly and Ozbas (2010), who show that industries related through the supply chain present significant cross-momentum. Hou (2007) finds large firms transmit shocks to small firms in the same industry, and the former returns' lead the latter ones. Using a machine learning approach, Rapach et al. (2019) report that lagged returns for the financial sector and commodity and material-producing industries have forecasting ability for most industries. They also show an investment strategy that goes long the industries with the largest forecasted returns and short the industries with the lowest ones generates an annualized alpha higher than 8%.

The effect of technological closeness on stock returns is analyzed in Lee et al. (2019). The authors show that firms whose peer group exhibited a positive return in the past month outperform the ones whose peer group return was negative.

The issue of the instability in equity premium predictive models is a common concern amongst financial researchers. Baetje and Menkhoff (2016) report that equity premium forecasts based on technical indicators are stable, but those based on economic indicators are not. A frequent choice to model predictive instability is Markov switching models, such as in Henkel et al. (2012) and Zhu and Zhu (2012). Both authors find that regime-switching models outperform the traditional linear model and deliver consistent out-of-sample forecasting gains. Furthermore, they show that predictability is mainly present in recessions. Guidolin and Hyde (2012) find that a simple three-state Markov switching model delivers a higher certainty equivalent return than more complex VAR models. Sander (2018) follows an alternative approach and identifies the recession state in the economy through observable dummies, based either on the ADS Business Confidence Indicator or the Purchasing Managers' Index. He shows that this model performs significantly better than a simple Markov-switching one and provides significant certainty equivalent return gains relative to the no predictability benchmark.

An alternative form to model the variability in predictive coefficients is through dynamic linear models that, unlike Markov-switching models, generate smoothly changing coefficients. This is the approach adopted in Dangl and Halling (2012) to forecast the monthly returns of the S&P 500. The authors find that models with time-varying coefficients dominate constant coefficients ones and, deliver relevant economic gains for a mean-variance investor.

3. Methodology

3.1 Model Specification and Estimation Method

The prior evidence on equity premium forecast instability has motivated me to compare the predictive performance of a traditional constant coefficients model with two time-varying ones. The first model is specified as follows

$$R_t = \alpha + \beta I_{t-1} + \varepsilon_t \qquad (1)$$

where R_t is the equity premium in month t, I_{t-1} is the excess return of the industry over the riskless rate in month t-1, and ε_t is a normal error.

The first time-varying model that I estimate is a standard, two-state, Markov-switching model

$$R_t = \alpha(s_t) + \beta(s_t)I_t + \varepsilon(s_t) \qquad (2)$$

where $s_t \in \{1,2\}$ represents the state, and the transition probabilities are constant. I follow Henkel et al. (2011) and achieve identification by assuming that the residual volatility is higher in the second regime.

I also consider another switching model that is based on the state of the economy. The most commonly used business cycle classifier in the US is the National Bureau of Economic Research (NBER) one. However, the recession dates are only available with a significant lag, which prevents their direct use in a forecasting model. To circumvent this problem, I follow Berge and Jorda (2011) and Sander (2018) and use the Arouba-Diebold-Scotti Business Conditions Index[1] (ADS) to generate a dummy variable that identifies recessions. Specifically, I use the Receiver Operating Characteristic (ROC) curve to find the thresholds that maximize the ability to correctly identify NBER recessions. Let TP(c) and FP(c) represent the true and false positive identification rates for recessions, respectively

$$TP(c) = P[ADS_t \geq c | NBER = 0] \qquad (3)$$

[1] The Arouba-Diebold-Scotti Business Conditions Index is an indicator designed to assess economic activity in real-time. It used a dynamic factor model to filter economic information from various sources.

$$FP(c) = P[ADS_t \geq c | NBER = 1] \tag{4}$$

where NBER is a dummy variable that assumes the value 0 (1) during recession (expansion) months and c is the threshold. I obtain the optimal threshold by solving the following maximization problem in each month

$$max_c\left(2\hat{\pi}\widehat{TP}(c) - \hat{\pi}\right) - \left(2(1-\hat{\pi})\widehat{FP}(c) - (1-\hat{\pi})\right) \tag{5}$$

where π is the unconditional recession probability, and the variables with a hat are sample estimates of the ones without a hat. Since NBER recession dates are not available in real-time, I estimate the threshold for month t using only the data up to month t-3, as in Sander (2018).

I employ Gibbs sampling, with uninformative priors, to estimate all the models. For each model, I consider two versions: the first one has no restrictions, and, in the second one, I impose the condition that the expected equity premium must be non-negative. Several authors, such as Campbell and Thompson (2008), Pastor and Stambaugh (2009, 2012), and Pettenuzzo et al. (2014), reveal that parameter restrictions improve equity premium predictions. In this study, I follow Pettenuzzo et al. (2014) and apply a rejection step in the Gibbs sampling algorithm. That is, I reject the draws that generate a negative equity premium prediction for any time up to the estimation month, in the constant parameter models. In the time-varying models, this restriction is applied separately for each state. Note that this procedure is more efficient than the one used in Campbell and Thompson (2008), that merely truncates negative equity premium forecasts, and does not allow this information to alter their estimated coefficients.

I also examine the performance of forecast combinations based on individual models. Past research, such as Pettenuzzo and Ravazzolo (2016), Rapach et al. (2010), Dangl and Halling (2012), and Avramov (2002), show this method generates smoother and more precise predictions than the ones based on single predictors. In this study, I analyze the performance of the following forecast combinations, for each model: simple average, median and weighted average based on the inverse of the mean-squared prediction error, as in Rapach et al. (2010).

3.2 Performance Evaluation

The forecasts, based on the method described above, are obtained by estimating the model recursively, using an expanding window. That is, I estimate the model with data up to month t to obtain an equity premium forecast for month t+1. Then, I add another month and re-estimate the model to get the t+2 equity premium forecast. This procedure is repeated until the end of the sample.

I use the pseudo R-squared out-of-sample to measure the predictive accuracy of the individual model and combined forecasts

$$R^2_{OOS} = 1 - \frac{MSPE_{mod}}{MSPE_{hist}} \tag{6}$$

, where $MSPE_{mod}$ is the mean-squared prediction error over the out-of-sample period based on the model, and $MSPE_{hist}$ represents the mean-squared prediction error computed from the equity premium historical average. The statistical significance of the prediction is tested through the MSPE-adjusted statistic, developed by Clark and West (2007). This test is an approximately normal modification of the McCraken (2007) MSE-F statistic. According to its null hypothesis, the unrestricted and restricted models possess equal forecasting ability, while, under the alternative hypothesis, the former exhibits a lower MSPE than the later. A simple way to implement this test is to compute

$$\hat{f}_t = \left(R_t - R_t^{hist}\right)^2 - \left[\left(R_t - R_t^{mod}\right)^2 - \left(R_t^{hist} - R_t^{mod}\right)^2\right] \tag{7}$$

, where R_t^{hist} and R_t^{mod} represent the equity premium forecasts based on the historical average and the model, respectively. The MSPE-adjusted statistic is calculated by regressing $\hat{f}_t$ on a constant. The null hypothesis of equal predictive ability is rejected at the 5% level if the resulting t-statistic exceeds 1.645 (one-sided test).

I assess the economic value of the forecast combinations by comparing the realized utility for an investor who uses these predictions to support his investment decisions, with the utility an investor would get if he relied, exclusively, on the historical average returns. The fraction of wealth invested in the stock market[2], at month t, for an investor with a coefficient of relative risk aversion γ , who uses the forecasts based on model combinations is

$$w_t^{mod} = \frac{1}{\gamma} \frac{\widehat{R}_{t+1}^{mod}}{\widehat{\sigma}_{mod,t+1}^2} \tag{8}$$

, where $\hat{R}_{t+1}^{mod}$ and $\hat{\sigma}_{mod,t+1}^2$ represent the expected equity premium and variance based on the model combination. An individual who uses only historical information to drive his investment strategy chooses

4. Data

I extracted from Ken French's website the monthly returns on 38 value-weighted industry portfolios for the period comprised between March 1960 and the end of 2018. Six industries- agriculture, forestry and fishing, sanitary services, steam supply, irrigation systems, public administration, and other- were dropped due to missing data. I also obtained, from this website, the one-month Treasury bill rate (risk-free rate) and the excess return over the risk-free rate on the market value-weighted return of all the CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ (equity premium) for the same period.

[2] I follow Campbell and Thompson (2008) and assume that the fraction of wealth invested in stocks can neither exceed 150% nor be negative.

The monthly series of the Arouba-Diebold-Scotti (ADS) Business Conditions Index and the NBER recessions indicator are from the Federal Reserve Bank of Philadelphia and the NBER websites, respectively.

Table 1: Descriptive statistics for the equity premium (EP) and the 32 industries' monthly returns.

Industry	Mean	Std	Industry	Mean	Std	Industry	Mean	Std
EP	0.52%	4.38%	**PAPER**	0.48%	5.48%	**CARS**	0.59%	5.60%
MINES	0.57%	8.05%	**PRINT**	0.48%	5.76%	**INSTR**	0.58%	5.20%
OIL	0.58%	7.27%	**CHEMS**	0.57%	4.44%	**MANUF**	0.44%	6.66%
STONE	0.79%	7.81%	**PTRLM**	0.69%	5.04%	**TRANS**	0.58%	5.74%
CNSTR	0.55%	7.18%	**RUBBER**	0.62%	5.88%	**PHONE**	0.41%	4.80%
FOOD	0.70%	4.32%	**LETHR**	0.77%	5.25%	**TV**	0.90%	6.41%
SMOKE	0.93%	6.08%	**GLASS**	0.51%	6.72%	**UTILS**	0.48%	3.96%
TXTLS	0.62%	7.07%	**METAL**	0.28%	7.26%	**WHLSL**	0.60%	5.67%
APPRL	0.57%	6.71%	**MTLPR**	0.66%	5.33%	**RTAIL**	0.69%	5.25%
WOOD	0.59%	7.74%	**MACHN**	0.58%	6.34%	**MONEY**	0.61%	5.38%
CHAIR	0.57%	6.52%	**ELCTR**	0.61%	6.73%	**SRVC**	0.72%	6.38%

Table 1 presents the mean and standard deviation of the industry monthly excess returns over the risk-free rate, and the equity premium. The average monthly equity premium over the period considered was 0.52%, and its standard deviation was 4.38%. The industry exhibiting the highest average monthly return was smoke (0.93%), and metal (0.28%) had the lowest one. The standard deviations range between 3.96% for utilities and 8.05% for mines.

5. Results

In this section, I present and discuss the main out-of-sample results, which cover the period comprised between January 1990 and December 2018. The out-of-sample period starts, approximately, 20 years after the beginning of the sample because it is essential to have a sizable number of observations to obtain reliable parameter forecasts.

Table 2 shows the R-squared out-of-sample for all the models. In the unrestricted version of the constant coefficients model, most R-squared are negative (22 out of 33), and none is statistically significant. Imposing the constraint that equity premia cannot be negative improves the forecasts: all the R-squared become positive and 5 are significant at the 10% level (Chair, Phone, TV, Utilities, and Money). The Markov-switching model delivers disappointing results. All the R-squared are negative in the unrestricted model, and, in the restricted one, the R-squared fluctuate around zero. The ADS model without restrictions is the best performing one. Eighteen out of thirty-three R-squared are positive, and there is statistical evidence of predictability at the 5% level for Chair and Retail, and at the 10% level for Apparel, Glass, Machinery, Transport, TV, and Money. In this model, requiring that equity premia are non-negative leads to a deterioration in predictive ability.

Table 3 decomposes the predictive ability of the best performing model between periods classified as expansions and recessions, according to the Arouba-Diebold-Scotti Business Conditions Index. In the unrestricted model, predictability is concentrated mostly during recessions, which is consistent with Sander (2018). Several industries, such as Rubber, Retail, and Money, exhibit R-squared values higher than 3%, and 10 out of the 33 R-squared are statistically significant. During expansions, no industry can forecast the equity premium. Curiously, the restriction of non-negativity for the equity premium destroys the forecasting ability of this model in recessions but markedly improves its performance during expansions. All R-squared for the restricted model are positive during expansions, and eleven are statistically significant.

Table 2

	No Switch		MS Switch		ADS Switch	
	Un	Res	Un	Res	Un	Res
MINES	-0.53%	0.1%	-1.73%	-0.14%	-1.19%	-0.17%
OIL	-0.43%	0.07%	-2.27%	-0.19%	-0.69%	-0.15%
STONE	-0.08%	0.09%	-1.17%	-0.04%	-0.04%	-0.13%
CNSTR	-0.28%	0.14%	-1.15%	-0.08%	0.01%	-0.03%
FOOD	-0.59%	0.14%	-1.52%	-0.08%	0.33%	-0.03%
SMOKE	-1.07%	0.06%	-1.81%	-0.13%	-3.46%	-0.51%
TXTLS	-0.96%	0.15%	-1.74%	-0.08%	-0.97%	-0.06%
APPRL	-0.36%	0.18%	-0.92%	-0.01%	0.71%[b]	0.05%
WOOD	-0.57%	0.1%	-1.29%	-0.06%	0.04%	0.01%
CHAIR	0.41%	0.23%[b]	-0.72%	-0.06%	0.78%	-0.14%
PAPER	-0.55%	0.09%	-1.46%	-0.11%	-0.83%	-0.16%
PRINT	-0.71%	0.26%	-0.78%	-0.02%	0%	-0.03%
CHEMS	0.09%	0.18%	-1.32%	-0.04%	0.28%	0.03%
PTRLM	-0.13%	0.11%	-1.63%	-0.06%	-0.52%	-0.11%
RUBBER	0.03%	0.14%	-0.80%	-0.11%	1.71%[a]	0.24%
LETHR	-0.63%	0.27%	-1.81%	-0.06%	0.24%	0.01%
GLASS	-0.41%	0.12%	-0.85%	-0.01%	0.81%[b]	0.19%
METAL	-0.49%	0.1%	-1.90%	-0.15%	-0.52%	-0.04%
MTLPR	-0.73%	0.12%	-1.14%	-0.01%	0.67%	0.01%
MACHN	-0.01%	0.17%	-0.74%	-0.01%	0.98%[b]	0.03%
ELCTR	0.42%	0.23%	-0.62%	-0.18%	0.23%	-0.13%
CARS	-0.69%	0.12%	-1.15%	-0.08%	-0.77%	-0.16%
INSTR	-0.27%	0.13%	-1.28%	0%	-0.21%	-0.09%
MANUF	-0.64%	0.11%	-1.2%	0.01%	-0.28%	-0.05%
TRANS	0.02%	0.18%	-0.84%	-0.07%	1.12%[b]	0.19%
PHONE	0.33%	0.43%[b]	-1.52%	-0.04%	-1.23%	-0.11%
TV	0.33%	0.43%[b]	-0.36%	0.15%	0.68%[b]	0%
UTILS	0.17%	0.38%[b]	-0.63%	0.09%	0.34%	0.03%
WHLSL	-0.16%	0.16%	-0.87%	-0.03%	-0.14%	-0.09%
RTAIL	-0.03%	0.21%	-0.28%	0.04%	1.33%[a]	0.15%
MONEY	0.09%	0.36%[b]	-0.76%	0.09%	1.29%[b]	0.05%
SRVC	0.01%	0.24%	-0.66%	0.05%	0.45%	-0.02%

R-squared out-of-sample for the constant coefficients model (No Switch), the Markov-switching model (MS Switch), and the switching model based on the ADS Business Conditions Index (ADS). For each model, the first column (Un) displays the R-squared out-of-sample for the unrestricted model, and the second one (Res) exhibits the R-squared based on estimations that impose non-negative equity premia.

a- Significant at 5%, b- significant at 10%.

Tables 4 and 5 display the statistical and economic performance of the predictions based on combinations of forecasts from the individual models. All the models deliver negative out-of-sample R-squared, except the unrestricted ADS one. For this last model, all the R-squared are positive, irrespective of the combination method chosen. The weighted average generates the highest R-squared (0.41%), and the median the lowest one.

Table 5 shows that all the models deliver positive utility gains for a mean-variance investor, whose coefficient of relative risk aversion equals 3. The most successful one is the unrestricted ADS model, followed by the restricted ADS model. Both Markov-switching models provide low benefits for this investor. The utility gains are not very sensitive to the combination method chosen but vary markedly across model types.

Table 3

	Expansion		Recession	
	Un	Res	Un	Res
MINES	-0.49%	0.68%	-1.78%	-0.9%
OIL	-0.47%	0.55%	-0.86%	-0.74%
STONE	1.04%[b]	0.58%	-0.97%	-0.73%
CNSTR	-0.63%	0.60%	0.55%	-0.56%
FOOD	0.31%	0.75%[b]	0.34%	-0.69%
SMOKE	-2.27%	0.24%	-4.47%	-1.15%
TXTLS	-0.78%	0.72%[b]	-1.13%	-0.72%
APPRL	-0.76%	0.69%[b]	1.95%[b]	-0.49%
WOOD	-0.41%	0.66%	0.43%	-0.55%
CHAIR	-1.04%	0.44%	2.34%[b]	-0.64%
PAPER	-0.12%	0.67%	-1.44%	-0.87%
PRINT	-2.68%	0.36%	2.29%[b]	-0.36%
CHEMS	-0.09%	0.70%[b]	0.59%	-0.54%
PTRLM	-0.06%	0.59%	-0.91%	-0.70%
RUBBR	-0.32%	0.83%[b]	3.44%[a]	-0.25%
LETHR	0.53%	0.94%[b]	-0.02%	-0.78%
GLASS	-0.52%	0.82%[b]	1.94%[b]	-0.34%
METAL	-0.66%	0.66%	-0.40%	-0.63%
MTLPR	-0.52%	0.75%[b]	1.68%	-0.62%
MACHN	-0.74%	0.6%	2.45%[b]	-0.44%
ELCTR	-1.40%	0.41%	1.62%	-0.58%
CARS	-1.16%	0.52%	-0.44%	-0.74%
INSTR	-0.27%	0.63%	-0.15%	-0.7%
MANUF	0.28%	0.78%[b]	-0.75%	-0.76%
TRANS	-0.24%	0.75%[b]	2.28%[b]	-0.30%
PHONE	-1.29%	0.41%	-1.18%	-0.55%
TV	-1.95%	0.42%	2.92%[b]	-0.36%
UTILS	0.52%	0.71%[b]	0.19%	-0.55%
WHLSL	-0.17%	0.60%	-0.12%	-0.68%
RTAIL	-1.22%	0.5%	3.5%[a]	-0.16%
MONEY	-1.25%	0.38%	3.45%[a]	-0.23%
SRVC	0.23%	0.56%	0.65%	-0.52%

R-squared out-of-sample for the unrestricted (Un) and restricted (Res) ADS models, during periods classified as recession and expansion, according to the Arouba-Diebold-Scotti Business Conditions Index.

a- Significant at 5%, b- significant at 10%.

Table 4

	No Switch		MS Switch		ADS Switch	
	Un	Res	Un	Res	Un	Res
Weighted	-0.19%	-0.09%	-1.15%	-0.31%	0.41%	-0.31%
Simple	-0.21%	-0.09%	-1.16%	-0.31%	0.38%	-0.31%
Median	-0.23%	-0.12%	-1.10%	-0.30%	0.34%	-0.30%

R-squared out-of-sample for forecast combinations from the constant coefficients model (No Switch), the Markov-switching model (MS Switch), and the switching model based on the ADS Business Conditions Index (ADS), using the weighted average (Weighted), the simple average (Simple), and the median (Median).

Table 5

	No Switch		MS Switch		ADS Switch	
	Un	Res	Un	Res	Un	Res
Weighted	1.20%	1.28%	0.28%	0.69%	3.46%	2.43%
Simple	1.16%	1.28%	0.28%	0.69%	3.42%	2.42%
Median	1.11%	1.19%	0.34%	0.65%	3.46%	2.44%

Annualized utility gains for forecast combinations from the constant coefficients model (No Switch), the Markov-switching model (MS Switch), and the switching model based on the ADS Business Conditions Index (ADS), using the weighted average (Weighted), the simple average (Simple), and the median (Median).

6. Conclusion

In this study, I show that traditional linear constant coefficients models, using industry indexes, can no longer predict the broad market. My results also reveal that imposing an economic motivated non-negativity constraint on the equity premium improves the forecasts. Markov-switching models fail to improve the forecasting ability of industry indexes because they cannot identify accurately the regimes in real-time.

I consider another model that identifies expansionary and recessionary regimes, in real-time, based on the Arouba-Diebold-Scotti Business Conditions Index. Using this model, 8 out of 33 industry indexes predict the market out-of-sample. The predictive ability is concentrated, essentially, during recession periods, which is coherent with past studies. Curiously, imposing a non-negativity restriction on the equity premium improves the predictions substantially during expansions, but not in recessions. It would be interesting to test if this pattern also holds when a different set of predictors is considered. I also show the forecast combinations based on the ADS model provide sizable utility gains for a mean-variance investor, which are higher than the ones from the other models.

These results are compatible with the investors' inattention hypothesis, which states they lack the time and resources to thoroughly study all the different markets. Thus, the news does not flow swiftly, and some industries lead the market. This effect is particularly notorious during recessions when several industries exhibit sizable out-of-sample R-squared for the unrestricted model. Therefore, investors should be attentive to signals coming from these industries that may anticipate a turning point in the broad market tendency.

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REAL-TIME DETECTION OF VOLATILITY IN LIQUIDITY PROVISION

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Abstract

Previous research has found that high-frequency traders will vary the bid or offer price rapidly over periods of milliseconds. This is a benefit to fast traders who can time their trades with microsecond precision, however it is a cost to the average market participant due to increased trade execution price uncertainty. In this analysis we attempt to construct real-time methods for determining whether the liquidity of a security is being altered rapidly. We find a four-state Markov switching model identifies a state where liquidity is being rapidly varied about a mean value. This state can be used to generate a signal to delay market participant orders until the price volatility subsides. Over our sample, the signal would delay orders, in aggregate, over 0 to 10% of the trading day. Each individual delay would only last tens of milliseconds, and so would not be noticeable by the average market participant.

Keywords: High-Frequency Trading; Liquidity; Markov-Switching Models

JEL: G10; G12; C24; C45

1. Introduction

The goal of this analysis is to construct methods to determine, in real-time, when the volatility of the liquidity provided is being rapidly changed around a mean value, which is consistent with the effect of an algorithm or set of algorithms. Such methods would allow the creation of orders which can be cancelled, or delayed, if the market switches to such a regime with unstable liquidity. This is analogous to the crumbling quote signal from the Investors Exchange (outlined in Bishop (2017)).

Such real-time detection is a difficult task, though identification does not have to be perfect. The threshold is that investors choose to use the order—that it is correlated enough with undesirable activity that it adds value to the investor to submit the order type. For the order type to have worth to investors algorithmic activity, or other processes which rapidly change liquidity around a mean value, which is a cost to the average investor must exist.

Hasbrouck (2018) found evidence for substantial volatility in the bid and offer prices which was not due to fundamental changes in the asset value. The cost of this volatility is not borne equally by traders. Faster traders are able to choose the point (in microseconds) at which they trade. Slower traders, however, will receive a trade price some time later (maybe seconds) after they attempt to submit a marketable order. This trade price is a random variable, and they are exposed to price risk which is a function of the expected variation of the bid (or offer) price over the time from when they submitted the order to when it is matched by the exchange.

So, when fast traders change the bid/ask price quickly, slower traders still *expect* to receive/pay the same amount for each sell/buy order, however they have increased uncertainty. This increased risk without increased compensation should be avoided by any rational investor. The goal of our analysis is to help investors find ways to delay their order until the execution price of their order has more certainty. Since the volatility can occur in milliseconds, the method of identification must itself be algorithmic.

Note, investors should attempt to avoid these periods of increased uncertainty even if the source of the uncertainty is not high-frequency traders. We therefore don't attempt to determine the source of uncertainty, but rather, in real time, identify when such variations in liquidity are occurring.

Both spread and depth pose substantial risk, particularly for institutional investors who tend to trade in quantities far larger than what is available at the inside quotes. Despite this many seminal models of market making under asymmetric information ignore market depth by assuming a unit size for all trades (Copeland and Galai (1983); Glosten and Milgrom (1985); Easley (1992)). Alternatively, in Kyle (1985) market depth is implicitly incorporated in the model through requiring specialists to supply complete pricing functions. In our analysis we will consider the time-series of liquidity available in the orderbook within a set distance from the bid-ask midpoint.

Our algorithm will attempt to filter out the other various drivers of price and market depth changes. For example, French and Roll (1986) found evidence that stock price volatility is driven by private information being incorporated into market prices via trading. Lee, Mucklow, and Ready (1993) studied the relationship between spreads and depth around earnings announcements. So, we are attempting to find a state where price and market depth are changing in a manner inconsistent with trading on private information or around events. Notably, this first source of price and depth change would impart a directional bias to prices, and in the case of Lee, Mucklow, and Ready (1993) the spread widened. Alternatively, the high-frequency trading we are attempting to identify does not change *mean* price or market depth as in these former cases.

2. Data

We use data for the heavily traded E-Mini S&P 500 Futures contract. Price discovery in the equity market occurs in this contract (Hasbrouck (2003)). Trading hours from Sunday–Friday from 6:00 p.m. to 5:00 p.m. Eastern Time (ET). Contract value is $50 times the futures price. Cash delivery with expirations every 3 months. Traded on the Chicago Mercantile Exchange (CME) (pit and electronic (Globex)).

The reason we use CME Data ES is because, in addition to being the first place that information is incorporated into prices and trading overnight, all trades and quotes take place in this one central book. So, there is no delay in orders due to location.

Data are Market Depth Data[1] for E-Mini S&P 500 futures (Globex), for the trading week from November 7 to November 11, 2016. The data were purchased directly from the CME. We focus our results on November 9 2016 because it was the trading day where results of the US Presidential election were released, and therefore there were high levels of trade and quote volume, which makes the presence of algorithmic activity more likely.

Market Depth Data contains all market messages (trade/limit order updates) to and from the CME, and is time-stamped to the nanosecond. The data also includes tags for aggressor side. Using this data, we can recreate the ES orderbook with nanosecond resolution and up to 10 levels deep. The data are encoded in the CME's FIX/FAST message specification[2]. We have made the translation scripts used in this analysis freely available[3].

In the following charts and analysis, it is helpful to note the difference between clockand markettime. When considering the nanosecond (one-billionth of a second) level, the market has long periods of inactivity interspersed with periods of activity. Our data set only contains these periods of activity (and of course the length of time since the previous period of activity). Otherwise we would require a time series of 1 billion data points to analyse each second.

3. Methods

Our challenge is that of *unsupervised learning* - we are attempting to identify a state without training data providing the states for a sample of data. A classic problem of this type in the economics literature is to determine if the economy is in an expansion or recession. In this expansion/recession analysis Markov regime-switching regressions are used (see for example the method employed by the US Federal Reserve). We'll use a similar approach in our analysis to determine periods of stable, and unstable, liquidity driven by algorithmic activity. Our exact model is outlined below.

We measure liquidity on each side of the book as the amount of ES that can be bought within one point of the present bid-offer midpoint. One point is equivalent to 4 ticks (so maximum the inside quote and 3 additional levels of the book). Results below are for the November 9, 2016 trading day, which is the most likely to exhibit algorithmic trading activity due to the large public release of information, and the consequent portfolio rebalancing and increased trade volume.

3.1 Markov-Switching Model

There is no test for the proper number of states in a multiple state model. We thus estimate an increasing number of states and let the interpretation of the results and standard tests of the residuals, in each state, to guide us to finding a state consistent with algorithmic activity.

The two-state version of our model is:

$$Liq_t = \begin{cases} \alpha_1 + \beta_{11} Liq_{t-1} + \beta_{12}\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0,\sigma_1) \\ \alpha_2 + \beta_{21} Liq_{t-1} + \beta_{22}\Delta BAM + \epsilon_2, & \epsilon_2 \sim N(0,\sigma_2) \end{cases} \tag{1}$$

$$P(s_t = j \,| s_{t-1} = i) = p_{ij} \;\; for \;\; i,j \in \{1,2\} \;\; and \;\; \textstyle\sum_{j=1}^{2} p_{ij} = 1 \tag{2}$$

where Liq_{t-1} is the liquidity in the previous period and ΔBAM is the most recent change in the bid-ask midpoint. There are two states, denoted by s_1 and s_2, and p_{ij} denotes the probability that the state is j given the state was i in the previous period. We estimate the model via the

Hamilton Filter with a custom implementation in $C{+}{+}$ due to the large number of points in our time series.

Similar to the bid and ask volatility estimate in Hasbrouck (2018), we estimate the model for the bid and ask sides of the book separately. This is because the rapid deviations from a mean liquidity value, which we are attempting to identify, largely affect one side of the book, and so are more likely to be an artifact of the trading process rather than due to fundamental information. Nonetheless, modelling the entire book (bid and ask sides jointly) would include more information in the parameter estimates, such as spillover effects. However, this would increase the time required to estimate parameters as well as the time it takes to create a state prediction. Since the algorithm must be very quick to be useful, we err on the side of speed relative to the benefit of the information in both sides of the spread.

3.1.1 Two States

The two-state model is picking up states of changing liquidity and stable liquidity. In both the bid and offer models, the first state had a coefficient of 1 on the previous liquidity, and a small residual standard deviation. This state is consistent with no public or private information being incorporated into prices, and little in the market changing.

The second state, which has a higher residual variance, exhibits evidence of changing liquidity. However, the coefficient on previous liquidity, and the intercept are significantly different between the two models. Accordingly, state 2 may be driven by liquidity changing for various reasons. These results motivate a 3-state model where we differentiate the state with changing liquidity into two states—one representing changing liquidity due to HFT activity:

- Stable liquidity
- Normal changing liquidity
- Changing liquidity due to HFT

Bid:

$$Liq_t = \begin{cases} 0.00 + 1.00Liq_{t-1} + 0.09\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.002) \\ -0.83 + 0.49Liq_{t-1} - 0.06\Delta BAM + \epsilon_2, & \epsilon_2 \sim N(0, 0.470) \end{cases} \tag{3}$$

Offer:

$$Liq_t = \begin{cases} 0.42 + 1.33Liq_{t-1} - 0.12\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.420) \\ 0.00 + 1.00Liq_{t-1} + 0.16\Delta BAM + \epsilon_2, & \epsilon_2 \sim N(0, 0.001) \end{cases} \tag{4}$$

3.1.2 Three States

The first state in the 3-state model again exhibits stable liquidity. The following two states exhibit varying volatility which is driven by different factors. In state 2 liquidity is driven by a change in the bid-ask midpoint. This is consistent with liquidity provision in reaction to a movement in the market - possibly driven by new information.

In state 3, however, a change in the bid-ask midpoint has no effect on liquidity. Similarly, previous liquidity explains only a quarter to a third of present liquidity, and the variance of the residual is the highest in state 3. If there is HFT activity present, it is most likely within state 3. Note, these results are consistent across both bids and asks. Lastly, we'll estimate the parameters of a 4-state model to see if state 3 is a composite of other states.

Bid:

$$Liq_t = \begin{cases} -0.00 \; + \; 1.00Liq_{t-1} - 0.12\Delta BAM + \; \epsilon_1, & \epsilon_1 \sim N(0, 0.004) \\ -0.09 \; + 0.22Liq_{t-1} + 1.02\Delta BAM + \; \epsilon_1, & \epsilon_1 \sim N(0, 0.292) \\ -0.01 \; + 0.32Liq_{t-1} + 0.004\Delta BAM + \; \epsilon_1, & \epsilon_1 \sim N(0, 0.400) \end{cases} \tag{5}$$

Figure 1: Two state Markov-Switching model of liquidity available at the bid

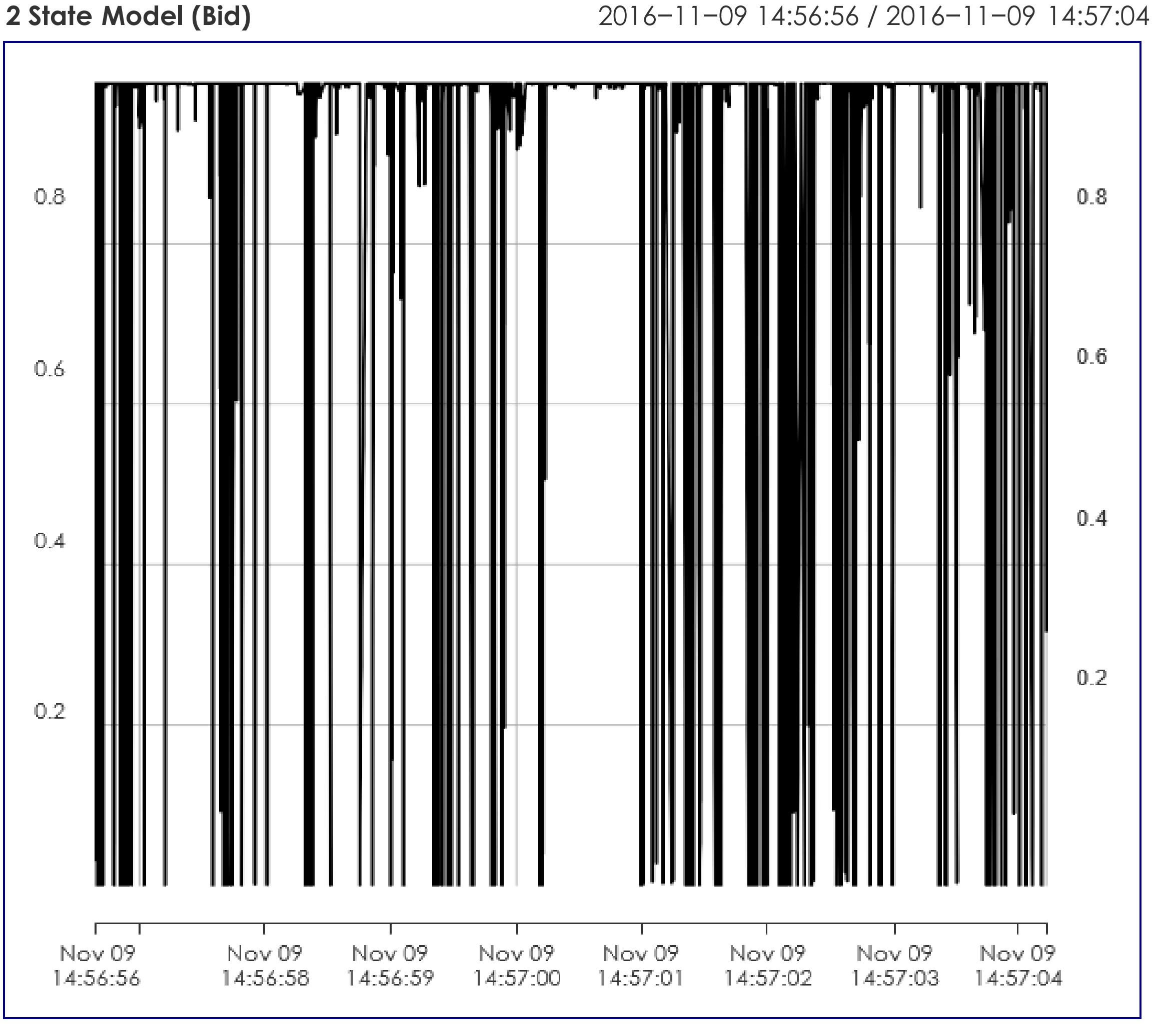


Figure 2: Two state Markov-Switching model of liquidity available at the offer

2 State Model (Offer) 2016−11−09 14:56:56 / 2016−11−09 14:57:04

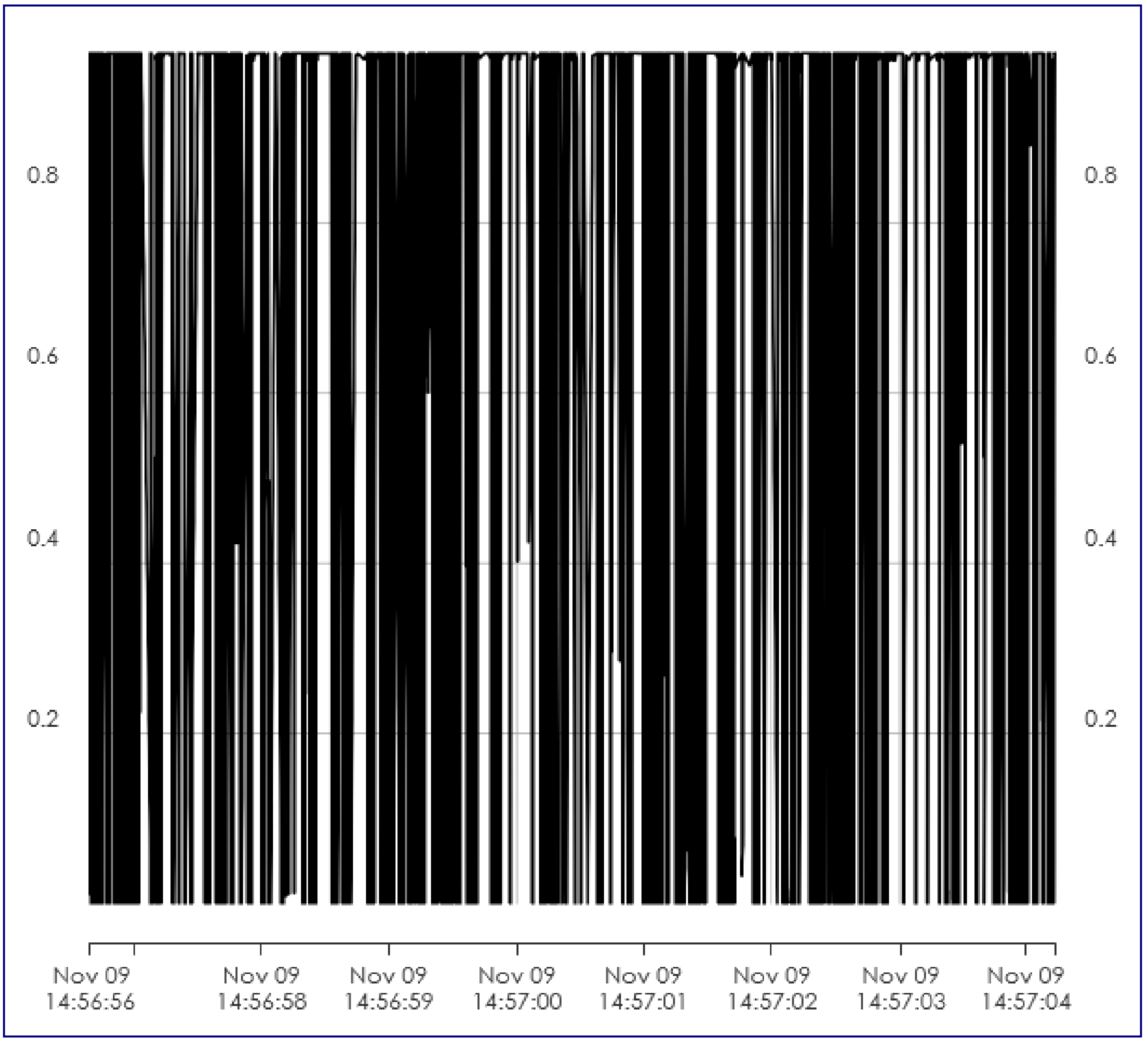
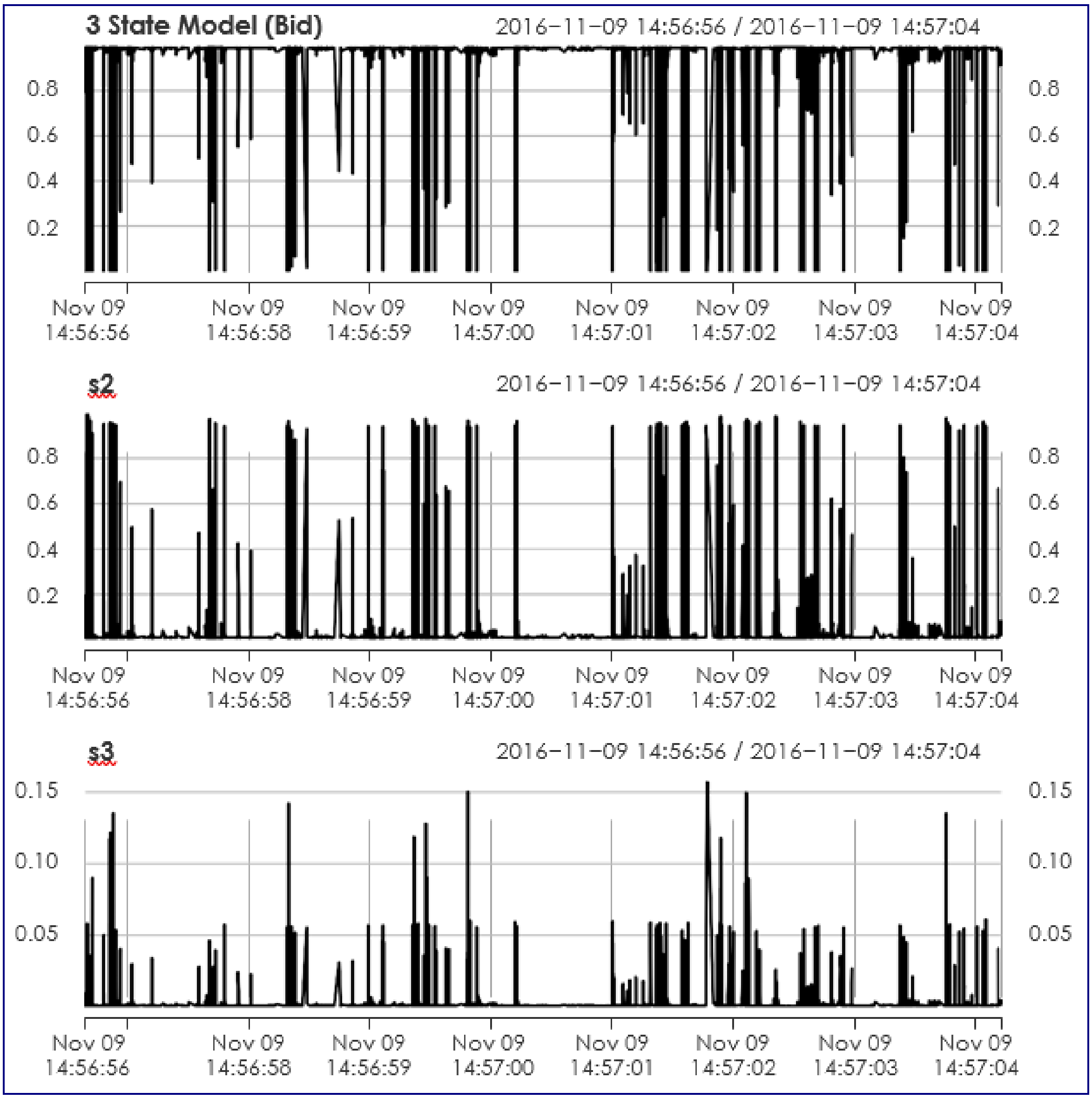


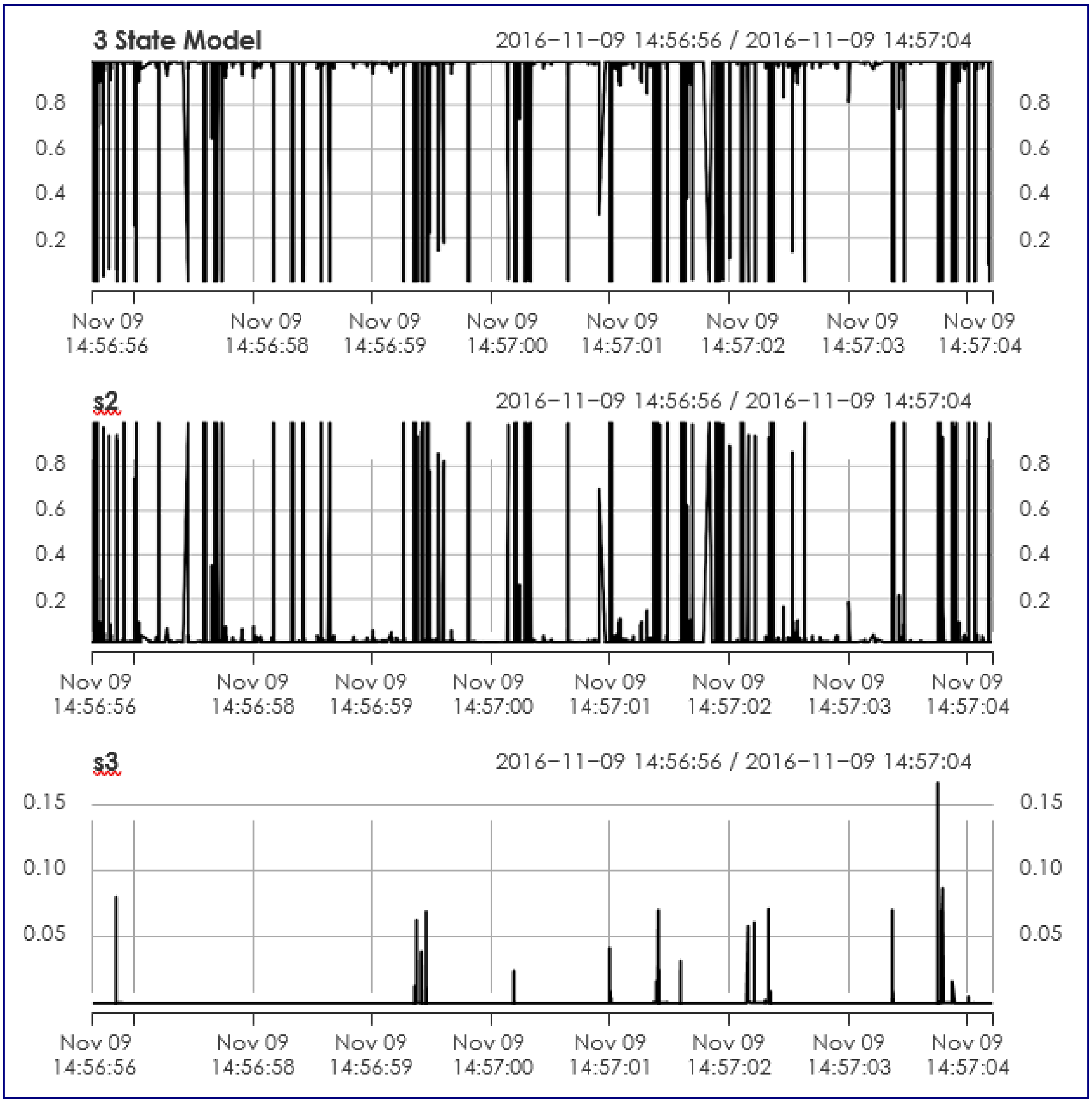
Figure 3: Three state Markov-Switching model of liquidity available at the bid



Offer:

$$Liq_t = \begin{cases} -0.00 \; + \; 1.00Liq_{t-1} - 0.10\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.004) \\ 0.38 - 0.03Liq_{t-1} + 0.81\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.078) \\ 0.12 \; + 0.25Liq_{t-1} + 0.01\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.900) \end{cases} \tag{6}$$

Figure 4: Three state Markov-Switching model of liquidity available at the offer



3.1.3 Four States

Similar to the three-state equation, the first two states represent stable liquidity, and changing liquidity driven by changes in the bid-ask midpoint. State 3 exhibits negative relationships between previous and present liquidity. The standard deviation of the error term is moderately high in this state, however it is about a quarter to a third of the standard deviation of the error term in state 4.

State 4 is most consistent with the type of HFT activity we are trying to identify. In state 4 liquidity remains constant with substantial variability around the stable mean liquidity amount.

Bid:

$$Liq_t = \begin{cases} 0.0024 \ + \ 0.9983Liq_{t-1} + 0.1319\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.0077) \\ -0.0594 - 0.3211Liq_{t-1} + 0.8524\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.2901) \\ 0.3796 - 0.0636Liq_{t-1} - 0.1802\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.2409) \\ -0.1626 + 0.9469Liq_{t-1} + 0.0791\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.6580) \end{cases} \tag{7}$$

Offer:

$$Liq_t = \begin{cases} 0.0000 \ + 1.0000Liq_{t-1} - 0.2681\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.0000) \\ -0.0055 + 0.9949Liq_{t-1} - 1.1200\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.0153) \\ -1.1325 - 03480Liq_{t-1} - 0.0122\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.1400) \\ -0.0048 + 1.0051Liq_{t-1} - 0.5034\Delta BAM + \epsilon_1, & \epsilon_1 \sim N(0, 0.6207) \end{cases} \tag{8}$$

Given the above estimates, and using 0.2 as our signal threshold for state 4, the signal fires, on average, 0.636 times per second on the bid side of the orderbook. On the ask side of the orderbook the signal fires 10.59 times per second on average. Assuming a 10 millisecond delay each time the signal fires, this implies the signal duration of 0.636% and 10.59% of the trading day on the bid and ask side of the orderbook respectively. This duration range is reasonable given anecdotal accounts of the pervasiveness of high-frequency trading in markets, such as Hendershott, Jones, and Menkveld (2011) which reported that as much as 73% of volume in US markets was due to high-frequency trading.

In tables 3 and 4 in the appendix we provide parameter estimates for the 4-state model, along with signal duration estimates, for the entire week (November 7 through 11, 2016). The parameter estimates are very similar across days for each side of the orderbook. Further the signal durations are also similar with the exception of the offer side of the book on the November 9th trading day. The large release of public information occurred on November 9th, and this orderbook asymmetry with regards to algorithmic activity is consistent with Hasbrouck (2018).

Table 1: Bid side of the orderbook.

Below are coefficient estimates from the Markov-switching regressions. The standard errors are next to the coefficient in parentheses. The coefficients were estimated using the nanosecond time-stamped orderbook ranging from 6:00 PM EST on November 8, 2016 to 5:00 PM EST on November 9, 2016. There are 9,965,673 changes to the orderbook for this period.

Coefficient	Two-State	Three-State	Four-State
α_1	0.00(0.0000)	-0.00(0.0000)	0.00(0.0000)
α_2	-0.83(0.0007)	-0.09(0.0250)	-0.05(0.0033)
α_3		-0.01(0.0140)	0.37(0.0025)
α_4			-0.16(0.0018)
β_{11}	1.00(0.0000)	1.00(0.0000)	0.99(0.0000)
β_{12}	0.09(0.1369)	-0.12(0.259)	0.13(0.4226)
β_{21}	0.49(0.0004)	0.22(0.003)	-0.32(0.0110)
β_{22}	-0.06(0.0075)	1.02(0.670)	0.85(1.1350)
β_{31}		0.32(0.000)	-0.06(0.0050)
β_{32}		0.00(0.0000)	-0.18(0.8833)

Coefficient	Two-State	Three-State	Four-State
β_{41}			0.94(0.0001)
β_{42}			0.07(0.0933)
σ_1	0.00(0.0490)	0.00(0.0661)	0.00(0.0000)
σ_2	0.47(0.0002)	0.29(0.0024)	0.29(0.0044)
σ_3		0.40(0.0001)	0.24(0.0033)
σ_4			0.65(0.0008)

Table 2: Ask side of the orderbook.

Below are coefficient estimates from the Markov-switching regressions. The standard errors are next to the coefficient in parentheses. The coefficients were estimated using the nanosecond time-stamped orderbook ranging from 6:00 PM EST on November 8, 2016 to 5:00 PM EST on November 9, 2016. There are 9,965,673 changes to the orderbook for this period.

Coefficient	Two-State	Three-State	Four-State
α_1	0.42(0.0000)	-0.00(0.0000)	0.00(0.0000)
α_2	0.00(0.0041)	0.38(0.0141)	-0.00(0.0970)
α_3		0.12(0.0196)	-1.13(0.7924)
α_4			-0.00(0.02269)
β_{11}	1.33(0.4078)	1.00(0.0000)	1.00(0.0083)
β_{12}	-0.12(0.0059)	-0.10(0.2259)	-0.26(0.1421)
β_{21}	1.00(0.0000)	-0.03(0.0192)	0.99(0.0001)
β_{22}	0.16(0.0009)	0.81(1.5312)	1.12(0.0018)
β_{31}		0.25(0.0027)	-0.34(0.0990)
β_{32}		0.01(1.3956)	-0.01(0.6147)
β_{41}			1.00(0.2876)
β_{42}			-0.50(0.9778)
σ_1	0.42(0.0011)	0.00(0.0000)	0.00(0.0000)
σ_2	0.00(0.0327)	0.07(0.0101)	0.01(0.0626)
σ_3		0.90(0.0002)	0.14(0.0115)
σ_4			0.62(0.0004)

4. Conclusion

In this analysis we have used Markov-Switching regression models to identify the presence of high-frequency traders who are rapidly changing volatility. Using a model with four states, we identify a state with a stable mean liquidity, but substantial variability in liquidity around the mean. That is there is rapidly changing liquidity, which does not affect overall liquidity or the price.

Figure 5: Four state Markov-Switching model of liquidity available at the bid

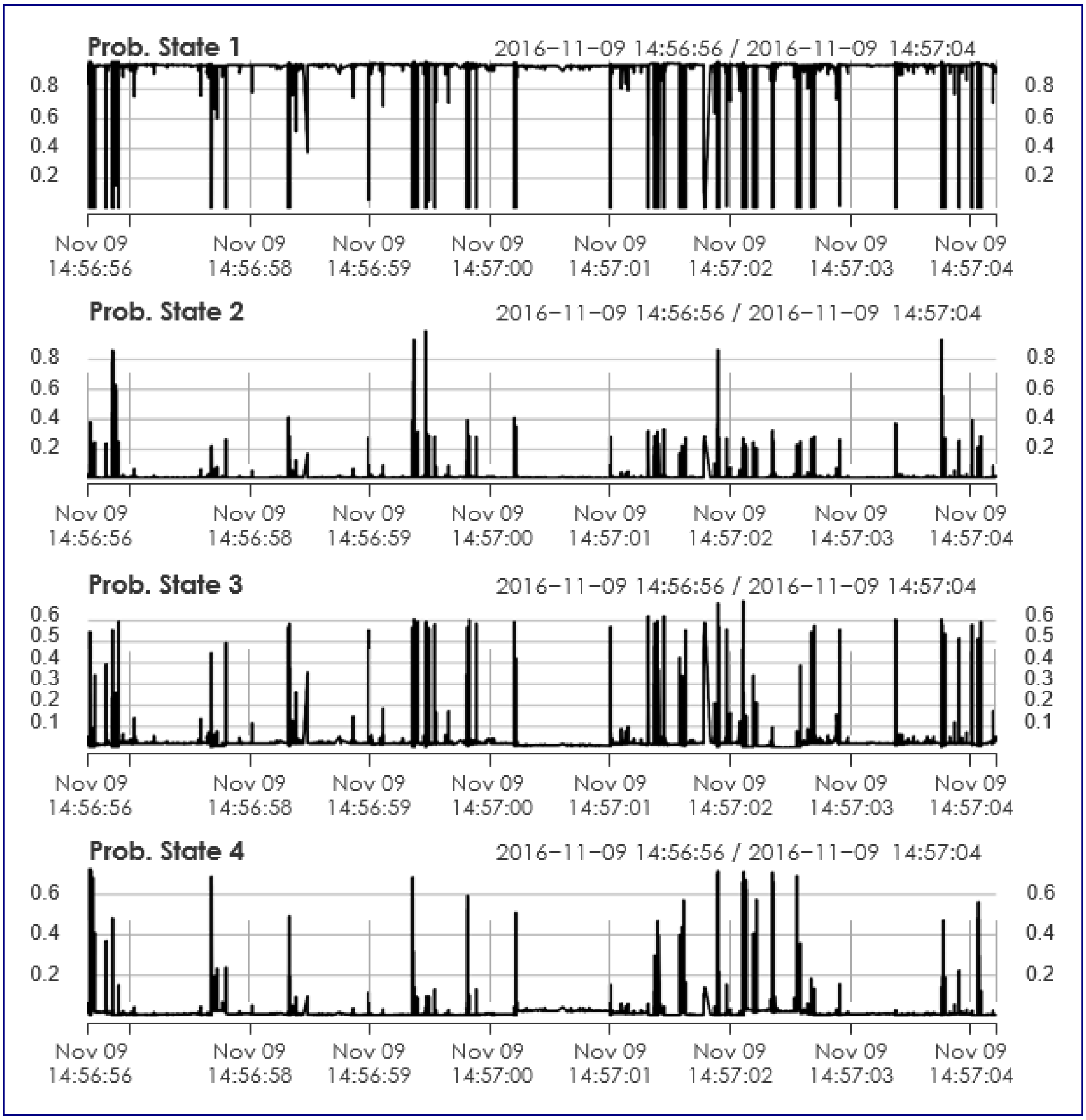
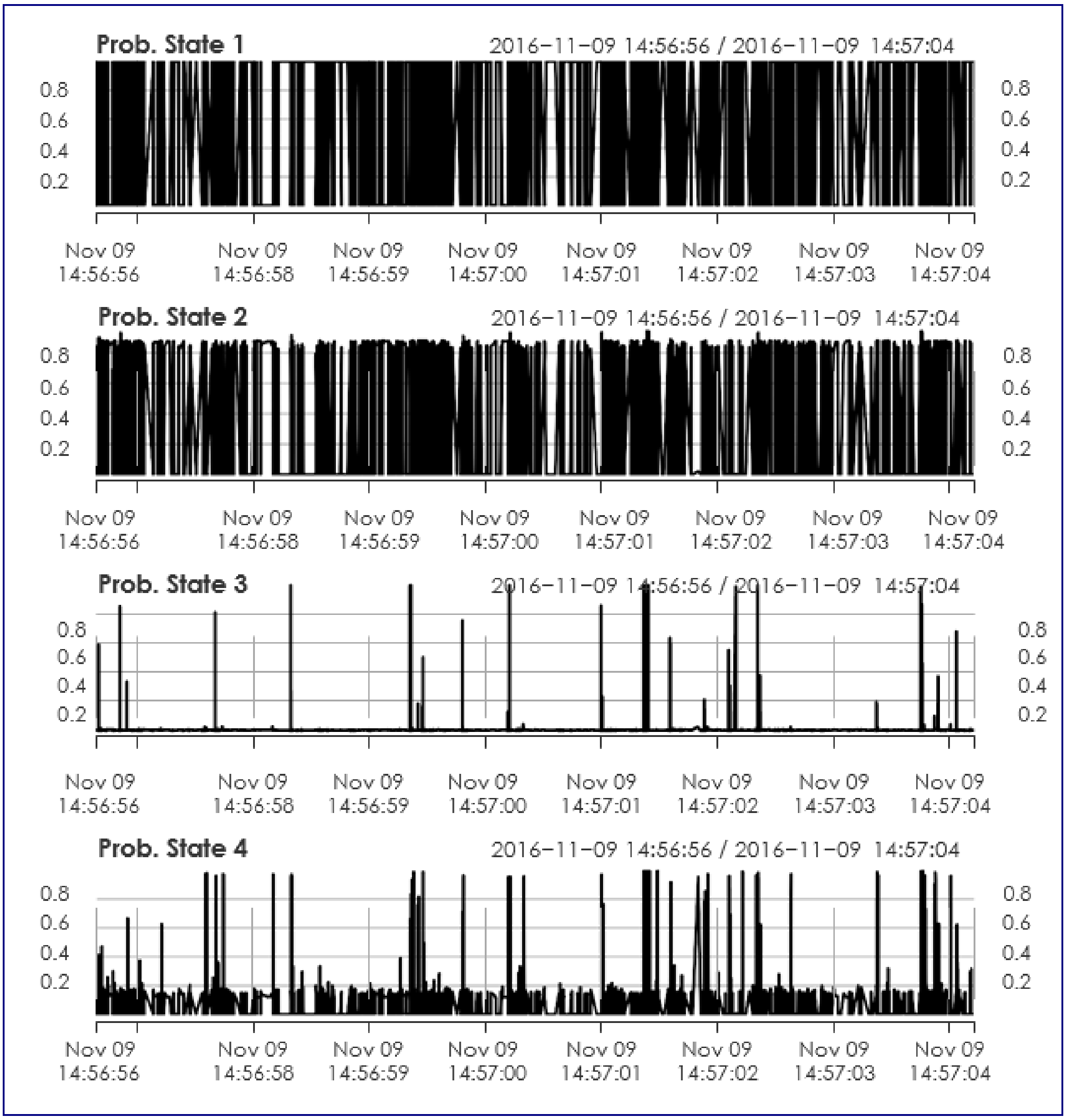


Figure 6: Four state Markov-Switching model of liquidity available at the offer



Since trading in this state benefits high-frequency traders at the expense of slower retail order flow, a transition to this state can serve as a signal to delay slower traders' orders. The delay being mere tens of milliseconds, it will not be perceptible to the typical trader. And while this may save each trade a small amount, in aggregate such a delayed order type would provide substatial savings across all non-high-frequency traders. Delaying orders due to the signal can be offered to retail traders through a particular order type. A similar strategy is used by the IEX's 'crumbling quote' order.

Appendix

In tables 3 and 4 below are parameter estimates from the following 4-state Markov-Switching model.

Table 3: Parameter estimates from a 4-state Markov-switching model

Parameter estimates from a 4-state Markov-switching model on the liquidity available on the bid side of the orderbook. There are 2,917,466 entries to the book over the Nov. 7 trading day. There are 3,502,097 book entries on Nov. 8. There are 9,965,673 book entries on Nov. 9, which is the trading day over which the results of the election were announced. There were 7,346,604 book entries on Nov. 10, and 4,905,882 on 11 November. The duration of the signal (Sig. Dur.) was calculated assuming a 10-millisecond delay for each signal, and a 0.2 threshold for the signal generation.

Coefficient	7 Nov.	8 Nov.	9 Nov.	10 Nov.	11 Nov.
α_1	0.0065	0.0431	0.0024	-0.0656	-0.0010
α_2	-0.1132	-0.1694	-0.0594	-0.4849	-0.4917
α_3	0.1121	0.3509	0.3796	0.3917	0.2975
α_4	-0.2210	-0.1783	-0.1626	-0.2966	-0.3563
β_{11}	1.0004	0.8102	0.9983	0.9500	1.0057
β_{12}	-0.1579	0.0754	0.1319	0.0174	0.2716
β_{21}	0.1741	0.0168	-0.3211	0.2004	0.2565
β_{22}	0.9270	0.8738	0.8524	0.8375	0.4647
β_{31}	0.0628	0.1031	-0.0636	0.0132	0.0101
β_{32}	-0.1324	-0.1707	-0.1802	-0.1676	-0.3864
β_{41}	0.6621	0.6239	0.9469	0.4445	1.1467
β_{42}	0.1151	0.0910	0.0791	-0.0752	-0.2919
σ_1	0.0221	0.0912	0.0077	0.0109	0.0219
σ_2	0.0920	0.1716	0.2901	0.4268	0.6963
σ_3	0.1701	0.0787	0.2409	0.0769	0.1083
σ_4	0.0065	0.0431	0.0024	-0.0656	-0.0010
Log Lik.	4880164	117503.2	16693395	20395.45	249944.1
Sig. Dur.	0.736%	0.020%	0.636%	0.000%	0.000%

Table 4: Parameter estimates from a 4-state Markov-switching model

Parameter estimates from a 4-state Markov-switching model on the liquidity available on the offer side of the orderbook. There are 2,917,466 entries to the book over the Nov. 7 trading day. There are 3,502,097 book entries on Nov. 8. There are 9,965,673 book entries on Nov. 9, which is the trading day over which the results of the election were announced. There were 7,346,604 book entries on Nov. 10, and 4,905,882 on Nov. 11. The duration of the signal (Sig. Dur.) was calculated assuming a 10-millisecond delay for each signal, and a 0.2 threshold for the signal generation.

Coefficient	7 Nov.	8 Nov.	9 Nov.	10 Nov.	11 Nov.
$\alpha1$	0.0000	0.0000	0.0000	0.0000	0.0000
$\alpha2$	-0.0007	0.0008	-0.0055	0.0011	-0.0051
$\alpha3$	-1.1325	-1.1374	-1.1325	-0.1314	-1.1329
$\alpha4$	-0.0042	0.0052	-0.0048	-0.0060	0.0015
$\beta11$	1.0054	1.0051	1.0049	1.0059	0.9979
$\beta12$	-0.2681	-0.2707	-0.2681	-0.2643	-0.0033
$\beta21$	0.9960	0.9977	0.9949	0.9991	0.9955
$\beta22$	-1.1161	-1.1034	-1.1200	-1.1195	-1.291
$\beta31$	0.3465	0.3481	0.3480	0.3487	0.3414
$\beta32$	-0.0121	-0.0153	-0.0122	-0.0082	-0.0064
$\beta41$	1.2411	1.2369	1.0086	1.2357	1.0148
$\beta42$	-0.5031	-0.5057	-0.5034	-0.5006	-0.5136
$\sigma1$	0.0000	0.0000	0.0000	0.0000	0.0000
$\sigma2$	0.0016	0.0018	0.0153	0.0030	0.0039
$\sigma3$	0.1400	0.1400	0.1400	0.1400	0.1400
$\sigma4$	0.6217	0.6369	0.6207	0.6316	0.6165
Log Lik.	841089.4	5872364	45918365	5637773	839429.5
Sig. Dur.	0.403%	0.797%	10.59%	0.704%	1.206%

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