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The Effect of Fraud Restatement Spillover on Lead Lender's 'Skin in the Game'

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Abstract

This paper examines the spillover effect of a firm's fraud events on credit market through the link of board interlock. A firm's fraud revelation is conjectured to potentially make its lenders cautious about the interlocked firms due to the failed monitoring by the interlocked directors in the fraud firms. Using fraud events as shocks, a difference-in-difference analysis shows that lead lenders' share in interlocked firms increases significantly after the exposure of fraud events of fraudulent firms. Furthermore, the spillover effect is more pronounced for firms facing greater information asymmetry. The results are robust to alternate measures, model specifications, and endogeneity concerns. Overall, the findings suggest that fraud events propagate through the board interlock channel in the form of increased share of lead lender's 'Skin in the Game'.

JEL classification: D22, G21, Z13
Keywords: board interlock; fraud restatement; loan syndication

Introduction

Corporate fraud has become a significant phenomenon with far reaching consequences on virtually all the stakeholders of firms and the economy. Over the last few decades, exposure of corporate fraud in companies like Enron, Lehman Brothers and Tyco have deeply impacted the confidence of stakeholders regarding the quality of firms' earnings statements and governance, and have received substantial attention from regulators, press and academics. Although regulators have been playing an active role to reduce corporate fraud, studies show that there has been an alarming increase in fraudulent behaviors by firms (e.g., Global Fraud Survey, 2015, 2016; Dyck, Morse, and Zingales, 2019). In essence, corporate fraud has become a significant phenomenon and it has consequences for all the stakeholders of a firm.

In this paper, the spillover effect of fraud through the board interlock channel is investigated. Specifically, whether the lead lender's share in a firm's syndicated loans increases following fraud revelation in a board interlocked firm is examined. Of particular interest is examining the board interlock channel since a number of studies document that corporate fraud propagates through board interlock (Kang and Tan, 2008; Bouwman, 2011; Chiu, Teoh, and Tian, 2013). Moreover, lead lender's share in syndicated loans is an interesting laboratory to test fraud propagation because of two reasons. First, studies show that creditors react negatively to fraud events. Cost of debt increases following accounting restatements (Graham, Li, and Qiu, 2008), class action lawsuits (Yuan and Zhang, 2015), and it takes a while for the fraud firm to rebuild its reputation in the credit market following fraud revelations (Farber, 2005; Chava, Huang, and Johnson, 2018; Du, 2017). Second, syndicated loan transactions are characterized by information asymmetry between the lead lender and participant banks (Sufi, 2007; Ivashina, 2009). Revelation of fraud in a board-interlocked firm is likely to aggravate information asymmetry between the lead lender and participating banks. Therefore, the participant banks would require the lead bank to enforce more intense due diligence and monitoring of the firms that are board-interlocked with fraudulent firms.

However, a post-fraud increase in lead lender's share of the syndicated loan in a firm that is board-interlocked with fraudulent firm is not necessarily a foregone conclusion. Research shows (Gopalan, Nanda, and Yerramilli, 2011) that the lead bank might be concerned about its reputation in the syndicated loan market. Thus, reputation concern would incentivize the lead bank to have intensive screening and monitoring of the borrowers that are board-interlocked with fraudulent firms regardless of their 'skin in the game'. As a result, participant banks would not feel the need for a larger share of loan from the lead arranger.

BoardEx data is used to generate board interlock information from 2001 to 2016. Following Fracassi (2017), the focus is on all board members and the top five executives with highest compensations. Fraud data is obtained from AuditAnalytics, loan data from Thomson Reuters' Dealscan, and financial data from Compustat. The primary dependent variable is the percentage of the loan that the lead arranger owns in a syndicate loan transaction.

By conducting univariate and multivariate tests, it is found that a lead bank's ownership of a loan granted to a firm that is board interlocked with fraudulent firm increases from 3.8 percent to 5.0 percent depending on different model specifications after the exposure of an earnings restatement by the fraudulent firm. The results suggest that following fraud revelation, interlocked firms experience an increase in lead lenders' share in syndicated loans compared to the loans taken before fraud events. This finding supports the conjecture that participating banks effectively bargain with the lead arranger to increase its ownership proportion of the loan granted to a firm that is board-interlocked with a fraud firm to ensure that the lead arranger has enough 'skin in the game'.

Cross sectional analysis is included. Since syndicated loan is characterized by information asymmetry between the lead and participant banks, it is conjectured that an opaque information environment is likely to trigger greater enforcement of 'skin in the game' to impose strict monitoring. In line with this hypothesis, it is found that the increase in lead lender's share of a loan granted to a fraud-interlocked firm during post-fraud period is prevalent among smaller, younger and low tangibility firms. The impact is also predominant for firms with higher M/B ratio and greater forecast dispersion. Together, these results suggest the increase in lead lender's share of loans granted to fraud-interlocked firms in the post-fraud period is stronger among firms with relatively high information asymmetry.

The results are robust to a battery of alternative tests. First, Herfindahl index of lead lender's share is used as an alternate dependent variable in a rerun of the baseline regressions. Second, alternate samples are tested. A subsample is created by keeping interlocked firms that took loan both before and after the fraud events. Third, additional control variables are shown to be determinants of lead lender monitoring in prior literature (e.g., Ball et al., 2008). Finally, alternate channels of fraud spillover are considered as a robustness check on the results. Since fraud may also propagate through industry peers (Beatty, Liao, and Yu, 2013) and geographic proximity (Parsons, Sulaeman, Titman, 2018), the baseline regressions are run by excluding interlocked firms that are within the same industry of the fraudulent firm or located close to the fraudulent firm. In all these robustness tests, the coefficient estimates of the post fraud dummy variable is still positive and significant.

Due to the nature of the data, results are less likely to be affected by common endogeneity concerns such as reverse causality or selection bias. Fraud events are exogenous shocks and further, the interlocked firms – which are not even the fraudulent firms – are examined. Therefore, it seems implausible that increased monitoring by lead lender may cause occurrence of fraud in interlocked firms. Nonetheless, several tests are run to address possible endogeneity issues. First, firm fixed effect regressions are run to rule out omitted variable bias. Results remain qualitatively unchanged in this specification. Second, a matched sample difference-in-difference analysis around the fraud events is conducted. Using propensity score matching method, a set of treatment and control firms each year is created. Treatment firms are the ones board interlocked with the fraudulent firms, and control firms are those without any board interlock with the fraudulent firms. Matched sample ensures the results are not explained by the variation in the covariates or any of the industry specific factors. The matched sample is then used to run a difference-in-difference regression by comparing the difference between the treatment and control firms five years before and after the fraud events. Results show that the spillover effect is significant in the treatment firms following fraud revelations. Overall, the tests for endogeneity concerns further solidify the conjecture that lead lenders become extra cautious on loans granted to firms that are board interlocked with fraud restating firms.

This paper makes several important contributions. First, the key result that a lead lender owns a relatively higher proportion of the syndicated loan in a fraud interlocked firm following fraud events, enhances the understanding regarding the syndicate loan contract dynamics between the lead lender and participating banks in the post fraud period. In addition, the cross-sectional analysis identifies the specific firm characteristics for which this impact will be stronger. Hence, these results will help a lead lender better anticipate the lending conditions that will prevail in terms of syndicate loans to board-interlocked peer firms after the earning restatement related fraud of a firm is exposed. Also, the uncertainty in the post fraud period regarding the borrowing outcomes is reduced for a board-interlocked firm.

Second, this paper adds to the growing literature on the dynamics of firm board connections (Cohen, Frazzini and Malloy, 2008; Hwang and Kim, 2009; Engelberg, Gao, and Parsons, 2012). Previous research indicate that various corporate decisions are propagated through board interlock. For example, Bizjak, Lemmon, and Whitby (2009) find the practice of employee option backdating spreads through board interlock. Bouwman (2011) shows that a firm's corporate governance practice moves in the same direction as the other firms where its directors serve at, and Cai and Sevilir (2012) provide empirical evidence that board connection facilitates M&A transactions. Further, Cai et al. (2014) demonstrate that interlocked directors facilitate the information sharing, which leads to the diffusion of corporate disclosure policy. Fracassi (2017) finds corporate policies such as capital investment, R&D expense, cash reserves and interest coverage ratio are clustered within companies with social ties. This research contributes to this stream of literature by showing how a syndicate loan structure changes for companies that are board-interlocked with fraudulent firms.

This paper also contributes to the general literature of corporate governance and bank monitoring. Extant research shows the importance of board governance on different aspects of corporate performance (e.g., Laksmana, 2008; Lyengar, Land, and Zampelli, 2010; Pathan and Faff, 2013; Kryzanowski and Mohebshahedin, 2016). Besides, firms' creditors have the control right (Nini, Smith, and Sufi, 2009, 2012; Roberts and Sufi, 2009; Denis and Wang, 2014) and share the role in terms of monitoring the firms' performance (Vashishtha, 2014). By demonstrating the spillover effect of fraud restatement on board-interlocked firms, the possible substitution effect between the two monitoring mechanisms are shown.

The rest of the paper is organized as follows. The next section presents the literature review, motivation, and develops the hypothesis. Following that, the next section includes discussion of data sources, estimation of key variables, sample generating procedures, and empirical methodology. Summary statistics and primary empirical results are then presented, after which, the results of robustness tests are reported. Endogeneity concerns are considered followed by a conclusion.

Literature Review and Hypothesis Development

Consequences of Fraud Events

Extant literature documents various consequences of fraud events. For instance, Firth, Rui, and Wu (2011) show that initial revelation of fraud results in significant negative return for the accused firm in the equity market. Palmrose, Richardson, and Scholz (2004) finds significant negative return around the announcement date of earnings restatement related frauds. Karpoff, Lee, and Martin (2008) document that a fraudulent firm suffers significantly as it encounters severe reputational penalty imposed by the market apart from the penalty enforced by the regulators.

Besides the firm itself, management of the fraudulent firms also faces significant penalties. Costello and Wittenberg-Moerman (2011) show that following restatements, lenders impose tighter monitoring on managers' actions. Dou (2017) finds that the labor market penalizes the directors of fraudulent firms. Firth et al. (2011) document that restating firms experience greater CEO turnover. Choi and Gipper (2019) report that fraud revelation negatively affects annual wages of the employees.

Fraud events impact not only the shareholders but also the debtholders. Graham et al. (2008) study the impact of accounting restatements in the corporate loan market and find that the average loan spread increases by 65-72 basis points relative to the pre-restatement spread of 141 basis points. When they separate the restatements by different types, they find that the fraud-related restatements further increase the loan spreads by nearly half a percent, relative to the non-fraud restatements. Furthermore, legal liabilities and reputation loss due to the restatement may worsen investors' prospects on the company's future performance. Yuan and Zhang (2015) investigate firms involved in class action lawsuits and conclude that these firms experience higher cost of debt and more stringent covenants following the lawsuits. Chava et al. (2018) find that fraudulent firms pay greater loan spreads than matched firms for at least six years following the fraud events.

Effect of Fraud on Peer firms

A number of studies document that fraud is contagious to the peer firms. Fich and Shivdasani (2007) find that when a firm faces shareholder class action lawsuits, firms interlocked with the fraudulent firms experience significantly negative abnormal returns around the lawsuit. Kedia, Koh, and Rajgopal (2015) show that a firm has a significant high probability of engaging in financial fraud if firms in the same industry or same geographic area are involved in fraudulent behavior. Kedia and Cheng (2018) provide evidence that a firm is more likely to get involved in financial fraud when its customers or suppliers are involved in fraud. Further, research documents spillover effect of other corporate events such as bankruptcy (Lang and Stulz, 1992), dividends (Firth 1996), mergers and acquisitions (Akhigbe and Martin, 2000), stock splits (Caton, Goh, and Kohers, 2003), and strategic partnerships (Boone and Ivanov, 2012). In summary, there is ample evidence suggesting that fraudulent activities can influence peer firms through different channels.

Board Interlock

Although there are various channels through which fraudulent practices can spread from one firm to another, this research focuses on the channel of board interlock. A board interlock is formed when the same person sits on board of multiple firms (Davis and Powell, 1992). When firms share interlocking directors, information and corporate governance practices can easily transpire between these firms. Indeed, extant literature provides overwhelming evidence that corporate policies, governance and other practices propagate through board interlocks. Bouwman (2011) finds that corporate governance practices are similar among firms that share common board of directors. Bizjak et al. (2009) show that the likelihood of option backdating practice increases when a firm has a director who sat on an interlocked firm that was involved in similar practice previously. Chiu et al. (2013) examine whether earnings management practice spreads through board interlock. They find that a firm is more likely to engage in earnings management when it shares a common director with a firm that is currently involved in earnings management. Cai and Sevilir (2012) examines merger transactions between board interlocked firms and argues that such connections may facilitate information flow and communication between acquirer and target. They find that acquirers' announcement returns are higher when a common director sits on the board of both the acquirer and the target. Chan, Lee, Petaibanlue, and Tan (2017) document that frequency and type of conference calls are similar between board-interlocked firms. Overall, it is evident from the literature that the poor corporate governance practice in a fraudulent firm is likely to spread through the board interlock channel.

Loan Syndication

A typical syndicated loan is characterized by a lead bank originating the loan, and then supplying part of the total funding. Other participant banks supply the rest of the fund. The lead bank arranges and maintains a relationship with the borrower. It assumes the role of ensuring due diligence before the loan is granted and monitors the borrower ex-post. Participant banks rarely interact with the borrower. As participant banks depend on the information collected by the lead bank in terms of their decision to participate in the loan syndicate, information asymmetry arises between the lead lender and the participant banks. Ivashina (2009) points out that this information asymmetry can give rise to adverse selection problem as the lead bank has incentives to syndicate bad or risky loans. Further, a moral hazard problem may exist because the lead bank's incentive to monitor the borrowing firm goes down after the lead bank sells fractions of the loan to participant banks. Sufi (2007) finds that higher information asymmetry between the lead lender and participant banks, results in a higher share of the loan that the lead lender needs to retain. He also provides evidence that lead arranger's share of the loan increases when the borrower requires more intense monitoring. Gopalan et al. (2011) argues that reputation consideration is likely to have an important role in the loan syndication market as the lead arranger usually is a repeat player. They show that lead arrangers that experience large bankruptcies by borrowers for whom they form the syndicate retain 4.95% more of the loans that they arrange. Lai, Lei, and Song (2018) show that the lending terms in terms of interest rate and loan covenants become more stringent on loans granted to firms that are board-interlocked with fraudulent firms.

Hypothesis Development

Based on the above discussion, it is evident that fraudulent practices are contagious and board interlock could be a likely channel of fraud propagation. Furthermore, information asymmetry between the lead bank and participant banks in loan syndications makes it an ideal laboratory to test whether lead lenders enhance monitoring following revelation of fraud in board-interlocked firms.

When a firm's earnings restatement fraud is revealed, stakeholders in the board-interlocked firms would anticipate that the interlocked firms would also engage in similar fraudulent activities. In addition, revelation of financial misconduct of a firm can influence investors to revise prospects of the peer firms (Gleason, Jenkins, and Johnson, 2008; Akhigbe and Madura, 2008; Goldman, Peyer, and Stefanescu, 2012). Besides changes in investor perception, fraud events also affect peer firms' investments (Durnev and Mangen, 2009; Beatty, Liao, and Yu, 2013), R&D and advertising expenditures (Li, 2016), and financing activities (Bonini and Boraschi, 2012). As a result, investors are likely to revise their valuation of peer firms' equity and riskiness of debt. If investors believe that peer firms make distorted investment and operating decisions as they are misled by the actions of the fraudulent firms, it can influence the equity holders and debt holders to reassess the value and quality of a peer firm's equity and debt.

It is argued that the expected propagation of fraudulent practices would aggravate information asymmetry between the lead bank and the participant banks. Therefore, the participant banks would require the lead bank to enforce more intense due diligence and monitoring of the firms that are board-interlocked with fraudulent firms.

However, participant banks might not necessarily react in this way. The participant banks might recognize that the lead bank will be extra cautious regarding giving loan to the peer firm as the lead bank will be very concerned regarding its reputation. Gopalan et al. (2011) show that lead arrangers of firms that experience large bankruptcies, retain 4.95% more of the loans that they arrange. Therefore, reputation concern would incentivize the lead bank to have intensive screening and monitoring of the borrowers that are board-interlocked with fraudulent firms regardless of their 'skin in the game'. As a result, participant banks would not feel the need for a larger share of loan from the lead arranger.

Further, Lai, Lei, and Song (2018) show that the interest rate and loan covenants become more stringent on loans granted to board interlocked peer firms upon the revelation of fraud committed by a firm. Since the loan spread increases and loan covenants become stricter pertaining to the loans granted to board interlocked peer firms, the participant banks might not see any reason of pushing the lead bank to retain a greater share of the loan. In fact, the increase in cost of debt and stricter loan covenants might cause the participant banks to feel comfortable even if the lead bank assumes a lesser share of the loan.

Therefore, the relation between lead lender's share and fraud restatement in board-interlocked firms remains an open empirical question, and is further considered through the following hypotheses:

H_0: Lead Lender's share of the syndicated loan granted to a firm that is board-interlocked with a fraud firm, ceteris paribus, will not change after the fraud firm's fraudulent behavior is exposed.
H_a1: Lead Lender's share of the syndicated loan granted to a firm that is board-interlocked with a fraud firm, ceteris paribus, will increase after the fraud firm's fraudulent behavior is exposed.

H_a2: Lead Lender's share of the syndicated loan granted to a firm that is board-interlocked with a fraud firm, ceteris paribus, will decrease after the fraud firm's fraudulent behavior is exposed.

Sample and Empirical Methodology

Data Source and Sample Selection

The Boardex database is used for data on board interlock, AuditAnalytics for data on fraud events, LPC Dealscan for data on syndicated loans, and Compustat for financial data of the sample firms. The sample covers U.S. firms for the period of 2001 to 2016. First, AuditAnalytics database is used which tracks no-reliance restatements disclosure from the company's 8K statements and the press releases to identify a set of firms that has experienced fraud events during the sample period. These firms are defined as '*fraud'* firms throughout the paper. Then the Boardex database is used to find firms that share at least one director with the fraud firms in the same year of the fraud event and these firms are referred to as '*interlocked*' or *'fraud interlocked'* firms in the paper. Since the focus is the spillover effect from a fraud restatement, interlocked firms that announce another fraud restatement itself within a ten-year time horizon are eliminated. In the next step, the sample of interlocked firms are merged with Dealscan data. The sample includes all the loans taken by interlocked firms five years before and after the fraud event of the fraud firms. Finally, the Dealscan-Compustat link file developed by Chava et al. (2008) is used to merge the loan data with financial data from Compustat.

Variables Description

In this study, the key variable of interest is the lead lender's share of the loan. Previous literature (Sufi, 2007; Ball, Bushman, and Vasvari, 2008; Amiram et al., 2017) is followed in generating two measures for this. The first is the percentage of the loan that the lead arranger owns in a syndicate loan transaction. The second proxy in terms of lead lenders' ownership of the loans is the syndicate ownership Herfindahl index. This index is calculated as the sum of square of lenders' percentage share in the loan. The higher the index, the more concentrated the ownership of the loan. All information needed to generate the two measures are available from Dealscan.

The lead arranger is defined using two variables. The first variable is "Lead arranger credit" and the second is "Lender role". The lender is considered as the lead banks if the "Lead arranger credit" is labelled as "Yes". If this variable is missing, the lender is designated as the lead arranger if the lender happens to be the administrative agent, agent, arranger, book-runner, lead arranger, lead bank, or lead manager. For cases with more than one lead arrangers in a facility, all the shares by the lead arrangers are aggregated (Ivashina, 2009).

In order to isolate the incremental impact on the lead lender, both firm and loan characteristics are included as control variables. Firm level controls include ROA (EBITDA over total assets minus cash), interest coverage (EBITDA over interest expense), tangibility (net property, plant and equipment over total assets), growth opportunity (market to book value of assets), leverage (long-term debt over assets), and size (log of total assets). All information is from Compustat. The loan level controls include loan maturity, facility size (facility amount over the firm's total assets), secured (a dummy variable indicating whether the loan is secured by some collateral), and seniority (a dummy variable indicating whether the loan is senior). Also included are industry and year fixed effects to control for time variant industry effects as robustness check. All variables are winsorized at one percent level.

Empirical Model

The following regression model is used to examine the spillover effect of fraud restatement:

$$PERC\_LEAD_{it} = \alpha_0 + \beta_1 POST_{it} + \beta_2 X_{2it} + \cdots + \beta_k X_{kit} + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{it} \quad (1)$$

where *PERC_LEAD* is the percentage of lead lender ownership of loans in interlocked firm$_i$ in year t. The main independent variable of interest is *POST,* which takes a value of one if interlocked firm$_i$ takes loan after the announcement of fraud event by the fraud firms, and zero otherwise. X_2 to X_k are the control variables specified before. A positive (negative) value of β_1 would indicate that the lead lender's share in interlocked firm's loans increases (decreases) during the years following fraud events. All regression models include industry and/or year fixed effects, and heteroscedasticity robust standard errors are reported in all the tables.

Empirical Analysis

Descriptive Statistics

Descriptive statistics of the sample data are presented are discussed next. First, focusing on the fraud occurrences and associated spillover firms, Table 1 reports the frequency of fraud events and related spillover firms by year. For example, in 2001, there are two distinct cases of fraud occurrences, and 39 spillover firms are identified. Table 1 shows that the highest number of fraud events occur in the year 2005, followed by 2004 and 2015. To be specific, in 2005, the data captures 14 distinct fraud events, which is about 19% of the total fraud occurrences reported by the fraud database. In 2004, the data shows that there are 12 specific fraud events (nearly 16% of the total number of frauds), while in 2015, there are 10 such occurrences (nearly 13% of the total number of frauds). Given the number of frauds in 2005, the total number of spillover companies identified is 111, whereas the total number of spillover companies in 2004 is 80, and that in 2015 is 67.

Table 1: Frequency of Fraud Events and Board Interlock

	Fraud Events	Percentage	Interlocked Firms	Percentage
2001	2	2.70%	39	8.39%
2002	2	2.70%	8	1.72%
2003	1	1.35%	12	2.58%
2004	12	16.22%	80	17.20%
2005	14	18.92%	111	23.87%
2006	8	10.81%	28	6.02%
2007	5	6.76%	23	4.95%
2008	5	6.76%	16	3.44%
2009	2	2.70%	11	2.37%
2010	3	4.05%	9	1.94%
2011	0	0.00%	0	0.00%
2012	5	6.76%	34	7.31%
2013	2	2.70%	14	3.01%
2014	2	2.70%	11	2.37%
2015	10	13.51%	67	14.41%
2016	1	1.35%	2	0.43%

This table presents the number of fraud restatement events in the sample from 2001 to 2016. The number of firms that are board interlocked with fraud firms through time are also shown.

Table 2 summarizes loan and firm characteristics. Lead lender's share in loans of interlocked firms (*PERC_LEAD*) shows considerable variation with mean of 40% and median of about 33%. Life of the loans in the sample has a wide range (from 5 months to 120 months), which reflects the diversity of loan types in the sample. Average spread of a loan over its base is about 206 basis points; however, the standard deviation is quite high reflecting that for different type of loans, the loan spread differs significantly.

Table 2: Summary Statistics

	Mean	Median	Std Dev	Minimum	Maximum	P25	P75
PERC_LEAD	40.15	33.33	25.97	6.36	100.00	20.00	51.25
LOAN SIZE	0.0959	0.0450	0.1387	0.0000	0.8289	0.0108	0.1216
SECURED	0.31	0.00	0.46	0.00	1.00	0.00	1.00
SENIORITY	0.9964	1.0000	0.0595	0.0000	1.0000	1.0000	1.0000
MATURITY	44.12	49.00	25.79	5.00	120.00	12.00	60.00
ROA	13.65%	12.35%	9.22%	-9.17%	47.16%	7.73%	17.81%
INTEREST_COV	12.17	6.56	18.04	-1.49	111.14	2.98	12.93
TANGIBILITY	0.27	0.20	0.23	0.00	0.86	0.08	0.45
GROWTH	1.75	1.40	0.99	0.84	6.07	1.12	1.94
LEVERAGE	0.25	0.21	0.20	0.00	1.03	0.11	0.36
SIZE	9.27	8.95	2.12	4.83	14.22	7.79	10.34

This table provides the summary statistics of the variables in the sample. Continuous variables are winsorized at the 1st and 99th percentile.

Most of the loans in the sample have seniority classification, and about 31% of the total loans in the sample are secured. Distribution of firm characteristics is also shown in this table. The average and median ROA are 13.65% and 12.35%, respectively, which indicates that firms in the sample are profitable, on average. The mean interest coverage ratio (12.17) and tangibility (27%) demonstrate that, on average, the sample firms have adequate capacity to cover their debt obligations. Further, the average leverage ratio is around 25%, suggesting that the firms have significant debt capacity. These firms also have relatively high growth opportunities depicted by the average market to book ratio of 1.75.

Univariate Analysis

Univariate analysis in provided in Table 3. The lead lender's share of the loans that firms take in absence of a fraud event is compared with that of loans that they take after the fraud event occurs. In addition, there is a comparison of key loan and firm characteristics pre and post the fraud announcement.

Table 3: Univariate Test

	Pre-Fraud	Post-Fraud	Difference	T-stat
PERC_LEAD	38.6283	42.5271	3.8988**	2.23
LOAN SIZE	0.0944	0.0981	0.0038	0.81
SECURED	0.3035	0.3121	0.0086	0.56
SENIORITY	0.9967	0.9961	-0.0006	-0.29
MATURITY	41.9289	47.0220	5.0931***	5.80
ROA	0.1396	0.1323	-0.0073**	-2.29
INTEREST_COV	11.9479	12.4682	0.5203	0.81
TANGIBILITY	0.2836	0.2559	-0.0277***	-3.37
GROWTH	1.8209	1.6511	-0.1698***	-5.09
LEVERAGE	0.2440	0.2633	0.0193***	2.87
SIZE	9.0678	9.5377	0.4699***	6.64

This table shows results of univariate analysis of lead lender's ownership, and other variables five years before and after a fraud announcement. Mean values are reported for the pre and post fraud sub samples. The column labeled T-stat reports the results of a t-test of equal means between the two groups.

Results of univariate tests show that lead lender's share, on average, increases from pre fraud event loans to post fraud event loans. The mean of lead lender's share (*PERC_LEAD*) of loans during the pre-fraud period is 38.63%, while it is 42.53% during the post-fraud period. The difference in mean is significant at 5% level. A test of the difference in loan and firm characteristics indicates most of the loan characteristics do not change significantly from the pre fraud years to the post fraud years. In terms of firm characteristics, certain firm characteristics change significantly between the pre fraud period and post fraud period. Leverage and size of the interlocked firms increase after the fraud event, and the increase is highly significant. On other hand, on average, in the post fraud period, interlocked firms' tangible assets, growth opportunity and ROA decreases significantly. This is consistent with the notion that the spillover firms' operating performances suffer, potentially through the channel of weak board monitoring. Overall, results of the univariate tests lend support to the hypothesis that when an interlocked firm takes loans after a fraud announcement by a fraud firm, the lead lender's share of loan increases. While most of the loan variables do not change from the pre to post fraud period, certain firm variables change significantly in the post fraud period compared to the pre fraud period.

Multivariate Analysis

Lead Lender Share and Fraud Spillover

Multivariate regression test results are presented next. In Table 4, Model 1 has with the percentage of the loan share owned by the lead lender (*PERC_LEAD*) as the dependent variable. The main independent variable is the indicator variable for post fraud period (*POST*), and controls are included for loan characteristics in columns (1) and (2). Results of the OLS regressions show that the coefficient of *POST* is positive and significant at 5% level across these specifications. The model is extended in columns (3) and (4) by including controls for firm characteristics. The post fraud dummy is still positive and statistically significant at 5% level. The results suggest that when a spillover firm takes loan after the fraud announcement of a board-interlocked firm, the proportion of the lead lender's ownership increases significantly compared to when the firm takes a loan before the fraud event occurs. Most of the loan and firm control variables are significant and they retain the expected signs.

Table 4: Baseline Regression

	(1)	(2)	(3)	(4)
POST	4.8901**	5.0195**	5.2935***	5.0301**
	(2.478)	(2.084)	(2.729)	(2.133)
ROA	-49.4713**	-52.9927***	-24.6152	-26.3092
	(-2.482)	(-2.740)	(-1.190)	(-1.319)
INTEREST_COV	0.1955**	0.1671*	0.1839**	0.1520*
	(2.437)	(1.933)	(2.326)	(1.789)
TANGIBILITY	-26.1144***	-25.5848***	-25.5150***	-26.3793***
	(-2.819)	(-2.722)	(-2.796)	(-2.874)
GROWTH	0.1332	-0.2348	0.1805	-0.2153
	(0.091)	(-0.152)	(0.125)	(-0.144)
LEVERAGE	18.0634**	13.3413	14.3469*	11.2206
	(2.273)	(1.554)	(1.857)	(1.354)
SIZE	-0.9761	-1.6288**	-1.2028	-2.0293***
	(-1.413)	(-2.407)	(-1.499)	(-2.587)
LOAN SIZE			-28.4323***	-32.6578***
			(-2.912)	(-3.245)
SECURED			8.8892***	9.2750***
			(3.091)	(3.195)
SENIORITY			-29.2376**	-31.8808***
			(-2.569)	(-3.046)
MATURITY			-0.0181	-0.0571
			(-0.406)	(-1.116)
Year FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
adj. R-sq	0.083	0.122	0.110	0.153
N	795	795	790	790

This table presents regression results of lead lender share on post fraud event dummy. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Cross-sectional Analysis of Information Asymmetry

Results of cross-sectional analysis, by the sub sample of firms facing different levels of information asymmetry, are presented next. If a firm's information environment is opaque, it is likely that the lenders would enforce greater 'skin in the game' to ensure increased monitoring. As a result, the effect of post fraud dummy on lead lender's share would be greater for higher information asymmetry firms. Firm size, age, growth opportunity, tangibility, and analyst forecast dispersion are used as proxies for information asymmetry and split sample around median.

Table 5 shows the results of cross sectional analysis by information asymmetry. Results show that the increase in lead lender share during post fraud period is prevalent among smaller, younger, and low tangibility firms; firms with higher M/B ratio; and greater forecast dispersion. Altogether, these results suggest that increase in lead lender share of interlocked firms during post fraud period is prevalent among firms facing greater information asymmetry.

Table 5: Cross-sectional Analysis of Information Asymmetry

	(1) Young	(2) Old	(3) Small	(4) Large	(5) Low Growth	(6) High Growth	(7) Low Tangibility	(8) High Tangibility	(9) Low Forecast Disp.	(10) High Forecast Disp.
POST	14.6266***	1.5086	6.9282**	3.5444	-1.2774	10.6704***	7.8733**	4.6576	0.9919	7.6820**
	(3.404)	(0.553)	(2.058)	(0.819)	(-0.331)	(3.268)	(2.046)	(1.335)	(0.224)	(2.477)
ROA	-15.2301	-5.5969	-36.4738	-3.9607	13.9899	-47.8683**	-18.0495	-11.1612	11.2458	-34.2233
	(-0.549)	(-0.188)	(-1.563)	(-0.074)	(0.276)	(-2.394)	(-0.565)	(-0.345)	(0.253)	(-1.349)
INTEREST_COV	0.1593	0.3149**	0.1344	0.3250	0.2773	0.1057	0.2772**	0.0255	0.1150	0.1837*
	(1.586)	(2.164)	(1.401)	(1.033)	(1.344)	(1.012)	(2.232)	(0.206)	(0.674)	(1.828)
TANGIBILITY	-29.6099*	-9.1064	-20.1579	-13.4051	-35.7726**	-25.2847**	44.7595	-18.3689	30.0856	-36.2601***
	(-1.759)	(-0.677)	(-1.465)	(-0.850)	(-2.149)	(-2.020)	(0.975)	(-1.440)	(0.918)	(-3.439)
GROWTH	-1.0283	-6.9686***	-0.0130	-3.8966	-1.6100	-1.3236	1.7039	-0.9088	-2.4774	-0.6348
	(-0.525)	(-3.026)	(-0.008)	(-0.947)	(-0.148)	(-0.854)	(0.892)	(-0.346)	(-0.781)	(-0.356)
LEVERAGE	11.6664	26.2813**	19.7050	-1.9719	28.8029	9.2381	9.4719	11.4081	17.4636	5.8404
	(0.837)	(2.148)	(1.622)	(-0.082)	(1.634)	(0.823)	(0.650)	(1.073)	(0.855)	(0.512)
SIZE	0.0224	-1.6471	-3.6238*	0.5421	-3.7897***	-2.4437**	-1.8237	-3.0786**	-2.9682	-1.6937*
	(0.012)	(-1.504)	(-1.739)	(0.244)	(-2.729)	(-2.166)	(-1.550)	(-2.470)	(-1.603)	(-1.775)
LOAN SIZE	-36.6093**	-21.4647*	-30.7531**	-45.3445	-90.5831***	-25.4459**	-29.9262**	-55.9934***	-52.9554***	-30.0784**
	(-2.158)	(-1.694)	(-2.540)	(-1.623)	(-4.205)	(-2.102)	(-2.467)	(-3.524)	(-3.192)	(-2.453)
SECURED	15.8156***	1.6620	9.8850***	3.4293	3.0959	9.7761**	15.8059***	3.7317	5.7043	9.4127**
	(3.342)	(0.425)	(2.629)	(0.470)	(0.703)	(2.081)	(3.003)	(0.932)	(0.657)	(2.539)
SENIORITY	-12.0538	-56.9594***	-26.8064*	0.0000	-44.6743***	-6.4578	2.8570	-44.8456***	0.0000	-26.8689**
	(-1.220)	(-13.133)	(-1.732)	(.)	(-8.544)	(-0.778)	(0.290)	(-6.110)	(.)	(-2.058)
MATURITY	-0.1048	-0.0362	-0.2042**	0.0333	0.0188	-0.1213*	-0.1906**	-0.0156	-0.1537*	-0.0329
	(-1.137)	(-0.590)	(-2.547)	(0.479)	(0.235)	(-1.770)	(-2.190)	(-0.239)	(-1.941)	(-0.494)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	0.240	0.208	0.186	0.141	0.218	0.156	0.259	0.139	0.186	0.159
N	274	509	413	371	327	450	340	440	252	533

This table shows results from cross sectional analysis of information asymmetry. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample is split around median by firm age in columns (1) and (2), firm size in columns (3) and (4), market-to-book ratio in columns (5) and (6), tangibility in columns (7) and (8), analyst forecast dispersion in columns (9) and (10). Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Robustness Tests

In this section, robustness checks of the results are performed by running tests with an alternative dependent variable and alternative sample. The possibility that the results are biased by alternate explanations of fraud propagation, such as industry peers or geographic proximity is ruled out.

Alternative Dependent Variable

For an alternative specification of the dependent variable, the lead lender's Herfindahl Index (*HHI*) is used instead of the percentage of loan share owned by the lead lender (*PERC_LEAD*). Equation (1) is re-estimated with *HHI* and the results are reported in Table 6. Coefficient estimates show that the post fraud dummy (*POST*) is positive and significant across all specifications. Although some of the loan and firm controls are not significant in the full specification, the most important ones are significant and retain the expected signs. Overall, Table 6 provides strong evidence that regardless of the measure used for lead lender's share of loan, results continue to hold.

Table 6: Robustness Tests – Alternative Dependent Variable

	(1)	(2)	(3)	(4)
POST	0.0671***	0.0461**	0.0786***	0.0494***
	(3.979)	(2.483)	(4.933)	(2.871)
ROA	-0.4751***	-0.5158***	-0.2290	-0.2290
	(-3.124)	(-3.381)	(-1.456)	(-1.422)
INTEREST_COV	0.0012	0.0010	0.0011	0.0008
	(1.519)	(1.313)	(1.409)	(1.032)
TANGIBILITY	-0.0910	-0.0920	-0.0827	-0.0920
	(-1.274)	(-1.277)	(-1.213)	(-1.355)
GROWTH	0.0151	0.0148	0.0147	0.0145
	(1.196)	(1.198)	(1.188)	(1.218)
LEVERAGE	0.0896	0.0737	0.0655	0.0577
	(1.032)	(0.812)	(0.779)	(0.676)
SIZE	-0.0391***	-0.0415***	-0.0449***	-0.0488***
	(-7.542)	(-7.688)	(-8.711)	(-8.837)
LOAN SIZE			-0.3379***	-0.3816***
			(-4.320)	(-4.466)
SECURED			0.0777***	0.0844***
			(3.221)	(3.367)
SENIORITY			-0.3998***	-0.4004***
			(-5.597)	(-4.539)
MATURITY			-0.0008**	-0.0012**
			(-2.004)	(-2.579)
Year FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
adj. R-sq	0.109	0.141	0.173	0.211
N	810	810	803	803

This table reports regression results based on alternative dependent variable. *HHI* is the dependent variable, which is defined as the Herfindahl Index of lead lenders' share in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Alternative Sample

In the baseline models, the sample includes interlocked firms that take loans only before or after fraud events, and also the firms that take loans both before and after fraud events. Now a sub-sample of interlocked firms taking loans both before and after the fraud events is constructed. This would ensure a cleaner estimation of the post fraud dummy. Again, Equation (1) with this alternate sample is re-estimated and the results are reported in Table 7.

Table 7: Robustness Tests – Alternative Sample

	(1)	(2)	(3)	(4)
POST	5.5013***	4.9127*	6.0990***	5.0479**
	(2.665)	(1.924)	(3.005)	(2.022)
ROA	-49.6425**	-51.6529**	-26.7590	-27.3442
	(-1.998)	(-2.071)	(-1.068)	(-1.105)
INTEREST_COV	0.1689*	0.1313	0.1584*	0.1166
	(1.779)	(1.269)	(1.672)	(1.143)
TANGIBILITY	-27.4348***	-27.9180***	-26.7831***	-28.9285***
	(-2.785)	(-2.810)	(-2.767)	(-2.975)
GROWTH	0.6615	0.1135	1.1085	0.6466
	(0.309)	(0.050)	(0.532)	(0.299)
LEVERAGE	20.1397**	16.8730*	17.0721**	16.1092*
	(2.266)	(1.721)	(1.981)	(1.712)
SIZE	-1.3644*	-1.9873**	-1.5377*	-2.4588***
	(-1.705)	(-2.569)	(-1.687)	(-2.770)
LOAN SIZE			-32.3555***	-38.6647***
			(-2.887)	(-3.289)
SECURED			9.2595***	9.3846***
			(3.085)	(3.140)
SENIORITY			-32.1395**	-35.0652***
			(-2.422)	(-2.750)
MATURITY			-0.0174	-0.0553
			(-0.376)	(-1.049)
Year FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
adj. R-sq	0.084	0.128	0.116	0.163
N	742	742	737	737

This table presents regression results of lead lender share on post fraud event dummy for an alternative sample. This sample includes fraud-interlocked firms that took loan both before and after fraud events. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Results show that the coefficient of post fraud dummy (*POST*) is positive and highly significant. It reinforces the baseline findings that following fraud events, lead lenders significantly increase their ownership of loans in firms that are board interlocked with fraud firms. The majority of loan and firm controls remain significant as well.

Additional Control Variables

A number of control variables that are determinants of lead lender ownership are now included, following prior literature (Ball et al., 2008). The quantity of covenants is controlled for with the number of financial (*N_FIN_COVENANTS*) and number of nonfinancial (*N_NON_FIN_COVENANTS*) covenants. The intensity of covenants is controlled for by adding the Bradley and Roberts index (*BR_INDEX*) (Bradley and Roberts, 2015) and the Mansi index (*MANSI_INDEX*) (Mansi, Qi and Wald, 2021). Regression results with these additional controls are in Table 8. Coefficient estimates of the post fraud dummy (*POST*) continue to hold for models with additional control variables.

Exclude Industry Peers and Geographic Proximity Firms

Besides board interlock, fraud may also propagate through industry peers (Beatty, Liao Yu, 2013) and geographic proximity (Parsons, Sulaeman, Titman, 2018). After a fraud event, investors update their beliefs based on the financial quality of the peer firms (Gleason, Jenkins, Johnson, 2008; Goldman, Peyer, Stefanescu, 2012). Therefore, fraud revelation is likely to affect firms within the same industry or same geographic area. In order to rule out the possibility the results are affected by these factors, robustness tests are run by excluding firms within the same industry as the fraud firm or firms located in close geographical proximity to the fraud firm.

Table 9 shows the results of regressions run on the sample that excludes industry peers or closely located firms. In columns (1) through (4), if a fraud firm and an interlocked firm are in the same industry, defined by 2 digit SIC code (columns (1) and (2)) or 3 digit SIC code (columns (3) and (4)), then these interlocked firms are excluded from the sample. Similarly, in columns (5) through (8), if a fraud firm and an interlocked firm are located within the county, defined by 3 digit ZIP code (columns (5) and (6)) or 5 digit ZIP code (columns (7) and (8)), then these interlocked firms are excluded from the sample. Coefficient estimates of the post fraud dummy variable are positive and significant across all specifications suggesting the results are not driven by fraud propagated through industry peers or closely located firms.

Table 8: Robustness Tests – Additional Control Variables

	(1)	(2)	(3)	(4)	(5)
POST	5.0301**	4.2184*	4.1086*	4.0496*	4.1074*
	(2.133)	(1.783)	(1.728)	(1.705)	(1.726)
ROA	-26.3092	-26.9979	-25.4517	-23.9206	-25.2501
	(-1.319)	(-1.368)	(-1.287)	(-1.217)	(-1.283)
INTEREST_COV	0.1520*	0.1619*	0.1635*	0.1702**	0.1631*
	(1.789)	(1.895)	(1.927)	(2.032)	(1.910)
TANGIBILITY	-26.3793***	-27.5967***	-26.5993***	-25.3974***	-26.5311***
	(-2.874)	(-2.982)	(-2.884)	(-2.780)	(-2.855)
GROWTH	-0.2153	-0.5598	-0.6458	-0.8187	-0.6486
	(-0.144)	(-0.381)	(-0.437)	(-0.551)	(-0.439)
LEVERAGE	11.2206	11.2319	11.1322	12.9330	11.0871
	(1.354)	(1.311)	(1.292)	(1.499)	(1.269)
SIZE	-2.0293***	-2.9753***	-2.8741***	-2.7937***	-2.8671***
	(-2.587)	(-3.473)	(-3.304)	(-3.228)	(-3.243)
LOAN SIZE	-32.6578***	-32.0482***	-32.4538***	-32.5984***	-32.5086***
	(-3.245)	(-3.317)	(-3.350)	(-3.377)	(-3.353)
SECURED	9.2750***	11.2835***	10.0742***	4.7541	10.0951***
	(3.195)	(3.836)	(2.853)	(0.951)	(2.844)
SENIORITY	-31.8808***	-33.3682***	-33.7731***	-33.9187***	-33.8159***
	(-3.046)	(-3.255)	(-2.980)	(-3.282)	(-3.006)
MATURITY	-0.0571	-0.0487	-0.0468	-0.0368	-0.0461
	(-1.116)	(-0.958)	(-0.923)	(-0.730)	(-0.895)
N_FIN_COVENANT		-3.1321***	-3.4543***	-4.5373***	-3.7327
		(-2.898)	(-3.053)	(-3.551)	(-1.172)
N_NON_FIN_COVENANT			0.7989	-2.7111	0.5626
			(0.804)	(-1.212)	(0.200)
BR_INDEX				4.7517*	
				(1.689)	
MANSI_INDEX					0.2875
					(0.088)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
adj. R-sq	0.153	0.163	0.163	0.165	0.162
N	790	790	790	790	790

This table presents regression results of lead lender share on post fraud event dummy including additional control variables. This sample includes fraud-interlocked firms that took loan both before and after fraud events. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Table 9: Robustness Tests – Exclude Industry Peers and Geographic Proximity Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SIC2	SIC2	SIC3	SIC3	3 digit ZIP	3 digit ZIP	5 digit ZIP	5 digit ZIP
POST	4.9370**	4.2005*	5.4497***	5.3077**	5.5287***	5.1186**	5.6309***	5.3561**
	(2.467)	(1.733)	(2.776)	(2.226)	(2.813)	(2.129)	(2.874)	(2.240)
ROA	-30.9140	-35.0561*	-27.7163	-30.4270	-24.8226	-26.3555	-24.8345	-26.3906
	(-1.440)	(-1.675)	(-1.321)	(-1.504)	(-1.194)	(-1.320)	(-1.197)	(-1.320)
INTEREST_COV	0.1542*	0.1238	0.1708**	0.1405	0.1859**	0.1525*	0.1809**	0.1497*
	(1.781)	(1.348)	(2.126)	(1.621)	(2.290)	(1.750)	(2.285)	(1.760)
TANGIBILITY	-26.3040***	-25.8255***	-25.2948***	-25.8349***	-24.7755***	-26.0058***	-24.7660***	-26.0304***
	(-2.846)	(-2.777)	(-2.750)	(-2.792)	(-2.692)	(-2.818)	(-2.702)	(-2.829)
GROWTH	0.9028	0.6331	0.8073	0.4913	0.2446	-0.1552	0.2791	-0.1481
	(0.581)	(0.397)	(0.539)	(0.317)	(0.168)	(-0.103)	(0.193)	(-0.099)
LEVERAGE	12.1301	9.6346	12.5867	9.3637	14.2317*	10.9489	14.1790*	11.0529
	(1.522)	(1.134)	(1.611)	(1.114)	(1.839)	(1.319)	(1.834)	(1.332)
SIZE	-1.2132	-1.9178**	-1.2650	-2.0897***	-1.2908	-2.0827***	-1.2981	-2.1006***
	(-1.421)	(-2.314)	(-1.569)	(-2.663)	(-1.589)	(-2.627)	(-1.608)	(-2.663)
LOAN SIZE	-28.3957***	-30.9175***	-26.7377***	-30.1515***	-29.5229***	-33.5140***	-29.3786***	-33.4005***
	(-2.896)	(-3.078)	(-2.746)	(-3.025)	(-2.991)	(-3.287)	(-2.988)	(-3.292)
SECURED	8.1534***	8.1728***	8.9912***	9.1445***	9.1001***	9.5804***	9.0059***	9.4275***
	(2.796)	(2.800)	(3.098)	(3.144)	(3.163)	(3.288)	(3.129)	(3.234)
SENIORITY	-28.7178**	-30.0054***	-28.8277**	-31.4709***	-27.5872***	-30.8681***	-27.5322***	-30.7705***
	(-2.470)	(-2.681)	(-2.482)	(-3.006)	(-2.700)	(-3.147)	(-2.677)	(-3.131)
MATURITY	-0.0139	-0.0460	-0.0139	-0.0479	-0.0200	-0.0608	-0.0192	-0.0581
	(-0.303)	(-0.884)	(-0.308)	(-0.936)	(-0.447)	(-1.178)	(-0.430)	(-1.135)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R-sq	0.104	0.146	0.111	0.156	0.110	0.152	0.111	0.152
N	743	743	776	776	782	782	786	786

This table presents regression results of lead lender share on post fraud event dummy for a sample that excludes interlocked firms within the same industry or interlocked firms located within the same geographic area as the fraud firm. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Define industry peer by using 2 digit SIC in columns (1) and (2), and 3 digit SIC in columns (3) and (4). Define geographic proximity by using zip code of the firm headquarters. In columns (5) and (6) firms located within the same 3 digit zip code are excluded, and in columns (7) and (8) firms located within the same 5 digit zip code are excluded. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Endogeneity Concerns

It is possible the results are biased by endogeneity issues. For example, omitted variable bias may arise due to unobservable factors that are common across the interlocked firms. Other concerns in this setting could arise from self-selection bias, reverse causality, etc.

Firm Fixed Effect Regressions

Although the common firm level determinants of lead lender share are controlled for, some unknown omitted variable may bias the spillover effect of fraud restatement. This issue is addressed by running firm fixed effect regressions in this section. The same specification shown in Table 4 is used and instead of industry fixed effects, firm fixed effects are applied in all specifications in Table 10. Results indicate that coefficient estimates of post fraud dummy remain qualitatively unchanged in firm fixed effects regressions, which suggests that the results are not affected by omitted variable bias.

Table 10: Endogeneity Concerns – Firm Fixed Effect Regressions

	(1)	(2)	(3)	(4)
POST	5.4452**	6.3209*	5.6401**	6.2444*
	(2.157)	(1.899)	(2.185)	(1.890)
ROA	-19.9946	-20.9967	-9.2267	-12.8056
	(-0.670)	(-0.703)	(-0.305)	(-0.427)
INTEREST_COV	0.0902	0.0564	0.0987	0.0551
	(0.573)	(0.338)	(0.630)	(0.338)
TANGIBILITY	-54.8373**	-45.6359*	-59.0842**	-53.3178**
	(-2.261)	(-1.851)	(-2.454)	(-2.148)
GROWTH	-7.6205**	-8.6756**	-6.0866*	-7.2185**
	(-2.286)	(-2.436)	(-1.826)	(-2.071)
LEVERAGE	8.9672	16.1692	11.9398	18.1340
	(0.602)	(1.037)	(0.811)	(1.159)
SIZE	-7.2287	-5.6562	-7.0102	-5.6979
	(-1.621)	(-1.052)	(-1.552)	(-1.068)
LOAN SIZE			-31.9075***	-36.3614***
			(-2.701)	(-2.797)
SECURED			5.7797	6.2531
			(1.284)	(1.347)
SENIORITY			-27.9694*	-29.9474*
			(-1.715)	(-1.876)
MATURITY			0.0055	-0.0294
			(0.109)	(-0.512)
Year FE	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
adj. R-sq	0.227	0.245	0.236	0.262
N	755	755	750	750

This table presents regression results of lead lender share on post fraud event dummy with firm fixed effect specification. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Matched Sample Difference-in-Difference Analysis

To further address endogeneity concern, a matched sample difference-in-difference (DID) analysis is performed and the results reported in this section. Propensity score matching is used to match the interlocked firms in the sample with firms having similar size, leverage, tangibility, interest coverage and ROA within the same industry. Through the matching procedure, it is ensured the control firms are not affected by fraud events. Using this matched sample, the following DID model is estimated:

$$PERC\_LEAD_{it} = \alpha_0 + \beta_1 POST_{it} + \beta_2 TREAT_{it} + \beta_3 TREAT_{it} * POST_{it} + \beta_4 X_{2it} + \dots + \beta_k X_{kit} + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon_{it} \quad (2)$$

where *PERC_LEAD* is the percentage of lead lender ownership of loans in interlocked firm$_i$ in year t. *POST* is the post-fraud time dummy, which takes a value of one if interlocked firm$_i$ takes loan after the fraud announcement by fraud firms, and zero otherwise. *TREAT* is the indicator variable for treatment firms, which takes a value of one if loan is taken by interlocked (treatment) firm, and zero for the matched (control) firm. The variable of interest in this model is the interaction term. A positive coefficient on β_3 would suggest that after the fraud announcement by a fraud firm, the lead lender's shares in an interlocked firm increase compared to the matching industry peer, which do not have board interlock with the fraud firm.

Table 11: Endogeneity Concerns – Matched Sample Difference-in-Difference Analysis

	(1)	(2)	(3)	(4)
TREAT	-7.3281***	-7.9165***	-7.2484***	-7.8454***
	(-3.455)	(-3.684)	(-3.524)	(-3.764)
POST	-2.7656	-5.9680**	-2.6630	-6.0471**
	(-1.137)	(-2.093)	(-1.095)	(-2.154)
TREAT * POST	7.9415**	9.6077***	7.9817**	9.7696***
	(2.466)	(2.900)	(2.512)	(2.992)
ROA	-45.9696**	-43.0713**	-35.0531*	-31.3655
	(-2.346)	(-2.154)	(-1.802)	(-1.593)
INTEREST_COV	0.0609***	0.0548***	0.0594***	0.0531***
	(4.309)	(3.380)	(4.104)	(3.245)
TANGIBILITY	-15.1658	-15.6220	-14.4642	-16.1614
	(-1.462)	(-1.397)	(-1.399)	(-1.461)
GROWTH	0.7520	0.7412	1.5088	1.3590
	(0.503)	(0.470)	(1.020)	(0.886)
LEVERAGE	15.4763**	12.2153*	11.1464	9.9555
	(2.229)	(1.648)	(1.575)	(1.324)
SIZE	-2.1668***	-2.1734***	-2.2126***	-2.6168***
	(-3.180)	(-3.121)	(-2.689)	(-3.165)
LOAN SIZE			-25.5701***	-32.8703***
			(-3.295)	(-4.015)
SECURED			7.7157***	7.2295***
			(2.982)	(2.746)
SENIORITY			-20.3489	-18.7513
			(-1.606)	(-1.447)
MATURITY			0.0323	0.0107
			(0.832)	(0.247)
Year FE	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes
adj. R-sq	0.130	0.144	0.156	0.169
N	1294	1293	1285	1284

This table presents results of matched sample difference-in-difference analysis. For each of the fraud restating years, define *TREAT* as 1 for the firms that are interlocked with fraud restating firms, 0 for all other firms. Then based on propensity score matching, match each treatment firm with a control firm based on size, leverage, tangibility, interest coverage, ROA, and industry. *PERC_LEAD* is the dependent variable, which is defined as the percentage of lead lenders' ownership in syndicated loan transactions. *POST* is the main independent variable, which takes a value of one for post fraud period, zero otherwise. Sample period is from 2001 to 2016. t-stats based on robust standard errors adjusted for heteroskedasticity are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1%, respectively.

Table 11 reports results of the DID analysis. The coefficient estimate on the interaction term is positive and significant. It suggests that firms interlocked with fraud firms (treatment) experience increase in the share of lead lender in the years following fraud events compared to the firms (control) that do not share any interlocked board member with the fraud firms. Overall, the evidence from DID analysis corroborates the main findings that fraud restatement has spillover effect on firms that are board interlocked with fraud firms.

Conclusion

In this paper, the spillover effect from a corporate fraud restatement to peer companies through the channel of board interlock is investigated. The results strongly support that the ownership of a loan by the lead lender increases significantly when that loan is granted to a spillover firm after the fraud event takes place compared to when a loan is granted to the firm before the fraud event takes place. Regardless of whether the lead lender's percentage ownership of the loan is used as the dependent variable or the HHI index, the findings remain strong and highly significant. It supports the hypothesis that after a fraud event occurs, the syndicate members of a loan become concerned regarding granting a loan to a spillover firm. The negative signal of peer fraud serves as a fire alarm of poor monitoring by the corporate board. As a result, participating arrangers want the lead lender to possess a higher share of the loan so that the lead lender will monitor the activities of the firm more intensely. The main results emphasize the importance of board interlock on companies' corporate performance.

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The Impact of Weather on Indoor Attendance: The Case of the NBA

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Abstract

NBA Attendance from 2013-14 to 2019-20 is examined in the context of the role weather plays in NBA fan decisions to attend live games. Although weather has been investigated as a determinant of demand for outdoor sports, limited studies address the role of weather for indoor sports, such as the NBA. Detailed weather data, temperature, humidity, snowfall, and barometric pressure were each shown to significantly impact attendance for NBA games. An alternative model using weather clusters, combining the factors noted above, yielded five clusters of different weather combinations that impact attendance in specific ways.

JEL Codes: Z2, D1
Keywords: Sports, Basketball, Attendance, Weather

Introduction

The role of weather as it relates to sports attendance is well-known for outdoor events. Factors such as cold weather or precipitation could make sitting in an outdoor stadium an unenjoyable experience, despite the action on the field or pitch, for many fans interested in attending matches. Conversely, nice weather increases the opportunity cost of alternative outdoor activities, which may discourage fans from attending sporting events. While weather factors have been shown to have statistically significant effects on attendance in sports such as baseball, the role of weather as it relates to indoor events has not been studied as intently.

When a game or match is played indoors, the role of weather is lessened in the mind of many who study or discuss the subject. However, weather may still play a very important role in consumer decisions to attend sporting events even if the game is played inside a temperature-controlled arena. The act of getting to the game from home or work and traveling home after the game is played likely still leads to weather considerations when fans make the decision to attend a sporting event. Even though one may not need to sit in the cold, once they are comfortably in their seat, the act of driving, walking, or waiting to pass through lines and security to enter the arena still makes cold weather and precipitation a deterrent from attending a game. If travel is the primary consideration, snow may even be more of a factor than rain when considering the impact of weather on indoor arena attendance.

Beyond temperature and precipitation, other weather factors may also play a role in the decision to attend indoor sporting events. Humidity could make going outside uncomfortable, even in the absence of precipitation, and may discourage fans from venturing to the arena, but rather choose to watch the game on television or online. Barometric pressure, which has been linked to changes in activity levels in wildlife and humans may contribute to people feeling more or less likely to undertake an activity and could influence consumer behavior when it comes to the decision to stay at home or make the trip to the arena. In short, many different weather factors could still play an important role when considering attendance at indoor sporting events. By improving a team's understanding of the factors that drive attendance, teams may be able to improve pre-game attendance forecasts, allowing partner organizations to adjust event staffing for facilities, concessions, parking, security teams, as well as food preparation and staging, and event preparation in general before the game is played and the fans start arriving. Also, since teams use fluid dynamic pricing for tickets, adjustments to prices could be made in anticipation of weather conditions.

To directly test the role of weather factors on fan attendance, data from the National Basketball Association (NBA) is considered. Using data from the 2013-14 season through the 2019-20 season, attendance for NBA games, which were exclusively played indoor in their respective home arenas during the sample, are used. The percentage of capacity is the measure of attendance to account for different size cities and arenas across the association. Attendance as a percentage of capacity is modeled based upon factors such as team success, game expectations, day of the week, and controls for the home and away teams. In addition, weather factors, gathered from www.weatherunderground.com for the respective NBA cities in the form of temperature, humidity, snowfall, precipitation, and barometric pressure are included to investigate the role of these variables as it relates to fan decisions to attend games. Results are shown through three general models, OLS, OLS only including non-sellout games, and Tobit model results, used due to the presences of sellouts in the sample.

Beyond the basic models, the interconnectivity of the different weather variables and their collinear nature is considered. For instance, high humidity is often accompanied by rain or snow. Snow can only occur at low temperatures. These and other factors could be disguising the true role of the individual weather factors on attendance. To offer an alternative model, clustering is utilized to break the weather into different groups. K-means clustering, using the elbow and silhouette method to determine the optimal number of clusters, allows for different weather categories to be generated, noted, and then entered into the regression model as dummy variables to allow for an investigation of the role of various weather variable clusters. In both the basic regression approach and in the regression model with the clusters, weather factors are shown to have statistically significant and logical effects on fan attendance for NBA games.

The paper proceeds as follows. The next section provides a literature review on the role of weather on attendance in sporting events. The third section presents the model of attendance and its results using individual weather factors as independent variables in various specifications. The fourth section describes the clustering process of the weather variables and presents the regression model results substituting the weather clusters for the individual factors. The final section discusses the findings and offers conclusions.

Literature Review

Many variables impact attendance demand, with a summary of the empirical literature around this topic noted by Mueller (2020). Some examples include ticket pricing (Humphreys and Soebbing, 2012; Sweeting 2012), day and time of a game (Tainsky and Winfree, 2010), promotions (Kappe et al., 2014), weather (Ge et al., 2020), and team success (Bradbury, 2019), among others. Several papers have examined these demand factors specifically for the National Football League (e.g. Coates and Humphreys, 2010; Diehl et al., 2016; Gropper and Anderson, 2018). Other approaches to modeling attendance demand stem directly from the theory of outcome uncertainty (Rottenberg, 1956). According to Rottenberg (1956), fans prefer games with uncertain outcomes. Coates, et al. (2014) examined the theoretical implications of this theory in their research.

Borland and MacDonald (2003) identified five main subcategories of determinants of demand for attendance at live sporting events: form of consumer preferences, economic price, quality of viewing experience, characteristics of the viewing contest, and supply capacity. This study introduced weather into the demand function. Weather directly impacted the quality of the viewing experience, as poor weather likely reduces the quality of the gameday experience. Indirectly, weather can impact the economic price of attending a sporting event because of bad weather on increased traveling costs. For domed stadiums, bad weather can also decrease competition for consumer dollars by removing otherwise available outdoor substitutes.

Popp et al. (2019) and Schreyer et al. (2019), examined the role of weather and other factors on fan no-shows at sporting events. Popp et al. (2019) found rainy weather led to more no-shows for NCAA football attendance, but temperature had no effect. Schreyer et al. (2019) found temperature had a statistically significant U-shaped quadratic relationship in the German Bundesliga, but no statistically significant effect of precipitation. Many studies have identified a negative relationship between game day attendance and current rainfall. Kalist (2010) and Agha and Rhoads (2018) illustrated current rainfall reduced demand for both major league and minor league baseball.

Ge et al. (2020) utilized adverse weather shocks to investigate habit formation and persistence in attending live sporting events for Major League Baseball. Adverse weather reflects a source of variation in attendance demand uncorrelated with past attendance and unobserved fan characteristics. They identify that lagged rainfall had a positive impact on current attendance. They also examine different specifications for current day precipitation and conclude that forecasted accumulated rainfall has a greater impact on attendance demand than actual accumulated rainfall two hours prior to the game and four hours prior to the game, suggesting that fans rely heavily on weather forecasts when making their purchasing decisions. When examining the effects of domed stadiums, they find that attendance increases on rainy days, suggesting that indoor baseball games serve as strong substitutes for other indoor entertainment options. Paul, et al. (2021) examined the role of weather for NFL attendance. With limited home games in a season, the NFL has more of a special event feel than many other sports. In addition to the impact of temperature and precipitation, cloud cover and wind speed also were found to play an important role. Barometric pressure has also been identified as a potential factor that may lead to increases or decreases in activity among wildlife (Peterson, 1972; Knight, 1936; Stokes, Slade, and Blair, 2001), and humans. Suminski et al. (2008) find an inverse correlation with barometric pressure and both the number of walkers on an outdoor track, and the duration of walking, although the authors find no statistically significant influence of meteorological conditions on joggers during weekdays. McAlindon et al. (2007) find changes in barometric pressure are associated with osteoarthritis knee pain severity.

Model

The regression model used attendance as a percentage of arena capacity as the dependent variable. The percentage of capacity is used to control for arena size difference across the league. Percentage of capacity allows for better accounting of sell-outs which occur in different arenas across the league at different times. Given the capacity constraints based on arena size, a Tobit model is used to control for the upper limits of sellouts. The model investigates the determinants of attendance with a main focus on the role of weather and if it influences fan decisions to attend indoor games in the NBA. The model focuses on key elements related to the game itself and game timing in addition to the weather factors. The win percentage going into the game is included as an independent variable as a measure of home team quality. For the first game of the season, a win percentage of 50% was used for all teams in the sample. If fans prefer to see more successful teams, this variable should have a positive and significant effect on attendance.

A variety of factors are used to control for expected quality of the individual game itself. In one specification, the absolute value of the point spread is used to control for outcome uncertainty to determine if fans prefer to watch expected close games compared to expected blowouts. In addition to the absolute value of the point spread, a dummy variable for if the home team is a favorite is used to test if fans prefer to attend games when the home team is expected to win. An additional model specification allows for the possibility that fans prefer to distinguish between when the home team is a favorite and when it is an underdog by interacting the point spread and a dummy for home favorite or road favorite. Beyond the individual game matchup of quality between teams, also included is the betting market total in the market to account for the role of expected scoring by both teams. If fans prefer more scoring to less, the total should have a positive and significant effect on attendance.

Weather variables are included across a spectrum of factors. Temperature is included as an independent variable in the model. If fans prefer higher temperatures to lower temperatures, this variable should have a positive and significant effect on attendance. Humidity is another weather variable included. More humid conditions are typically less enjoyable for people and although the NBA games are played indoors, humidity is evaluated for any impact on if fans choose to attend games in person. Precipitation is considered in two ways. In one model specification, precipitation is directly included in the model in the form of inches of precipitation (rain or snow). Given that snow presents many more challenges in leaving home or work to attend an NBA game, a separate model specification where snowfall is the only form of precipitation is included in the regression model. Last, barometric pressure is included as an independent variable. Barometric pressure may influence activity as typically lower barometric pressure is associated with less activity and higher barometric pressure with more activity. If this influences fan decisions to leave home to attend games, it will have a significant effect in the regression model.

Beyond the team, game, and weather variables, dummy variables are used for the day of the week (Friday is the reference category). Weekends are likely to be more popular to attend games than weekdays due to the opportunity cost of time with commitments such as work and school for people and families. Dummy variables are included for the home team and the visiting team in the model. These are not shown due to space considerations but are available directly from the authors if desired.

Summary statistics for the key variables of interest are shown in Table 1 below.

Table 1: Summary Statistics

Variable	Mean	Median	Standard Deviation
Attendance	18031.06	18308.50	2107.36
Percentage of Capacity	0.94	1.00	0.10
Win Percentage	0.49	0.50	0.20
Abs(Point Spread)	6.24	5.50	3.71
Total	209.71	209.50	12.25
Temperature	48.39	49.00	15.48
Humidity	67.15	68.00	15.81
Precipitation	0.11	0.00	0.31
Snow	0.10	0.00	0.67
Barometric Pressure	30.05	30.07	0.27

Results of the regression models are shown in the tables below. Table 2 models include the absolute value of the point spread and a home favorite dummy to account for game quality, while Table 3 uses an alternative specification and substitutes the interaction of a home favorite dummy times the absolute value of the point spread and a road favorite dummy (one minus the home favorite dummy) times the absolute value of the point spread for the absolute value of the point spread and home favorite dummy. This allows for differentiating between fan reaction to home or road favorites and their expected magnitude of margin of victory in the game. In each table, specification I is the OLS results for the entire sample, specification II is the OLS results for the non-sellout games only, and specification III is the Tobit model results. The Tobit model is generally preferred, due to the existence of the sellouts, and the LM test revealed heteroskedasticity within the results and with a Tobit model, robust standard errors do not correct the problem and may bias the coefficients. Due to this, the OLS results for the full sample are included, which presents issues due to the upper limit on attendance due to arena capacity, and for the restricted sample, which ignores these sellouts. As each specification has issues, the results are compared across the specifications for insights. In the OLS specifications, robust standard errors in the form of Newey-West HAC standard errors and covariance are presented.

Table 2: OLS and Tobit Model Regression Results

Variable	I - OLS	II – OLS (Restricted)	III - Tobit
Intercept	-0.5568***	-0.4844	-1.6167***
	(-4.4024)	(-1.6314)	(-6.6167)
Win Percentage	0.0807***	0.0945***	0.2016***
	(12.5463)	(6.9746)	(14.8001)
ABS(Point Spread)	0.0024***	0.0030***	0.0054***
	(7.8437)	(4.4095)	(8.1745)
Home Favorite Dummy	0.03581***	0.0323***	0.0795***
	(14.0197)	(4.9171)	(15.3037)
Total	0.0005***	0.0010***	0.0005***
	(5.8963)	(3.5359)	(2.9276)
Temperature	0.0006***	0.0007***	0.0019***
	(6.0335)	(2.8618)	(9.2456)
Humidity	-0.0003***	-0.0004**	-0.0006***
	(-3.9330)	(-2.1023)	(-4.0311)
Snow	-0.0084***	-0.0076**	-0.0075***
	(-5.4584)	(-2.0946)	(-2.6943)
Precipitation	0.0035	-0.0017	0.0125
	(0.9973)	(-0.2469)	(1.6233)
Barometric Pressure	0.0071*	0.0037	0.0378***
	(1.7768)	(0.0397)	(4.5892)
Sunday	-0.0123***	-0.0157***	-0.0342***
	(-3.3707)	(-2.3766)	(-4.3118)
Monday	-0.0417***	-0.0664***	-0.0892***
	(-11.9572)	(-9.9310)	(-12.2988)
Tuesday	-0.0372***	-0.0702***	-0.0794***
	(-9.9572)	(-9.1191)	(-10.0110)
Wednesday	-0.0367***	-0.0549***	-0.0784***
	(-11.4771)	(-8.8299)	(-11.7509)
Thursday	-0.0180***	-0.0374***	-0.0342***
	(-4.3333)	(-4.2702)	(-3.7114)
Saturday	0.0120***	0.0241***	0.0321***
	(3.5345)	(4.0524)	(4.2731)
Home Team Dummies	Yes	Yes	Yes
Road Team Dummies	Yes	Yes	Yes

Dependent Variable: Attendance Expressed as Percentage of Arena Percentage
*-significant at the 10% level, **-significant at the 5% level, ***-significant at the 1% level

Across all model specifications, there were similar findings for most of the key variables of interest. The days of the week dummy variables were each found to be statistically significant compared to the reference category of Friday. The only day with higher attendance in terms of percentage of capacity was Saturday, as it had a positive and significant coefficient. The other days of the week all had negative coefficients, which were statistically significant, compared to Friday, as weekdays generally have lower attendance figures due to the opportunity cost of time due to work.

Home team win percentage was shown to have a positive and significant effect on attendance in terms of percentage capacity. Better teams were shown to attract more fans than poorer quality teams. In terms of game quality, the absolute value of the point spread was shown to have a positive and significant effect and the home favorite dummy was also shown to have a positive and significant effect on attendance. In this specification, fans do not appear to prefer outcome uncertainty, but they do appear to prefer to attend games where the home team is expected to win. In the alternative specification (Table 3), it is clear that fans prefer to attend games where the home team is expected to win more easily (higher point spreads), when the home team is the favorite, but when the road team is the favorite, fans prefer outcome uncertainty (lower point spreads). Across all model specifications, the total was shown to have a positive and significant effect on attendance as fans prefer to attend games where the teams are expected to score more points rather than fewer.

In terms of the weather-related variables, many of the variables were found to have statistically significant effects on the percentage of capacity as it relates to game attendance. Temperature was shown to have a positive and significant effect on attendance as fans preferred to attend games on warmer days, with its marginal effects being around a 0.6% increase per degree of temperature. Humidity, on the other hand, was shown to have a negative and significant effect on attendance as higher humidity days led to fewer fans as a percentage of capacity. Snowfall, measured in inches, was also shown to have a negative and significant effect on attendance as fewer fans attend games in inclement weather related to snow. Through computation of marginal effects, an inch of snow leads to around an 0.8% decrease in attendance. Precipitation was not statistically significant. The impact of precipitation for games with indoor attendance seems to be dependent on snowfall, rather than rainfall, which makes sense in terms of relative danger of travel in snow and ice conditions compared to rain. Finally, as it relates to the weather variables, barometric pressure was also shown to have a positive and significant effect on attendance in the general OLS model (specification I) and in the Tobit model (specification III). Although not significant in the restricted sample of games not including sellouts, barometric pressure may play a role in fan decisions as higher barometric pressure is typically associated with greater activity, while lower barometric pressure is related to more sluggish activity. Overall, the combination of weather factors being statistically significant translates into weather still being an important determinant of attendance, even for sporting events played indoors.

Table 3: OLS and Tobit Model Regression Results – Alternative Specification

Variable	I - OLS	II – OLS (Restricted)	III - Tobit
Intercept	-0.5359***	-0.4650	-1.5576***
	(-4.2705)	(-1.5866)	(-6.0492)
Win Percentage	0.1031***	0.1358***	0.2662***
	(15.4143)	(8.2987)	(18.7137)
Home Favorite Dummy	0.0046***	0.0064***	0.0117***
*ABS(Point Spread)	(14.3781)	(7.0880)	(16.5316)
(1-Home Favorite Dummy)	-0.0035***	-0.0033***	-0.0080***
*ABS(Point Spread)	(-7.6286)	(-2.9134)	(-8.6051)
Total	0.0006***	0.0010***	0.0006***
	(6.2218)	(3.8818)	(3.3604)
Temperature	0.0006***	0.0007***	0.0018***
	(5.8539)	(2.8091)	(9.1697)
Humidity	-0.0003***	-0.0005**	-0.0007***
	(-4.0303)	(-2.3421)	(-4.3915)
Snow	-0.0081***	-0.0071*	-0.0066***
	(-5.2953)	(-1.9109)	(-2.4423)
Precipitation	0.0032	-0.0015	0.0122
	(0.9113)	(-0.2235)	(1.6142)
Barometric Pressure	0.0066*	-0.0006	0.0359***
	(1.6736)	(-0.0645)	(4.4201)
Sunday	-0.0124***	-0.0170	-0.0355***
	(-3.4224)	(-2.6251)	(-4.5595)
Monday	-0.0421***	-0.0685***	-0.0912***
	(-12.1547)	(-10.2969)	(-12.7938)
Tuesday	-0.0376***	-0.0714***	-0.0811***
	(-10.1363)	(-9.4091)	(-10.3974)
Wednesday	-0.0368***	-0.0564***	-0.0791***
	(-11.6154)	(-9.1423)	(-12.0724)
Thursday	-0.0190***	-0.0392***	0.0375***
	(-4.6049)	(-4.5581)	(-4.1386)
Saturday	0.0124***	0.0234***	0.0328***
	(3.6653)	(3.9854)	(4.4404)
Home Team Dummies	Yes	Yes	Yes
Road Team Dummies	Yes	Yes	Yes

Dependent Variable: Attendance Expressed as Percentage of Arena Percentage
*-significant at the 10% level, **-significant at the 5% level, ***-significant at the 1% level

Cluster Model

Due to the collinearity between the various weather-related variables, an alternative approach to modeling the impact of weather on attendance is offered. A machine learning-based approach utilizing clustering of weather effects is used. Specifically, K-means clustering in R is used to break the weather data into specific groups. K-means clustering allows for the selection of clusters by the user, with the proper number of clusters depending on the variance explained by clustering, the number of observations in each cluster, and the summary stats of each variable used in the clustering.

Although the user chooses the number of clusters, the elbow method and silhouette method were used to determine the optimal number of clusters to use for the model. The elbow method compares the variance explained by the number of clusters utilized. The optimal number of clusters is chosen where increasing the number of clusters leads to negligible increases in variance explained. As a rule, increasing the number of clusters will increase the variance explained, but at a decreasing rate. Furthermore, the silhouette method measures how close data points in each cluster are to other clusters, and therefore, how well the clusters separate data points. Various combinations of the weather were assessed, starting with just two factors and building to all of the factors discussed in the regression model. Ultimately, constructing clusters using temperature, humidity, snow, and barometric pressure (given that precipitation was not statistically significant in the regression model, only snow was used rather than snow and precipitation). Using the four weather variables to create the clusters is somewhat problematic to visualize with so many dimensions, but Table 4 below provides the cluster means for the variables of each clusters formed. Table 5 provides a brief verbal description of each cluster for quick reference.

Table 4: Cluster Means for Weather-Related Variables

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
# Observations	1848	1731	1400	1539	1220
Temp	42.07	54.14	27.17	66.87	50.83
Humidity	83.05	62.76	60.53	78.48	42.61
Snow	0.203	0.002	0.304	0.000	0.002
Pressure	29.99	30.05	30.19	29.99	30.09

Table 5: Weather-Related Cluster Descriptions

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Low Temp	Mid Temp	Very Low Temp	High Temp	Mid Temp
High Humidity	Mid Humidity	Mid Humidity	High Humidity	Low Humidity
High Snow	Low Snow	Very High Snow	No Snow	Low Snow
Low Pressure	Mid Pressure	High Pressure	Low Pressure	Mid Pressure

Each cluster of weather variables is next converted into five dummy variables, one for each cluster of game day weather. For simplicity, the reference category is cluster five and the four other clusters are included in a similar regression model to what was shown in the previous section. The key difference is that instead of using the individual weather variables, the weather cluster is substituted. Results are shown in Table 6 and Table 7 below.

In the Tobit models, the cluster-based weather model revealed statistically significant results as it relates to attendance as a percentage of arena capacity. In terms of the weather clusters, cluster five was the reference category. Clusters one, two, and three were found to have statistically significant and negative results. Compared to the more-ideal weather conditions of cluster five, the games in clusters including snow or higher humidity led to fewer fans in attendance. In the OLS model, only cluster three was shown to have negative and statistically significant results, likely due to high snow. In the restricted sample (no sellouts), the clusters were not shown to be statistically significant. This is likely due to the clustering being based on the whole sample, not the subset used. Therefore, new clusters were created, the midpoints computed, and the model was run again with the new clusters for specification II. These results, and a table describing the clusters, are shown in the appendix.

Although clustering offered some encouraging possibilities in the Tobit model, it was not as insightful in the OLS models. With the presence of heteroskedasticity in the Tobit model, these results could be biased and as they are not as evident in the OLS models, may not yield as informative results. This said, the clustering approach is presented as a way of potentially handling many interactive factors that concurrently exist, such as weather, and this approach may yield benefits in the future.

Discussion and Conclusions

Although the effects of weather conditions have been studied for outdoor sports, its role in fan decisions to attend indoor games is also likely to be important. Poor weather conditions, especially snow, are likely to cause problems for travelers attending a sporting event. Nice weather may also impact the decision to attend a sporting event as beautiful days may lead consumers to pursue outdoor activities other than attending a game. As weather may pose a cost to those thinking of attending a game, weather was tested to see if it plays a significant role in attendance at major sporting events. If weather factors do systematically influence attendance, including it in a forecast model can help teams better forecast game-night attendance, which can help the teams and contractors in setting up the optimal levels of arena, security, and concession staff, as well as reaching the optimal quantity of food preparation and readiness, etc. that goes on in the arenas not only during the game, but also before the game actually starts. This provides the fans with a better overall experience, on average, without wasteful over-staffing and excess food waste when fewer than anticipated fans show up, or the problems associated with under-staffing and running out of popular food items when attendance surprises to the upside. In addition, with the use of dynamic pricing, teams can alter prices in anticipation of weather conditions to influence fan attendance and improve ticket revenues.

This study tested the role of weather on NBA attendance expressed as a percentage of arena capacity. All NBA games in the sample were played indoors and weather was included in OLS and Tobit models as independent variables in the form of individual factors (temperature, humidity, snow, precipitation, barometric pressure) and in the form of clusters through a k-means process. The number of clusters were determined by the use of the elbow method and confirmed through the silhouette method. Tobit models were used due to multiple sellouts of games in the sample.

In all specifications where the weather variables were included as separate independent variables, control variables for team performance, game attributes, day of the week, and home and road team dummies were used. In these model specifications, fans were shown to prefer more successful teams as higher win percentages entering a game led to more fans in attendance. Weekday dummies revealed expected results as weekend days had more fans in attendance for NBA games. The betting market total was shown to have a positive and significant effect on attendance as fans preferred expected higher-scoring games. In terms of individual game quality, two models were shown. One model used the absolute value of the point spread and a dummy for home favorites. In these model specifications, the absolute value of the point spread was shown to have a positive and significant effect, which does not support the predictions of the uncertainty of outcome hypothesis. The home favorite dummy, however, was positive and significant implying that fans prefer to attend games when the home team is expected to win. The alternative model for individual game quality used an interaction of the home team dummy with the absolute value of the point spread and a road team dummy with the absolute value of the point spread to allow for asymmetry of views of expected closeness of a game. The first variable (home team dummy interacted with absolute value of the point spread) was shown to have a positive and significant effect on attendance, while the second variable (road team dummy interacted with the absolute value of the point spread) was shown to have a negative and significant effect. In this specification, it can be seen that fans prefer to attend games where the home team is more likely to win, while if the home team is likely to lose, they prefer to see a close game rather than an expected blowout.

In terms of the key variables of interest in the paper, the impacts of weather, in the model using the individual weather factors, temperature was shown to have a positive and significant effect on attendance. Fans preferred to attend NBA games in warmer weather (avoiding the cold) and on higher pressure days which typically relate to less sluggishness. Humidity and snow (precipitation overall was statistically insignificant) were both shown to have a negative and significant effect on attendance as humidity made venturing out of the home to the game less enticing and snowfall acted as a significant deterrent to traveling to and from the arena. Therefore, even for indoor games, weather conditions appear to impact attendance, as measured by percentage of capacity, which is important for arena operators when determining various game day policies and actions.

In an alternative approach, machine learning was used to group the weather conditions into clusters. Statistically significant and similar results were found in the Tobit model, but not in the restricted sample OLS model and only to a limited extent (likely due to games with heavy snow conditions) in the general OLS model. While the clustering approach may be useful in situations involving weather, more research is needed to ascertain its potential value.

Table 6: OLS and Tobit Model Regression Results Using Weather Clusters

Variable	I - OLS	II – OLS (Restricted)	III - Tobit
Intercept	-0.3246***	-0.4758***	-0.3890***
	(-7.5021)	(-7.2101)	(-9.0041)
Win Percentage	0.0821***	0.0943***	0.0223***
	(10.5787)	(6.9522)	(14.7715)
ABS(Point Spread)	0.0024***	0.0030***	0.0055***
	(6.2885)	(4.3143)	(8.1766)
Home Favorite Dummy	0.0369***	0.0337***	0.0826***
	(8.1893)	(5.0467)	(16.7627)
Total	0.0005***	0.0010***	0.0005***
	(2.9667)	(3.6834)	(2.6561)
Sunday	-0.0121***	-0.0150**	-0.0326***
	(-3.9880)	(-2.2642)	(-4.0777)
Monday	-0.0420***	-0.0660***	-0.0901***
	(-10.7302)	(-9.8627)	(-12.3200)
Tuesday	-0.0374***	-0.0707***	-0.0802***
	(-8.8496)	(-9.1801)	(-10.0277)
Wednesday	-0.0368***	-0.0547***	-0.0779***
	(-10.4030)	(-8.6949)	(-11.6046)
Thursday	-0.0180***	-0.0367***	-0.0340***
	(-4.4551)	(-4.2066)	(-10.0277)
Saturday	0.0117***	0.0241***	0.0328***
	(4.0935)	(4.0390)	(4.3208)
Weather Cluster 1	-0.0046	-0.0032	-0.0220***
	(-1.2957)	(-0.4789)	(-2.9756)
Weather Cluster 2	-0.0068	-0.0033	-0.0317***
	(-1.4000)	(-0.3719)	(-3.6737)
Weather Cluster 3	-0.0039**	-0.0054	-0.0371***
	(-2.3115)	(0.4686)	(-4.5995)
Weather Cluster 4	0.0043	0.0108	-0.0056
	(0.9145)	(1.2423)	(-0.6877)
Home Team Dummies	Yes	Yes	Yes
Road Team Dummies	Yes	Yes	Yes

Dependent Variable: Attendance Expressed as Percentage of Arena Percentage
*-significant at the 10% level, **-significant at the 5% level, ***-significant at the 1% level

Table 7: OLS and Tobit Model Regression Results Using Weather Clusters – Alternative Specification

Variable	I - OLS	II – OLS (Restricted)	III – Tobit
Intercept	-0.3191***	-0.4887***	-0.3919***
	(-7.7461)	(-7.7399)	(-9.2714)
Win Percentage	0.1049***	0.1362***	0.2674***
	(11.2407)	(8.2782)	(18.7157)
Home Favorite Dummy	0.0047***	0.0064***	0.0112
*ABS(Point Spread)	(9.7956)	(7.1359)	(16.7222)
(1-Home Favorite Dummy)	-0.0037***	-0.0035***	-0.0083***
*ABS(Point Spread)	(-4.8131)	(-3.0169)	(-8.8860)
Total	0.0006***	0.0011***	0.0006***
	(3.2355)	(4.0563)	(3.1305)
Sunday	-0.0122***	-0.0164**	-0.0339***
	(-4.0635)	(-2.5047)	(-4.3152)
Monday	-0.0423***	-0.0681	-0.0920***
	(-10.8888)	(-10.2334)	(-12.8043)
Tuesday	-0.03774***	-0.0718***	-0.0818***
	(-8.9918)	(-9.4605)	(-10.4107)
Wednesday	-0.0369***	-0.0563***	-0.0787***
	(-10.4605)	(-8.9953)	(-11.9152)
Thursday	-0.0190***	-0.0384***	-0.0373***
	(-4.7935)	(-4.5043)	(-4.0888)
Saturday	0.0121***	0.0238***	0.0336***
	(4.1955)	(3.9805)	(4.5054)
Weather Cluster 1	-0.0046	-0.0040	-0.0231***
	(-1.3209)	(-0.6085)	(-3.1867)
Weather Cluster 2	-0.0056	-0.0030	-0.0307***
	(-1.2387)	(-0.3455)	(-3.6284)
Weather Cluster 3	-0.0085**	-0.0069	-0.0383***
	(-2.2118)	(-0.9436)	(-4.8419)
Weather Cluster 4	0.0044	0.0105	-0.0062
	(0.9446)	(1.2428)	(-0.7742)
Home Team Dummies	Yes	Yes	Yes
Road Team Dummies	Yes	Yes	Yes

Dependent Variable: Attendance Expressed as Percentage of Arena Percentage
*-significant at the 10% level, **-significant at the 5% level, ***-significant at the 1% level

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Appendix: New Weather Clusters Using only Non-Sellout Games

Table 8: Cluster Means for Weather-Related Variables for Non-Sellout Games

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
# Observations	772	538	605	752	517
Temp	52.33	47.51	63.04	39.26	24.36
Humidity	62.38	42.96	80.73	82.62	61.75
Snow	0.001	0.000	0.000	0.266	0.450
Pressure	30.05	30.10	29.97	29.99	30.18

Table 9: Weather-Related Cluster Descriptions for Non-Sellout Games

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Mid Temp	Mid Temp	High Temp	Low Temp	Very Low Temp
Mid Humidity	Low Humidity	High Humidity	High Humidity	Mid Humidity
Low Snow	No Snow	No Snow	High Snow	Very High Snow
Mid Pressure	Mid Pressure	Low Pressure	Low Pressure	High Pressure

Table 10: OLS Regression Results Using Weather Clusters for Non-Sellout Games

Variable	I – OLS – New Clusters
Intercept	-0.4790***
	(-6.0614)
Win Percentage	0.0952***
	(6.9294)
ABS(Point Spread)	0.0030***
	(3.8803)
Home Favorite Dummy	0.0337***
	(4.2725)
Total	0.0010***
	(3.0429)
Sunday	-0.0154**
	(-2.2899)
Monday	-0.0663***
	(-9.7387)
Tuesday	-0.0711***
	(-8.9799)
Wednesday	-0.0551***
	(-8.5293)
Thursday	-0.0367***
	(-4.2432)
Saturday	0.0234***
	(3.9732)
Weather Cluster 1	0.0085
	(1.0130)
Weather Cluster 2	0.0161*
	(1.7865)
Weather Cluster 3	0.0045
	(0.4953)
Weather Cluster 4	0.0026
	(0.3041)
Home Team Dummies	Yes
Road Team Dummies	Yes

Dependent Variable: Attendance Expressed as Percentage of Arena Percentage
*-significant at the 10% level, **-significant at the 5% level, ***-significant at the 1% level

Housing Finance and Real Activity Over the Business Cycle

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Abstract

This study examines the influence of financial stabilization efforts on monetary policy effectiveness over the Great Recession business cycle for the housing sector. In a time-varying factor-augmented vector autoregression with stochastic volatility, bank mortgages respond procyclically to a monetary contraction, while some nonbank mortgages show countercyclical increases. Stability measures put in place after the Great Recession appear to help agency securitized mortgages increase following a monetary tightening. Housing indicators appear less influenced after the Great Recession. These findings suggest a limit to the ability of monetary policy to achieve economic stability following efforts to regain financial stability.

JEL Codes: E44, G20
Keywords: Monetary Policy, Mortgage Finance, Housing, Great Recession, TVP-FAVAR-SV

Introduction

The question of monetary policy's influence on macroeconomic activity through credit markets is of renewed interest since the recent financial crisis. Prior to the crisis, it was argued that a stable macroeconomy achieved through monetary policy actions provided sound financial conditions for well-functioning credit markets without the need to provide liquidity or enact regulations to prevent credit excesses. However, it was found that "beneath the still waters of macroeconomic stability […], deadly whirlpools of financial imbalances were forming" (Menon, 2015).

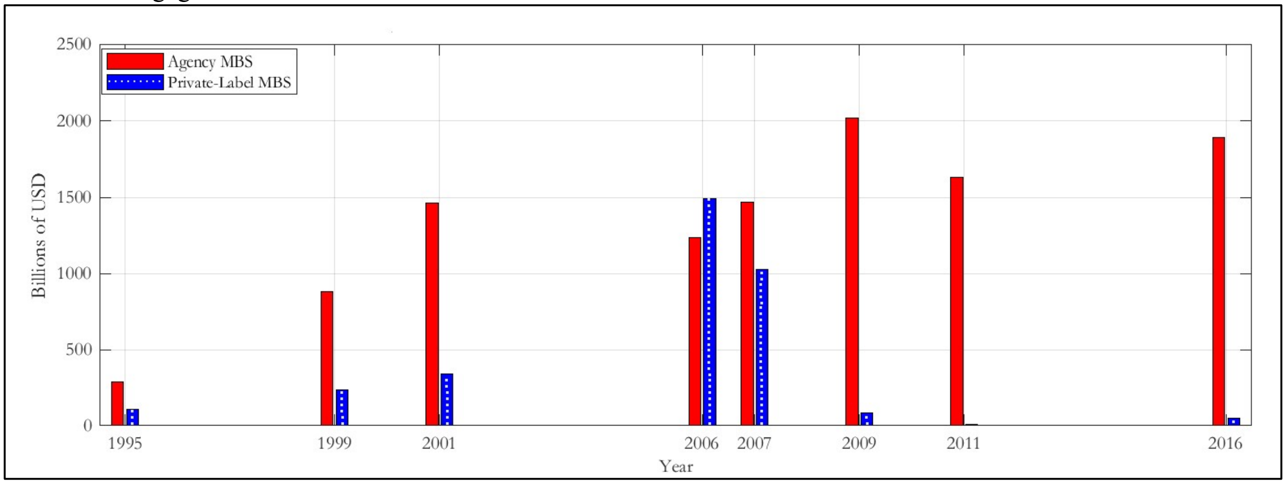
In the run up to the Great Recession, policymakers at the Federal Reserve prioritized macroeconomic stability over financial stability despite the growth in mortgage-related securities used to finance housing activity (see Figure 1) and the need for stable credit markets for effective monetary policy. Moreover, the different tools used to help achieve the two Fed stability missions essentially allowed policymakers to silo one function from the other (Praet, 2014). Yet the events of the Great Recession that centered on the vital housing sector and its interconnected credit markets along with the Federal Reserve's policy response show that macroeconomic and financial stability are, in fact, interlinked.

An important yet understudied question asks if efforts to stabilize the financial system weaken the effectiveness of monetary policy actions. The crisis response by the Federal Reserve to help shore up fragile housing credit markets and the macroeconomy places the central bank as the largest holder of mortgage-related securities (mortgage-backed securities or MBS) at over $1.78 trillion MBS outstanding at the end of 2017 according to its Flow of Funds data when the institution previously held none.[1] Moreover, the intervention by the government with the assistance of the Federal Reserve in government-sponsored enterprises (GSEs or agencies comprised of Fannie Mae, Freddie Mac, and Ginnie Mae) ensures GSE solvency through provided liquidity and guarantees on GSE debt obligations. Such a fundamental shift in the Federal Reserve's holdings of MBS and government involvement with the GSEs creates a unique opportunity to study linkages in housing credit and housing economic activity.

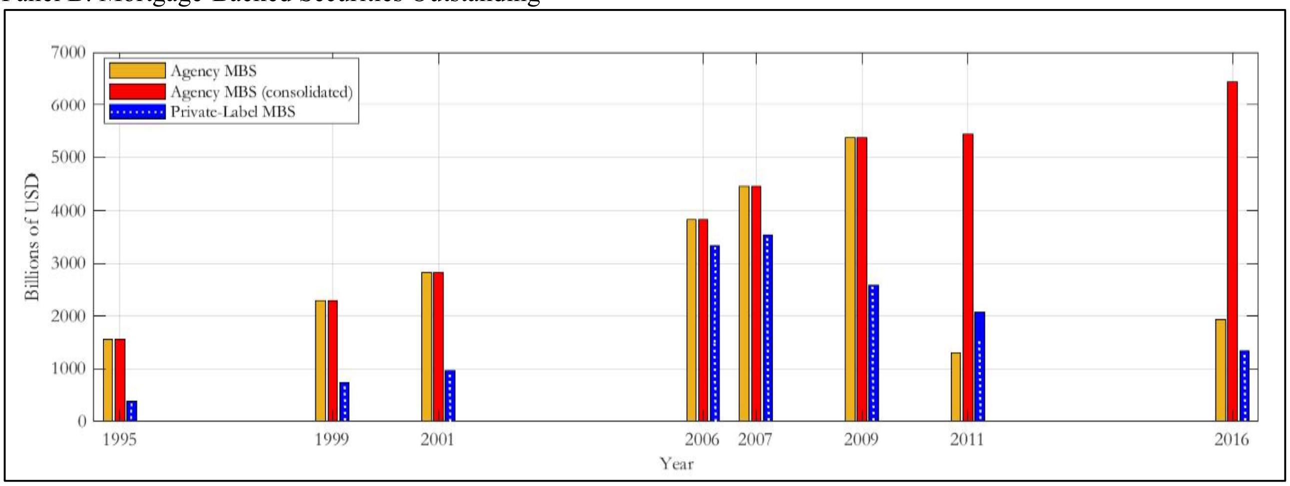
In this paper, the transmission of monetary policy changes is analyzed on different channels of mortgage credit comprised of banks, nonbanks that do not accept deposits, and funding from agency and non-agency (private-label) mortgage-related securities. In turn, the influence on housing market indicators of economic activity is investigated. The differentiation between bank and nonbank channels of transmission and within the nonbank channels has had limited investigation for the time period surrounding the Great Recession. As monetary policy affects funding markets of financial institutions differently (e.g., Altunbas et al., 2009), subsequent non-uniform responses of lenders' mortgage volumes are expected. This suggests that nonbank channels can influence monetary policy and macroeconomic fluctuations over the business cycle. This concept is explored in the responses of residential and commercial investment, housing prices, and building starts comprising housing market indicators from changes in mortgage credit and MBS markets. The housing sector (real estate, rental and leasing) is the largest industry contributor to U.S. GDP in 2021 at nearly 18 percent according to the Bureau of Economic Analysis.

The unprecedented and uncertain effects of financial stability policies on a monetary tightening after the Great Recession may have undesirable outcomes for housing activity in the economy. Not only do capital market participants have to consider the Federal Reserve increasing its target policy rate, but they must also determine the result of a slowdown or selloff of agency MBS when the Federal Reserve controls nearly 30 percent of all agency MBS outstanding according to the Board of Governors of the Federal Reserve System data. In general, scholars note that the severity of the recent crisis was driven by increased uncertainty that led to illiquidity in several sectors more so than deterministic risk related to loan defaults (see, e.g., Brunnermeier, 2009). In these studies, uncertainty from a monetary policy contraction is predicted to affect regulated institutions more because regulation and intense monitoring raise funding costs, particularly during recessions.

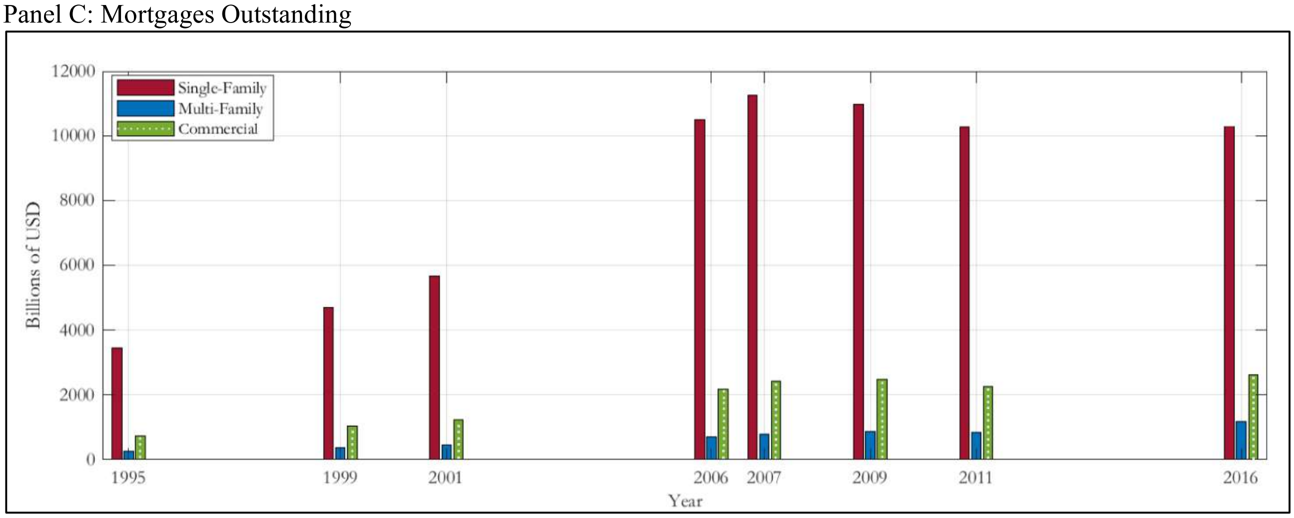
Figure 1: Mortgage-Related Securities Issuance and Outstanding
Panel A: Mortgage-Backed Securities Issuance



Panel B: Mortgage-Backed Securities Outstanding



Panel C: Mortgages Outstanding



Notes: Securitized mortgage data come from the Federal Reserve Flow of Funds and Securities Industry and Financial Markets Association. Issuance volumes for private-label securitized mortgages begin in 1996Q4. Consolidated agency mortgages result from accounting rule changes in the 2010Q1. Mortgage data by loan type come from the Federal Reserve Flow of Funds.

To investigate the above issues, the framework adopted accounts for the complexity of interactions across (bank and nonbank) mortgage credit markets and linkages to economic activity. A time-varying parameter factor-augmented vector autoregression with stochastic volatility (TVP-FAVAR-SV) model features varied parameter behavior under different and uncertain macroeconomic conditions over the business cycle. The period considered, 1965– 2016, allows for comparisons of responses to monetary policy changes before, during, and after the 2007–2009 financial crisis. A shadow policy rate developed by Bauer and Rudebusch (2016) summarizes the Federal Reserve's unconventional monetary policy moves and justifies the use of a policy rate to capture the monetary policy stance at the zero lower bound for a few years over the estimation period. The comprehensive data set for the TVP-FAVAR-SV model dynamically measures real activity, prices, money and interest rates, and mortgage credit volumes. By addressing the non-uniform responses of the different financial institutions among nonbanks using the TVP-FAVAR-SV model, the estimation expands on the real business cycle model of Nelson et al. (2018). The current estimation also extends the Leu and Robertson (2021) study on the effects of the Federal Reserve's normalization policy (i.e., reversal of unconventional policy actions after the recovery from the Great Recession) on mortgage finance in a TVP-FAVAR-SV model by presenting a fuller picture of the housing sector in the time period surrounding the Great Recession. In the current study, the responses of housing indicators along with mortgage finance are estimated over the business cycle.

The results suggest important channels of monetary policy shocks that affect the macroeconomy through the housing sector. An increase in the shadow policy rate that proxies for an increase in the federal funds rate and sale of MBS to capital markets results in shifts in mortgage credit availability from regulated banks to some but not all less monitored nonbanks considered in this study. Over three key time periods surrounding the Great Recession (2006, 2009, and 2015), depository institution (commercial banks and credit unions) and nonbank life insurance company mortgages behave procyclically and decrease following a monetary tightening, while finance company and private pension fund mortgages show countercyclical increases. Over the business cycle, the expected fall in housing starts and residential fixed investment is smaller in magnitude after the Great Recession following a tight monetary policy stance, and mortgage rates experience incomplete pass-through. Less effective monetary policy actions on housing finance markets and real activity indicators coincide with available mortgage funding from the rise in agency MBS. In contrast, mortgage funding is not provided through private-label MBS markets. The findings are consistent with intervention in agency MBS markets by the Federal Reserve as part of stability policy creating a net-zero total liquidity change through monetary policy changes in nonbank lending, even after the onset of the financial crisis. This paper contends the availability of relatively cheap nonbank mortgage credit is a partial reason for the predicted ongoing rise in housing prices through 2019 despite higher mortgage rates (Yale, 2018).

This paper's focus on the housing sector is shared by other studies. For example, Leamer (2007) also advocates that housing volumes are important indicators in the economy as a change in housing starts is perceived to be a good forward-looking indicator of the business cycle. Consequently, any central bank's attempt to control the business cycle should focus on how stability measures in nonbank financial institutions and markets mitigate monetary policy effects on housing through mortgage credit market liquidity.

The rest of the paper is organized as follows. The next section discusses the literature that directly relates to monetary policy, securitization, and interconnected stability issues within the housing sector. This next section also provides the theoretical explanations that underpin the hypotheses. Afterward, the paper describes the data used in the empirical analysis and summarizes the TVP-FAVAR-SV model followed by a section reporting the results from the estimated model for different components of the housing sector. The policy implications are discussed in the last section, which also concludes the paper.

Related Literature and Tested Hypotheses

A well-functioning housing sector, including liquid mortgage funding markets, is vital to the overall stability of the economy. The sudden decrease in mortgage funding that began in 2006 jeopardized housing-related activity comprising the largest sector of the U.S. economy. Despite this fact, an under-investigated topic is how the Federal Reserve's path of tightening following stability actions taken to recover from the economic downturn influences interconnected bank and nonbank mortgage credit markets funding housing activity. The literature has established the benefits to liquidity from large-scale purchases of MBS and associated agency debt along with lending to systemically important financial institutions and markets (see, e.g., Egly et al., 2016). Yet of the handful of studies exploring the interaction of monetary and financial stabilities policy actions, most examine the ability of monetary policy to promote financial stability (Bauer and Granziera, 2017). In contrast, the focus of this study on the effects of existing stability policies on monetary policy effectiveness has received less attention in the literature. Moreover, the analysis here concentrates on housing credit and activity that prompted the economic and financial stability responses.

In the related studies examining the effects of a monetary contraction on loan and nonbank funding channels, most document that the securitized assets (mortgages and other loan types) used by lenders eases their funding constraints (Bedendo and Bruno, 2009; Loutskina, 2011; Loutskina and Strahan, 2009; Nini, 2008). Over the business cycle and across the different types of financial institutions, securitized assets funding liquidity helps both banks and nonbanks maintain loan volumes to varying degrees during economic downturns (Kuttner, 2000; Minton et al., 1997). Schnure (2005) finds that the non-deposit or market-based housing finance system comprised mostly of MBS dampens swings in mortgage credit flows, real housing activity, and housing prices aiding economic stability in the period prior to the recent financial crisis known as the Great Moderation. During the 2007–2009 financial crisis, however, Gambacorta and Marqués-Ibanéz (2011) note that banks more exposed to market-based funding and volatile non-interest income activities cut back on general loans to a greater extent. As is suggested in this paper, Altunbas et al. (2009) surmise that relatively less lending during crises is most likely due to increased uncertainty on the part of securitized asset investors.

Three studies consider unconventional monetary policy effects on liquidity and pricing indicators in housing markets do so from an expansion angle. Specifically, Gabriel and Lutz (2015) use a similar FAVAR empirical framework as in this study to show that a monetary easing lowers mortgage rates and insurance costs of relatively more highly-rated but low-quality (i.e., subprime) mortgage-related debt. Similarly, Chiang et al. (2015) find that the added liquidity associated with a monetary easing helps housing starts to positively influence investment spending on single-family structures between 2005 and 2012. A liquidity measure based on GSE activities is found to be a key channel of transmission. In Huber and Fischer (2018), some differences exist in the increase in housing starts following expansionary monetary policy as the rise in housing starts is less during economic downturns compared to expansions.

Over the past few years, heavy regulation of bank capital and liquidity to stabilize the financial system has created opportunities for nonbanks to gain a dominant share of the housing mortgage sector.[2] Thus, this study considers interconnectedness within the nonbank finance sector and linkages to broader financial markets among the different types of institutions because of the minimal prescriptive research that exists on this topic. A handful of studies related to this paper examine securitized asset issuers and other nonbank institutions at the aggregate level to address how the nonbank finance system affects the reaction of loan volumes to monetary policy changes, and nonbanks typically combine securitization transactions and other non-depository institutions (Adrian and Shin, 2008).

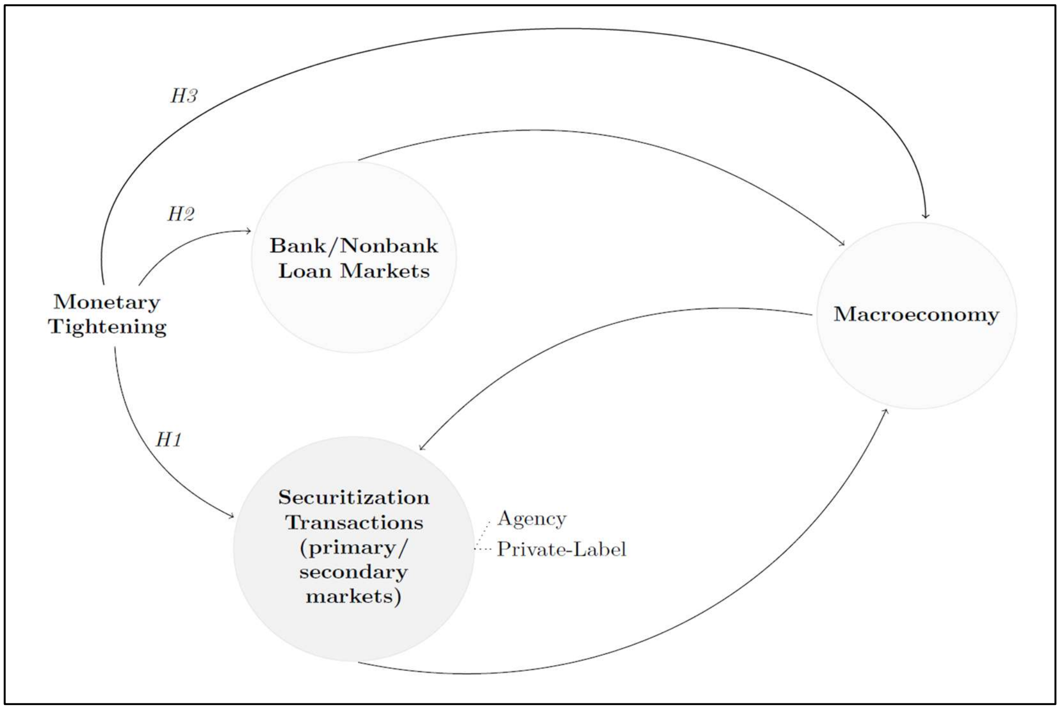
In a VAR model for the period before the Great Recession, Nelson et al. (2018) find that a monetary contraction negatively impacts commercial bank assets while those of nonbanks and securitized assets are positively affected. The authors suggest that securitized asset markets create gaps in monetary policy's effectiveness to slow lending, which hurts policymakers' objectives to pursue financial stability over the business cycle uniformly. Similarly, the VAR study of den Haan and Sterk (2010) show that residential mortgages of banks (nonbanks) tend to fall (rise) following a monetary tightening prior to the recent financial crisis. Pescatori and Solé (2016) also show that an increase in the monetary policy rate slows the growth of bank total mortgages and housing prices. As does this study, the authors distinguish between types of MBS but document different results in that agency (private-label) securitized assets decrease (increase) following a monetary tightening before the recent financial crisis. Nonbanks and changes in GSE holdings are targeted in a discussion of the potential causes of rising systemic instability. Over a similar time period, Igan et al. (2013) find procyclical, steep declines in commercial bank mortgages and securitizers' holdings (along with housing market indicators) relative to holdings of money-market mutual funds with access to repurchase funding. Closest to the empirical approach of a TVP-FAVAR-SV model estimated with a shadow policy rate over the years surrounding the Great Recession is Leu and Robertson (2021) who similarly find procyclical (countercyclical) responses of bank (nonbank) loans following a monetary tightening. To complement these findings, this study takes a more comprehensive approach of the macroeconomy to examine interconnections among mortgage lenders and markets, primary and secondary securitization markets, and housing market indicators.

Theoretically, these empirical studies rely on a transmission path of monetary policy through the financial health of banks as borrowers on capital markets and banks' perceived financial condition to lenders as described in Disyatat (2011). Lending volumes and terms of credit faced by banks' borrowers are thus determined by how monetary policy actions influence external funding costs of banks (Bernanke, 2007; Kashyap and Stein, 1995). Relatedly, Borio and Zhu (2012) rightly point out that more attention is needed on the interlinkages between monetary policy and economic agents' participation in funding markets. They argue that their research on monetary policy and funding markets adds to the prevailing macroeconomic paradigms that may not adequately capture connections in order to guide monetary policy decisions. The limited research is noticeable given that monetary policy changed dramatically after the recent financial crisis.

From a business cycle perspective, it is important to understand whether monetary policy shocks transmit through the shadow banking system under different economic conditions (Adrian and Shin, 2014). A monetary tightening could create a downward spiral due to the slowdown in home sales and private investment, causing home prices and new construction to fall as well as commercial development. Following this line of reasoning, issuance volumes should decline in securitized capital markets, unless the GSEs increase liquidity through agency issuance. Therefore, for the periods studied surrounding the Great Recession, a monetary tightening should make borrowing more expensive for individuals and corporations unless there is a shift towards the shadow banking system that includes nonbank loans and securitization transactions. Figure 2 captures the channels of monetary policy transmission that affect the shadow banking and housing sector. Financially interconnected segments in mortgage credit markets are comprised of banks, nonbanks, and securitization transactions.

The first set of hypotheses examines whether liquidity increases to the housing sector through the primary (issuance) and secondary (outstanding) MBS credit markets. In the few years before the Great Recession, the economy can be characterized by heightened private-label and agency activity in MBS markets as shown in Figure 1, a stable macroeconomy, and conventional policymaking by the Federal Reserve. After the onset of the recent financial crisis, the Federal Reserve becomes heavily involved in agency MBS and debt markets with its Large-Scale Asset Purchase (LSAP) program, which lower longer-term interest rates and ease financial conditions through direct purchases of high-quality agency MBS, agency debt, and long-term Treasury securities (Gagnon et al., 2011). Also, the government enacts a partial takeover of the GSEs through the Treasury Department. After the official end of the Great Recession in 2009, the Federal Reserve continues with its LSAP program with additional rounds of asset purchases. The analysis considers if investors are willing to buy private-label MBS following a monetary contraction over key time periods surrounding the Great Recession. For secondary MBS capital markets measuring net liquidity, the analysis also examines to what extent does GSE activity through the LSAP program induce investors to buy private-label MBS despite a contractionary monetary policy stance.

Figure 2: Hypothesis Testing Diagram



Notes: The figure shows the tested hypotheses among interrelated mortgage credit and housing markets. In this simplified monetary transmission diagram, policy actions may influence bank/nonbank mortgage and securitized mortgage capital markets. Following a monetary tightening (i.e., an increase in the monetary policy rate) the three hypotheses tested are H1: transactions in the primary and secondary securitized capital markets established to promote liquidity among mortgage markets; *H2*: bank and nonbank mortgage lending; and *H3*: housing market indicators including mortgage rate spreads and housing starts.

H1A: Issuance and outstanding volume of agency MBS increase over key time periods in response to a monetary tightening.
H1B: Issuance and outstanding volume of private-label MBS maintain levels or decrease over key time periods in response to a monetary tightening.

The second set of hypotheses predicts that bank and nonbank mortgage credit markets have independent effects across the housing sector. If GSE activity successfully breaks down the relationship between monetary policy actions and mortgage interest rates, the cost of financing to households and corporations would not depend on the stance of monetary policy. As a result, a tightening associated with a rise in the shadow policy rate would not decrease lending or lower the value of collateral used to secure lending.

H2A: The outstanding volume of bank residential and commercial mortgages decreases over key time periods in response to a monetary tightening.
H2B: The outstanding volume of nonbank residential and commercial mortgages increases or remains constant over key time periods in response to a monetary tightening.

To account for any effects on the macroeconomy, the third set of hypotheses determines if activity in MBS markets that would lead to increases in mortgage volumes also distorts housing sector indicators by increasing builders' housing starts and permits, private residential fixed investment, and lowering mortgage rate spreads.

H3A: Mortgage interest rate spreads decline over key time periods in response to a monetary tightening.
H3B: Housing starts, permits, and private residential fixed investment increase or remain constant over key time periods in response to a monetary tightening.
H3C: Housing prices rise over key time periods in response to a monetary tightening.

The Federal Reserve's intent of monetary policy actions is to maintain an economic path of stable growth, low inflation, and mitigated fluctuations through functioning financial markets. One of the key factors at the heart of the Great Recession was poorly functioning bank and nonbank funding markets relying on MBS as collateral (Gorton and Metrick, 2012). Therefore, even when regulated banks are required to be adequately capitalized to, in part, promote fully functioning financial markets, the financial system may still not be sufficiently resilient if a policy rate change does not influence funding in mortgage credit markets that are part of the broader nonbank credit system. If a monetary tightening has limited impact on nonbank mortgage funding in particular, the lack of response is concerning since it could lead to financial instability. The empirical analysis through the above hypotheses that address these issues emphasizes the links among monetary policy, the GSEs, mortgage credit markets, and the macroeconomy.

Data and Methodology

Shadow Policy Rate and Data

To account for the recent financial crisis, Bauer and Rudebusch (2016), among other researchers, construct a shadow policy rate to help identify the stance of monetary policy at the zero lower bound from 2008 to 2015. The commonly used proxy of the effective federal funds rate might not adequately reflect changing economic conditions in the recent zero lower bound environment. Unconventional monetary policy tools used by the Federal Reserve to lower interest rates in specific markets such as large-scale asset purchases and its communicative strategy of forward guidance at times generates a negative real effective rate referred to as the shadow policy rate. What differentiates the Bauer and Rudebusch (2016) shadow short rate from other rates developed in the zero lower bound environment is the addition of macroeconomic variables to a series of forward rates in dynamic term structure models used to estimate the latent factors capturing the driving forces behind interest rate movements. The purpose is to give plausible measures of rates faced by market participants.

The estimated TVP-FAVAR-SV model uses 197 data series (including the shadow policy rate) over a sample period from 1965Q1 to 2016Q4. Two main sites provide most of the series: the Federal Reserve Economics Database (FRED) and IHS Global Insight. Of the 197 data series, 110 cover measures of real activity, prices, credit measures, money aggregates, and interest rates. Standard measures are included in each category here. Real activity series include industrial production, personal and government expenditures, employment, housing, and manufacturing measures. Price indicators capture wages, consumer and producer prices, expenditure indices, and forward-looking stock and commodity prices. Credit series cover loans, consumer, trade, and security credit to firms and households extended by banks and nonbanks along with loan lending rates and spreads. Lastly, money and interest rate series are comprised of money stock measures, risk-free Treasury rates, and interest rate spreads.

The remaining 87 series summarize housing activity. Housing quantities and prices make up regional and aggregated indicators. Single-family, multi-family, and commercial markets comprise the mortgage market sector for different types of institutions. Banks are classified as U.S.-chartered depository institutions and credit unions, while nonbanks include finance and insurance companies, pension funds, and nonfinancial noncorporate businesses (i.e., sole proprietorships and limited partnerships).

Data from the Federal Reserve Flow of Funds and the Securities Industry and Financial Markets Association (SIFMA) are used to construct indicators for MBS outstanding volumes in secondary markets for the three markets described above (single-family, multi-family, and commercial). MBS issuance volumes in primary markets are only available by type of issuer: agency and private label.

The data are pre-processed in several steps for use in the TVP-FAVAR-SV model. When needed, the series are seasonally adjusted and converted to quarterly data for series with different frequencies. Factor analysis in the estimated model assumes stationarity in the series, which are then demeaned and standardized. Outliers in the transformed series as defined in McCracken and Ng (2020) with observations that deviate from the sample median by more than ten interquartile ranges are removed and treated as missing values. Finally, missing values in individual data series are re-populated following the McCracken and Ng (2020) EM algorithm. A full list of data sources, their descriptions, and transformation methods is presented in the online Appendix.

Empirical Methodology

The empirical framework used to examine the effects of policy rate changes on housing finance and housing indicators is a TVP-FAVAR-SV model that incorporates time-varying coefficients and stochastic volatility in the shocks as developed by Mumtaz (2010).[3] There are several advantages of this model used to study monetary policy actions. The large data set provides comprehensive information on macroeconomic activity, which creates less potential for omitted variable bias sometimes found in a conventional VAR setup. A conventional VAR may also suffer from a degrees-of-freedom problem with too many variables. Estimated factors presented below help reduce information in several variables into a few data series. However, the estimated factors often lack any economic interpretation such as a real activity or price factor proxied by an individual data series in a conventional VAR (Belviso and Milani, 2006).

Including time variation in the parameters allows for evaluation of the effects of policy rate changes simultaneously on different mortgage credit markets and housing indicators under different macroeconomic conditions over the business cycle. The added advantage of time-varying parameters avoids questionable assumptions found in a fixed-coefficient FAVAR approach over a long estimation period in which key structural relationships among macroeconomic variables do not change over the business cycle or that time series show no signs of instability (McConnell and Perez-Quiros, 2000; Stock and Watson, 1996). Despite these advantages of estimating time-varying parameters, there is a risk of overfitting as not all of the parameters may vary over time (Bitto and Frühwirth-Schnatter, 2019).

To develop the TVP-FAVAR-SV model, Equations (1) and (2) below present a (constant parameter) FAVAR model consisting of a factor model and a VAR model, respectively. A factor model summarizes the information in the large number of relevant data series to this study into a small number of common factors, and a VAR model captures the dynamics of the economy represented by the common factors. This gives

$$X_{i,t} = \Lambda_i Z_t + e_{i,t},\ e_{i,t} \sim N(0,R), \tag{1}$$

$$Z_t = c_t + \beta_1 Z_{t-1} + \ldots + \beta_L Z_{t-L} + u_t,\ u_t \sim N(0,U), \tag{2}$$

where $X_{i,t}$ for $i = 1, \ldots, N$ is a panel of observed variables over time period $t = 1, \ldots, T$. The common factors Z_t that summarize information in the large data set $X_{i,t}$ consist of $M = 1, \ldots, m$ unobserved factors $F_t = F_t^{\,1}, \ldots, F_t^{\,m}$ and the observed policy instrument PR_t. As in Bernanke et al. (2005), the shadow policy rate variable is assumed to be observed as policymakers use numerous data series to track economic activity and enact monetary policy. There are $M + 1 = K \ll N$ common factors that relate to the large data set $X_{i,t}$ through the factor loading matrix Λ_i. The idiosyncratic disturbances $e_{i,t}$ in the factor equation (1) have a covariance matrix R assumed to be diagonal.

The VAR equation (2) is written in $Z_t = [F'_t, PR_t]'$ of dimension $K \times K$. Other components of the VAR include the $K \times 1$ vector of constant terms c_t, the vector of disturbances u_t with a covariance matrix of U, and the $K \times K$ coefficient matrix β_j for $j = 1, \ldots, L$. Structural shocks in Equation (1) relate to the reduced-form shocks in Equation (2) through a structural matrix A_0 in $\epsilon_t = A_0 u_t$.

Time variation enters the model through the coefficients and the disturbance terms in the VAR equation (2). In state-space notation, the observation equation for the TVP-FAVAR-SV model is written as

$$X_t = \Lambda^F F_t + \Lambda^{PR} PR_t + e_t,\ e_t \sim N(0,R), \tag{3}$$

where $X_t = (X_{1,t}, \ldots, X_{N,t})'$ and $e_t = (e_{1,t}, \ldots, e_{N,t})'$. Loading matrices Λ^F and Λ^{PR} are elements of Λ and are of dimensions $N \times M$ and $N \times\times 1$, respectively. The transition equation is written as

$$Z_t = c_t + \beta_{1,t} Z_{t-1} + \cdots + \beta_{L,t} Z_{t-L} + u_t,\ u_t \sim N(0, U_t)\ . \tag{4}$$

Time-varying coefficients $\beta_{j,t}$ of dimension $K \times\times K$ and c_t are stacked into a K^2L+K-dimension vector $B_t = vec([c_t, \beta_{1,t}, \ldots, \beta_{L,t}]')$. The vector B_t is assumed to follow a random walk process

$$B_t = B_{t-1} + v_t,\ v_t \sim N(0,Q), \tag{5}$$

where the v_t disturbances have a constant variance Q to determine the degree of variability of the coefficients.

In the transition equation (4), vector u_t of $K \times 1$ observable disturbances has an associated covariance matrix U_t and is assumed to be independent of e_t. To identify the structural shocks, the time-varying covariance matrix U_t is factored as

$$U_t = A_t^{-1} H_t (A_t^{-1})' , \tag{6}$$

where a unitriangular matrix A_t has ones along the diagonal. Matrix A_t gives the contemporaneous relationships among the endogenous variables. All non-zero/non-one elements in row i and column j of A_t, $\alpha_{ij,t}$, are stacked in a $0.5K(K\text{-}1)$-dimension vector $\alpha_t = [\alpha\alpha_{21,t},\dots,\alpha\alpha_{K(K-1),t}]'$. Using the structural disturbances defined above as $\epsilon_t = A_0 u_t$, where $\epsilon_t \sim N(0, H_t)$, the diagonal matrix $H_t = diag[h_{1,t}^2,\dots,h_{K,t}^2]$ is comprised of the variances of the structural disturbances on the main diagonal. Row i elements $h_{i,t}$ in the vector $h_t = [h_{1,t}, \dots, h_{K,t}]'$ are the diagonal elements of $H^{0.5}$, which represent the standard deviations of the components of ϵ_t. Matrix H_t captures any changes in the size of the structural shocks.

All non-zero/non-one elements of the A_t and H_t matrices are assumed to evolve as a random walk and a geometric random walk, respectively:

$$\alpha_t = \alpha_{t-1} + \varsigma_t, \quad \varsigma_t \sim N(0,S), \tag{7}$$

$$\ln h_t = \ln h_{t-1} + \eta_t, \quad \eta_t \sim N(0,W). \tag{8}$$

The covariance matrices S and W are assumed to be constant, and the error terms of the time-varying parameters v_t, ς_t, and η_t are uncorrelated.

Identification and Estimation

To estimate the model, the number of unobserved factors used to summarize the relationships in the large data set is limited to two based on the Bai and Ng (2002) criteria.[4] The lag length in the transition equation (2) is set to two $L = 2$ as more lags lead to less precise results. Imposed restrictions on the factors and their loadings in the observation equation (3) help to identify the full model. Specifically, the upper $M \times M$ block of Λ^F (for $M=2$ estimated factors) is an identity matrix for all time periods, and the observed factor PR_t equation is an identity (see Bernanke et al., 2005). Therefore, the observation equation (3) is now

$$\begin{bmatrix} X_{1,t} \\ X_{2,t} \\ \vdots \\ X_{N,t} \\ PR_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ \Lambda_{N,1}^F & \Lambda_{N,2}^F \\ 0 & 0 \end{bmatrix} \begin{bmatrix} F_t^1 \\ F_t^2 \end{bmatrix} + \begin{bmatrix} \Lambda_1^{PR} \\ \Lambda_2^{PR} \\ \vdots \\ \Lambda_N^{PR} \\ 1 \end{bmatrix} [PR_t] + \begin{bmatrix} e_{1,t} \\ e_{2,t} \\ \vdots \\ e_{N,t} \\ 0 \end{bmatrix} . \tag{9}$$

Monetary policy shocks are identified using the Cholesky decomposition of the covariance matrix U_t with the shadow policy rate ordered last as policymakers are able to respond to any changes in economic activity contemporaneously. Following Bernanke et al. (2005), the large data set $X_{i,t}$ is divided into fast- and slow-moving variables. Fast-moving (slow-moving) variables are assumed to (not) respond to monetary policy shocks within the same period, which makes the Λ^{PR} coefficients in the transition equation (3) non-zero for the fast-moving variables.

A shortcoming often discussed in the empirical literature of the Cholesky decomposition approach to identify monetary policy shocks in (FA)VAR models in general is the lack of economic theory in the identification process. One alternative approach uses sign restrictions to determine the contemporaneous relationships among the variables based on causal links found in practice (see, e.g., Ellis et al., 2014). Here, economic-based causal links among a series of shocks is beyond the scope of this study, which focusses on responses of variables in the large data set to only monetary policy shocks.

The TVP-FAVAR-SV model is estimated using the Bayesian method outlined in the online Appendix, which includes the Gibbs sampling algorithm to approximate the joint distribution of the model. A one-step estimation procedure accounts for uncertainty in the model's factors and parameters and is robust to irregularities in the joint likelihood that are common in large cross-sections of data. As a robustness check, the model is estimated based on different prior assumptions given that starting values and prior distributions impact the estimation algorithm. Another check estimates the model with an alternative shadow policy rate. The results are qualitatively similar under the two alternative assumptions.

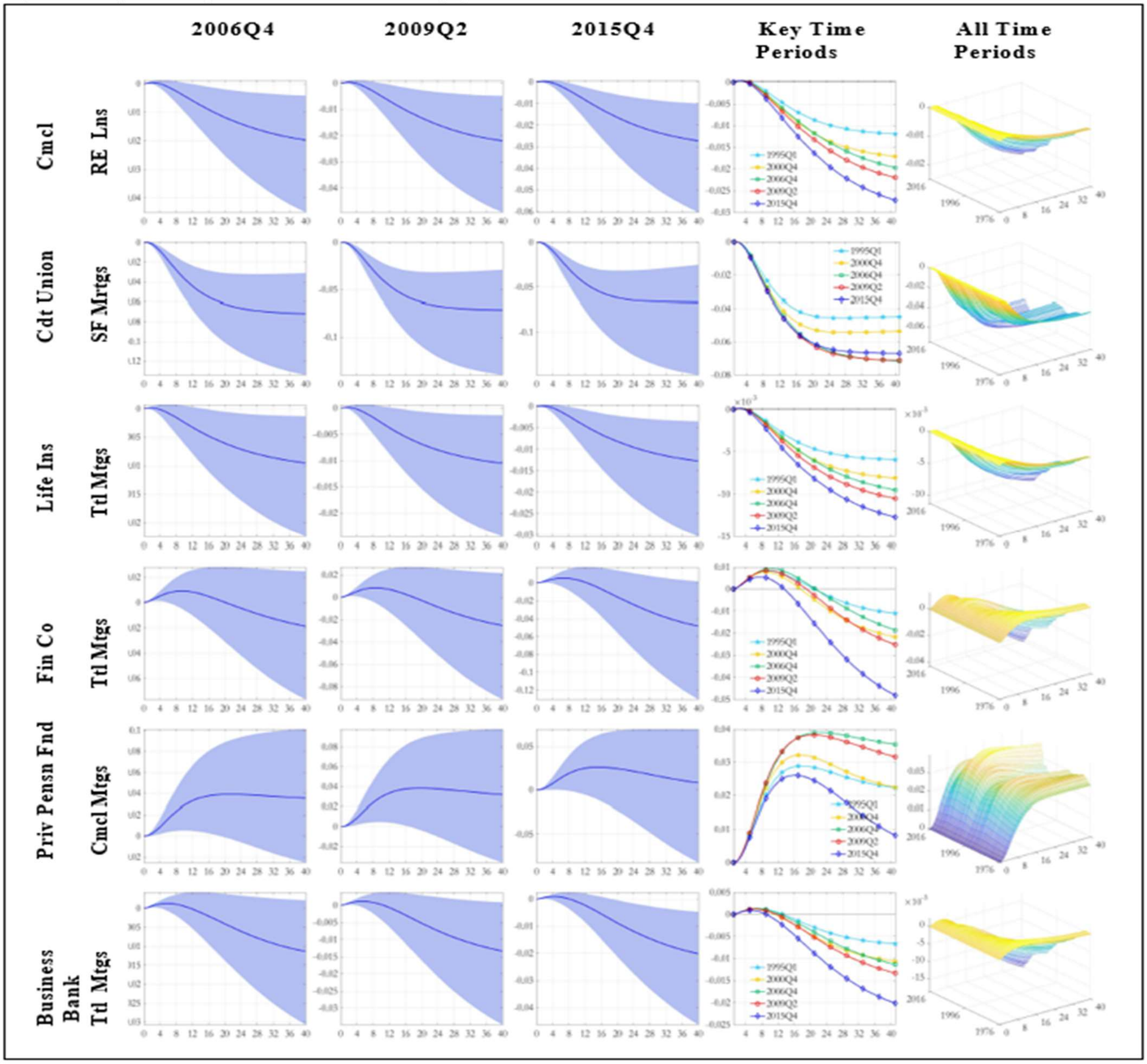
Results

The empirical results highlight the time surrounding the Great Recession as well as another recession and recovery period. Specifically, the first three columns in Figures 3 to 5 show results before (2006Q4), during (2009Q2), and after (2015Q4) the Great Recession. Results in the fourth column feature two additional time periods (1995Q1 and 200Q4) to cover two full recession and recovery periods. The last column shows results over all time periods estimated. Panels in the figures document the (cumulative) median responses to an unanticipated 100 basis point rise in the shadow policy rate. Shaded regions in the panels represent error bands that are the 16th and 84th percentiles of the responses derived from the Gibbs algorithm estimation output.

Residential and Commercial Mortgages

Rising interest rates will impact lending in the housing sector negatively unless a strong economy signals continued profitability to allow suppliers of housing and housing credit, for example, to pass on higher financing costs to those demanding housing.

Figure 3: Impulse Response Functions for Mortgage Markets



Notes: Median responses of variables in rows at time periods in columns are to a 100 basis point increase in the monetary policy rate; shaded error bands are 16th and 84th percentiles. The horizontal axis measures quarters after the policy rate shock, the vertical axis is in percent, and the lateral axis covers the (sample adjusted) estimation period from 1975Q4 through 2016Q4. Series examined by row are as follows: Commercial Bank Real Estate Loans, Credit Union Single-Family Mortgages, Life Insurance Company Total Mortgages, Finance Company Total Mortgages, Private Pension Funds Commercial Mortgages, Business Total Mortgages.

The results show that all commercial bank real estate loans and single-family mortgages originated by the smaller credit unions segment generally show delayed declines following a rise in the policy rate in the first two rows of Figure 3. Across the three dates highlighted in the first three columns related to the Great Recession, it appears that credit unions with less access to deposits tend to have steeper declines in 2009Q2.

Lending by other types of institutions in the less regulated shadow banking system generally rises, which suggests ineffective monetary policy actions to curb excessive credit in particular market segments. In the same figure following a monetary tightening, private pension funds (row 5) and finance companies (row 4) tend to increase the total mortgages across the key time periods. It is not surprising to find that private pension funds are able to increase volume levels of multi-family mortgages that are bought and held to a greater extent than life insurance companies shown in row 3 as such pensions are generally insured through a federal government program, the Pension Benefit Guarantee Corporation. To capital market participants, the financial backing acts similarly to what is now provided by the U.S. Treasury for agency securitization transactions. Moreover, renting becomes more attractive as the cost of buying a house escalates generally with higher rates.

The largest nonbank lender among those examined in this study, finance companies, are also able to increase total mortgages that are comprised of mostly single-family loans. The rise in mortgage volumes is by 0.005 percent with statistical significance for about four quarters across the three key time periods shown. For (nonfinancial noncorporate) businesses, which are sole proprietorships and limited partnerships, the countercyclical rise in loan volumes shown in the last row of Figure 3 is only marginally significant for about four quarters in the first two key time periods. The responses after the Great Recession in 2015Q4 pattern those of more regulated banks and credit unions with a decline of 0.02 in the long run following a monetary tightening.

The finding that mortgage lending in some of the above sectors of the shadow banking system is essentially unresponsive to a monetary tightening is consistent with securitization activity creating financial distortions as Nelson et al. (2018) find in their pre-Great Recession study, which combines all nonbank and securitized asset issuers. This part of the housing sector remained stable and continued to grow pre-crisis due to a strong economy fostering high occupancy rates particularly in commercial markets that did not suffer from oversupply (Maggiacomo, 2016). What should be a concern to policymakers is that less regulated nonbank mortgage lenders remain able to extend mortgage credit following a monetary tightening even in the post-crisis period after nonbanks in the shadow banking system were (partially) to blame for the housing-related slowdown (Acharya and Richardson, 2009). The next section of results considers if the findings for mortgage volumes can be traced back to securitized funding markets. Several pre-Great Recession studies, e.g., Bedendo and Bruno (2009), den Haan and Sterk (2010), and Loutskina (2011), find that securitization eases tight funding conditions on banks and weakens the influence of monetary policy actions on bank lending.

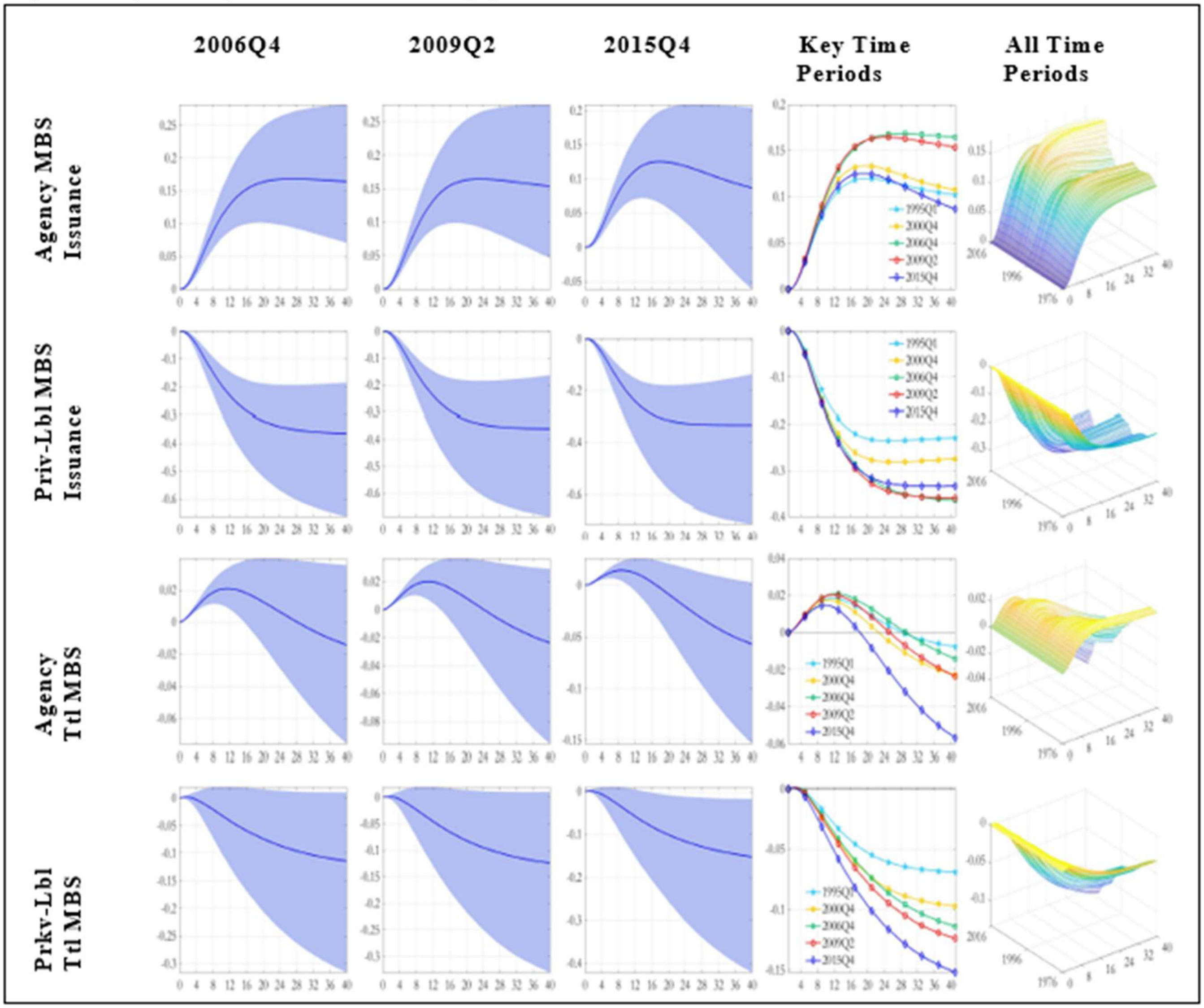
Securitized Credit Markets

During the recent financial crisis, turmoil in private-label MBS markets are reported to be an important factor in the distress of systemically important financial institutions within the shadow banking system starting in 2007 (Brunnermeier, 2009). In a securitization deal, the underlying mortgages are initially sold in the primary markets to a GSE, investment bank, or real estate investment trust (REIT) to package into tradable securities.[5] Prior to the Great Recession, both agency and private-label MBS markets experience a steady rise in volumes in both the primary issuance and secondary outstanding markets. According to Federal Reserve Flow of Funds and SIFMA data, outstanding volumes of private-label MBS rose tenfold from \$397.9 billion in 1995 to \$3,542.5 billion in 2007. However, after the Great Recession, the continued influence of Federal Reserve programs developed to maintain properly functioning mortgage finance markets on the GSEs positioned agency securitized markets to recover quickly from the recent financial crisis.

In row 1 of Figure 4, issuance volumes for total (residential and commercial) agency MBS increase across all of the periods in the column following a monetary tightening and maintain statistical significance for several quarters. The average maximum height is around 0.15 percent as shown in the fourth column. In contrast to the pre-Great Recession, small-variable VAR study by Pescatori and Solé (2015), the findings here show that the participation in securitized capital markets by the GSEs encourages investors to provide liquidity through the shadow banking system when the Federal Reserve attempts to slow down lending in the economy. Along with more liquidity provided by increases in primary market agency MBS issuance, there are corresponding increases in net liquidity for MBS outstanding volumes. In row 3 of Figure 4, total agency MBS outstanding dominated by single-family agency MBS outstanding volumes increase with statistical significance to a maximum height near 0.02 percent.

The onset of the downturn put the focus of the Federal Reserve on the deeper, agency MBS market given the collapse of private-label MBS. In contrast to issuance and outstanding volumes for agency securitized mortgages, the findings show that private-label securitized assets tend to decrease after a monetary tightening. The sustained and significant fall in private-label issuance tends to be greater than the decline found in private-label outstanding volumes, which reveals that investors appear not to find that holding agency MBS on-balance sheet is a position contrary to their liquidity goals.

Figure 4: Impulse Response Functions for Mortgage-Backed Securities Markets



Notes: Median responses of variables in rows at time periods in columns are to a 100 basis point increase in the monetary policy rate; shaded error bands are 16th and 84th percentiles. The horizontal axis measures quarters after the policy rate shock, the vertical axis is in percent, and the lateral axis covers the (sample adjusted) estimation period from 1975Q4 through 2016Q4. Series examined by row are as follows: Agency Mortgage-Backed Securities Issuance, Private-Label Mortgage-Backed Securities Issuance, Agency Total (Single-Family, Multi-Family, and Commercial) Mortgage-Backed Securities, and Private-Label Total (Single-Family, Multi-Family, and Commercial) Mortgage-Back Securities.

Row 4 of Figure 4 shows the tendency of all private-label MBS outstanding volumes to decline in the long run following a contractionary shock, which may reflect the flight to quality in the capital markets during this time in the business cycle (Brunnermeier, 2009). Therefore, increases in the monetary policy rate even after the Great Recession do not have a dampening effect on liquidity in securitized mortgage markets because the increase in total agency MBS issuance lessens the decrease in private-label MBS issuances even after accounting for the severe cutback in private-label MBS issuance that occurred after 2007. Chiang et al.'s (2015) findings suggest that less GSE participation in mortgage markets after 2006 leads to fewer housing starts and declines in real estate activity.

Housing Market Indicators

The next set of results helps to determine whether participants in housing markets are able to ignore tightening signals from the Federal Reserve by determining how several performance indicators identified in the housing and macroeconomic literatures respond to an increase in the policy rate. The federal government routinely writes about construction economics news that includes what investors, portfolio managers, and financial institutions use for their analyses.[6] Specifically, indicators of future construction spending (input prices and job growth) and investment activity (private fixed investment and commercial property development) are used to forecast the supply of housing and market trends in related housing sectors. The U.S. Census Bureau, for example, provides the New Residential Construction Report covering trends in new residential housing starts and building permits that serve as leading indicators of business cycles and inputs for forecasting consumer spending on housing-related items such as furniture or home appliances. In general, builders should decrease investment in residential housing when housing prices peak or even in a bullish economy with increasing home price indices if a monetary tightening signals less affordable or available funding from lenders. In this situation, housing starts and permits should decline following a contractionary shock in the monetary policy rate.

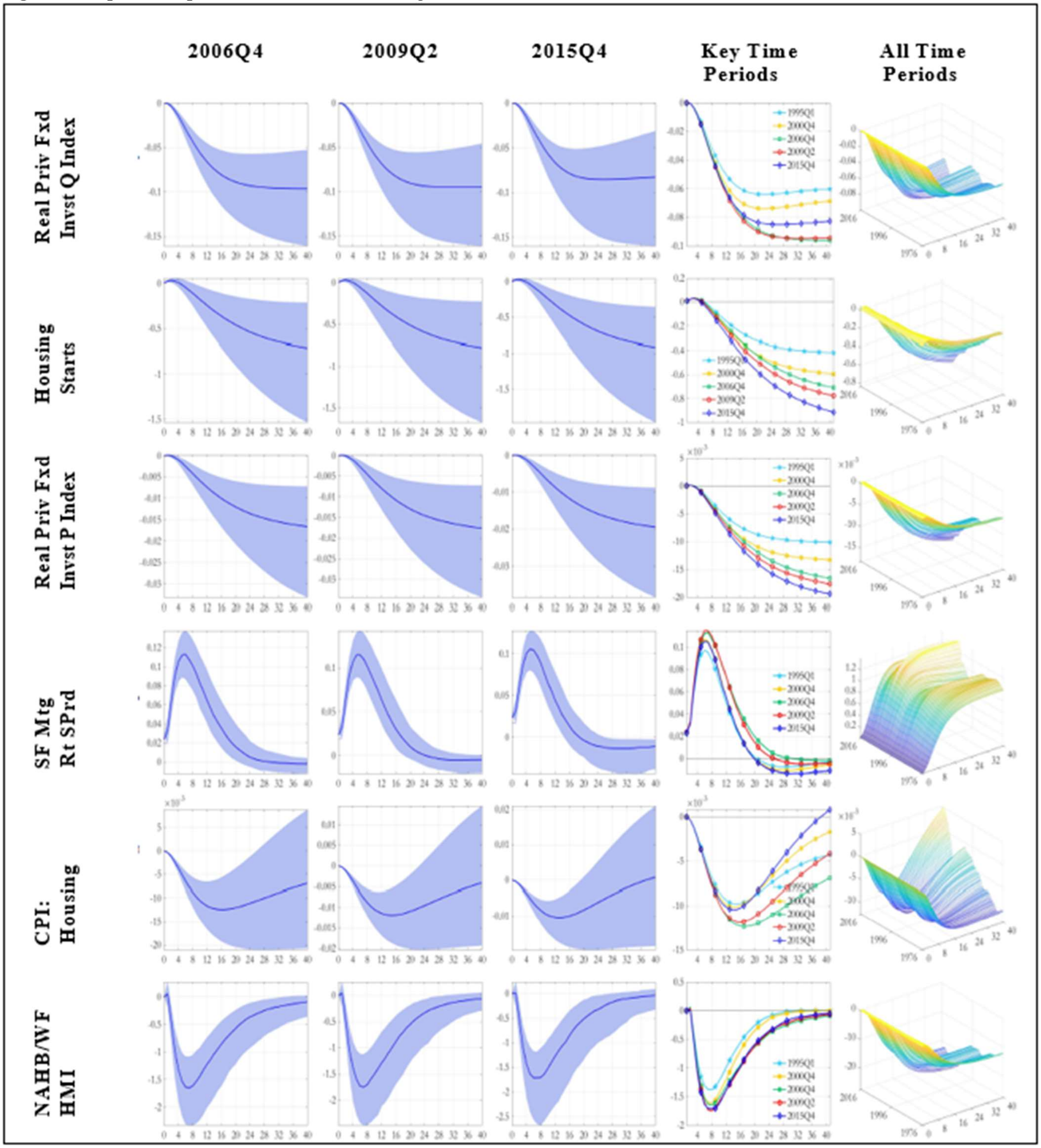
Consistent with the above line of reasoning, builders appear to be influenced by a tight monetary policy stance in their decision-making process for the three key time periods listed in Figure 5. Housing starts in row 2 reach their average maximum decline of 0.7 percent across the periods. This finding is not surprising given the fall in the real private residential fixed investment quantity and related price indices in rows 1 and 3, respectively. As residential fixed investment generally comprises about five percent of overall GDP according to Federal Reserve Flow of Funds data, it is important for this highly cyclical indicator to reflect the future state of housing following a monetary tightening.

Focusing on the residential fixed investment quantity index, a plausible explanation for the shallower drop after the recent financial crisis in 2015Q4 compared to both 2006Q4 and 2009Q2 points toward GSEs' transactions in securitized capital markets examined above. The behavior of the quantity index could also be the result of less than full pass through of monetary policy rate changes to the 30-year fixed mortgage rate shown in row 4. Relatively affordable housing would induce some homebuyers to accept more debt in order to buy more expensive housing. Therefore, it appears that GSE activity in MBS markets is a stronger signal to participants than the monetary policy stance allowing for ample liquidity in both loan and MBS capital markets.

The analysis estimates the responses for the National Association of Home Builders/Wells Fargo housing market index (NAHB/WF HMI) based on both current market conditions and single-family expected sales in the last row of Figure 5 to give another perspective of the behavior of participants in the housing sector. Interestingly, a 100 basis point increase in the monetary policy rate is followed by a maximum decline in the NAHB/WF HMI for current market conditions of 1.50 percent after eight quarters across the key time periods. Despite the smaller decline in the housing CPI after the Great Recession, there appears to be no discernable difference in the response to a monetary tightening in the three key time periods comprising the Great Recession business cycle. One explanation could be that the aggregated CPI housing index may be hiding regional price differences as shown in the pre-Great Recession study of Fischer et al. (2019). However, another possibility is that the builders surveyed for the housing market index consider a broader set of factors that shape their outlook for future home sales beyond simply funding markets.[7]

More narrow spreads post-Great Recession in 2015Q4 mentioned above do not point toward credit rationing as the driving force behind the behavior of housing-related indicators in the macroeconomy following a contractionary shock. Rather, an increase in the monetary policy rate may not lead to as effective of a slowdown of housing-related activity. The less responsive results post-Great Recession for the residential fixed investment quantity index, housing CPI, and the mortgage rate spread are similar to estimation results in Christou et al., (2019) for housing sales and prices in response to a rise in (economic and financial) uncertainty. Consistent with the discussion in Leamer (2015) about the economic circumstances when housing-related activity does not always indicate an economic slowdown, federal government intervention in mortgage credit markets and support of agency MBS appears to create enough liquidity to overcome a contractionary monetary policy rate shock.

Figure 5: Impulse Response Functions for Housing Market Indicators



Notes: Median responses of variables in rows at time periods in columns are to a 100 basis point increase in the monetary policy rate; shaded error bands are 16th and 84th percentiles. The horizontal axis measures quarters after the policy rate shock, the vertical axis is in percent, and the lateral axis covers the (sample adjusted) estimation period from 1975Q4 through 2016Q4. Series examined by row are as follows: Real Private Fixed Investment Quantity Index, Housing Starts, Real Private Fixed Investment Price Index, Single-Family Mortgage Rate Spread, Consumer Price Index for Housing, and National Association of Home Builders-Wells Fargo Housing Market Index.

Robustness

The findings based on the comprehensive TVP-FAVAR-SV empirical framework used in this study may be sensitive to alternative specifications of the policy rate and for the estimated factors. The figures of the impulse response functions are shown in the online Appendix.

Alternative Shadow Policy Rate

Along with the Bauer and Rudebusch (2016) shadow short rate that proxies the monetary policy stance used in the main results, another commonly used shadow policy rate is the Wu and Xia (2016) shadow federal funds rate. Both shadow rates are implied from longer-term government bond rates assuming that the short-term rate falls below zero and are a function of latent factors (i.e., the linear combinations of the bond rates) used to estimate the term structure. Wu and Xia (2016) use a series of forward rates in an extended Kalman filter to estimate the latent factors and the shadow rate, while Bauer and Rudebusch (2016) add macroeconomic variables to the forward rates to capture the driving macroeconomic forces behind interest rate movements. Krippner (2014) provides justification for the Bauer and Rudebusch (2016) shadow short rate used for the main results as it is robust to yield choice and the model's parameters as well as is a plausible reflection of information and rates faced by capital market participants. Table C.1 in the online Appendix shows that large-scale asset purchases of the Federal Reserve and its communication strategy of forward guidance summarized in both shadow rates effectively lowered the policy rate below zero. A more negative Wu and Xia (2016) rate during the Great Recession years should make finding supportive evidence for the main results more difficult.

Figures C.1 through C.3 in the online Appendix show the responses to a 100 basis point increase in the Wu and Xia (2016) shadow federal funds rate of mortgage loan markets, securitization markets, and housing indicators, respectively. All other estimation procedures discussed above remain unchanged. The results across these figures generally support the main findings. For all key time periods, bank and credit union mortgage volumes tend to decrease following a monetary tightening, business and pension fund mortgages rise, but the response of finance company total mortgages is now statistically insignificant in Figure C.1. In Figure C.2, MBS markets still see a rise in agency issuance volumes, and procyclical responses of housing market indicators are reduced in the key period after the Great Recession compared to the main results in Figure C.3.

Alternative Estimation of Factors

The steps of the estimation procedures outlined in the online Appendix, begin with the choice of the initial values for the factors summarizing information in the large data set. For the main findings, these factors are estimated by principal components analysis (PCA). Although the model assumes that the idiosyncratic components of equation (3) are homoscedastic, this assumption is partially relaxed to account for idiosyncratic heteroscedasticity, which is typically present in macroeconomic time series. Following Doz et al. (2011), the starting values for the factors are estimated in two steps. First, principal components are still estimated, and second, the Kalman smoother is applied. In this second step, the PCA estimates replace the parameters (i.e., the factors and loadings) of the factor model, and factor dynamics are based on the preliminary factor estimates. In Figure C.4, it appears that the PCA estimates are more volatile for both factors over the full estimation period, which should reflect in smaller responses under the current robustness check. However, any differences between the two estimation techniques for the factors are relatively small.

The responses in Figures C.5 through C.7 also support the main findings and the analysis for factors estimated following Doz et al. (2011). For example, the responses to a monetary tightening in the key time period 2006Q4 before the recent financial crisis for agency MBS issuance volumes shown in the first row of Figure 4 for PCA-based factors and in Figure C.6 for Doz et al.-based factors in the Appendix both show a nearly identical increase following the shock. However, the increase in the responses with PCA-estimated factors is slightly larger in magnitude compared to the Doz et al.-estimated factors (0.175 vs 0.160 percent) at their maximum response in 2006Q4 and 2009Q2, respectively.

Summary and Conclusion

Little is known about the effects of contractionary monetary policy shocks on different mortgage credit markets and housing indicators after the Great Recession under vastly different financial and economic conditions (Rahal, 2016). This study contributes to a relatively thin stream of literature examining the effects of a contractionary policy stance over the Great Recession business cycle on interrelated markets for bank and nonbank mortgage lending, MBS markets, and measures of housing-related activity.

The analysis studies the effects of a monetary tightening when the Federal Reserve dramatically changes its tools used to stabilize the macroeconomy and maintain functioning financial markets and when participation by the GSEs in mortgage credit markets changes as a result of the Great Recession. Prior to the economic downturn, mortgage financing originated from both regulated banks and less regulated nonbanks who then sold loans to agency and private-label issuers to be packaged into MBS. The focus on the conditional effect of monetary contractions during periods of conventional and unconventional monetary policy actions surrounding the Great Recession differentiates this study from other literature that may not explicitly account for the offsetting effects of the GSEs tasked with providing liquidity to mortgage credit markets.

A monetary tightening tends to produce mixed effects on lending across the shadow banking system and causes a decline in regulated commercial bank residential mortgages even though agency MBS issuance volumes rise appreciably. Any unresponsiveness to the monetary policy stance could be an unintended consequence following the severe economic downturn that may create financial instability in the future. Without incorporating interconnected bank, nonbank, and real sector markets as important channels for monetary policy, the comprehensive effects of a monetary tightening can potentially be missed. There perhaps may be limits to the ability of monetary policy actions to influence macroeconomic stability following years of stimulus to maintain financial stability as long as GSEs continue to their involvement in MBS markets and nonbanks remain mostly unregulated. The interplay between the sometimes-conflicting stability goals among government agencies under different economic circumstances is left for future research.

Acknowledgements

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Notes

1. These numbers are more staggering when considering asset purchases to help smooth credit markets in response to the ongoing COVID-19 pandemic. The Federal Reserve now holds over $2.65 trillion in MBS outstanding at the end of December 2022. See the release, H.4.1 Factors Affecting Reserve Balances, https://www.federalreserve.gov/releases/h41/.
2. For details, see https://globenewswire.com/news-release/2017/07/31/1064814/0/en/Mortgage-Daily-Q1-2017-Biggest-Lender-Ranking.html.
3. Development of the model in this section closely follows Leu and Robertson (2021).
4. To implement the Bai and Ng (2002) criteria to determine the number of factors, the maximum number of lags is set to eight with a floor of 0.10 for the amount of variance explained by a given factor. Under these assumptions, the first two factors capture just over 32 percent of the variation in the data series, which is half of the combined explanation for the maximum eight factors.
5. REITs are companies that manage housing assets to benefit shareholders who receive 90 percent of the companies' income. The companies primarily invest in MBS. For further information on REITs, see https://www.reit.com/.
6. See, for example, http://www.abc.org/en-us/newsmedia/constructioneconomics/constructioneconomicupdate.aspx.
7. For a description of the NAHB/WF Housing Market Index methodology, see https://www.nahb.org/news-and-economics/housing-economics/indices/housing-market-index

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Appendix

An online appendix that contains supplemental material on the estimation procedure and robustness checks can be found at the following website: https://1drv.ms/b/s!AmiEnn7y4dco2npWUc_j6bn3GZHk?e=Byk7dP.

The U.S. Financial Crisis, Oil and Market Returns: A Study of the Major Oil Producers in the Americas

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Abstract

The effects of the U.S. financial crisis on the relationship between the U.S. market volatility (VIX), oil price (OilWTI), and the stock returns of five of the largest oil producers in the Americas are examined herein. A VAR model is used to assess shocks on VIX and OilWTI and their impact on the countries' stock returns. A DCC-GARCH model identifies these stock markets become increasingly dependent on VIX and OilWTI during and after the U.S. financial crisis. A significant shift in the relationship between OilWTI and VIX is identified, corresponding with the latest U.S. efforts of becoming energy independent.

JEL Classification: G01, G15
Keywords: Oil Returns, Financial Contagion, Latin America, U.S. Financial Crisis.

Introduction

The purpose of this paper is to identify the effects of shocks on oil price returns (OilWTI) and U.S. market volatility changes (DVIX) on the stock market returns of the major oil-producing countries in the Americas due to the 2008-2009 U.S. financial crisis. During most of the 2000s, crude oil prices per barrel represented by the West Texas Intermediate rallied from about $18 to a maximum of $145/barrel by July 2008 and dramatically dropped to $39/barrel by December 2008. With the ending of the financial crisis, oil prices recovered and settled in the $100/barrel range until the last quarter of 2014, when oil prices began a downward trend that pushed prices to about $55/barrel.

The main contributions of this paper include the identification of the effects of shocks in U.S. market volatility and oil returns on stock market returns of the major oil producers in the Americas. Findings also include increases in the conditional correlations between OilWTI and these oil producers' stock returns during and beyond the U.S. financial crisis period. These contributions expand the findings from Mollick and Assefa (2013) beyond the U.S. stock markets. Findings herein identify the significant relationship shift between OilWTI and DVIX during and beyond the U.S. financial crisis, coinciding with the latest U.S. efforts to become a net oil exporter.

Several authors have identified the effects of the U.S. financial crisis on the subsequent oil crisis of 2008; Bhar and Malliaris (2011) attribute the oil price crash of 2008 to investors' rapid closing of oil positions, deleveraging speculative funds, and loss of liquidity during the 2008-2009 financial crisis. Mollick and Assefa (2013) find that the conditional correlations between the S&P 500 and oil prices significantly increase during and after the 2008-2009 U.S. financial crisis. It is known from Mollick and Assefa (2013) that the U.S. financial crisis created a shift in the relationship between OilWTI and U.S. stock returns, changing from being non-significant to significant after the financial crisis. The research question of interest is whether the same is true for other oil-producing countries.

Literature Review and Hypotheses Development

Global oil supply and demand are the key determinants of global oil prices, with global income identified as the principal driver of global oil demand (Hamilton, 2009), followed by worldwide income and geopolitical events (Hamilton, 2009; Hamilton, 2011). Increased demand for oil by China and other countries transitioning from agricultural to industrial economies, which grew faster than global production, contributes to the increase in oil prices during the 2000s (Hamilton, 2009).

Several recent papers study the relationship between oil prices and equity markets during high market volatility with mixed results. A few authors identify a positive correlation between oil prices and the stock markets, such as the case of Norway (e.g., Bjørnland, 2009; Jung and Park, 2011). Malik and Hammoudeh (2007) model the relationship between the global oil market, the U.S. equity markets, and Gulf equity markets finding evidence of spillover for Saudi Arabia. Arouri et al. (2011) detect volatility spillovers between oil prices and stock markets in the Gulf Cooperation Council countries (GCC) from 2005 to 2010. Lizardo and Mollick (2010) find that oil price increases will weaken the U.S. dollar against net exporters such as Canada, Mexico, and Russia.

A few studies investigate the effects of oil prices on oil exporters, including the leading Latin American producers. Wang et al. (2013) use the Vector Auto Regression Framework (VAR) to study oil-exporting and oil-importing countries' reactions to price shocks of oil. They use monthly data from January 1999 to December 2011 of nine oil-importers and seven oil-exporters, including Mexico, Venezuela, and Canada. They identify that the shocks depend on the importance of oil to each country's national economy. Shocks are more substantial and longer for oil-exporting countries than oil-importing countries, and oil-exporters tend to move together during these shocks.

Ghorbel et al. (2013) also use monthly data from January 1997 to June 2011 and identify shocks and contagion between oil and stock markets. They find evidence of herding contagion during the U.S. financial crisis between oil prices and 22 oil-importing and exporting countries, including Argentina and Brazil. Sadorsky (2014) models the volatility and correlations between oil, copper, wheat, and an index of 21 emerging market stock prices. His daily data spans from January 2000 to June 2012, finding evidence of long-term oil volatility spillovers to emerging markets. Qiang et al. (2019) investigate the time-varying dependence between BRICS stock returns and oil shocks, seeing a significant spillover from oil-specific demand shocks to BRICS stock returns. Xiao et al. (2018) use a newly published oil volatility index (OVX) and find that OVX has adverse and asymmetric effects on Chinese stock returns, presenting more substantial effects during bearish periods.

Jubinski and Lipton (2013) use a GARCH model to study the relationship from January 1990 to December 2010 among oil, gold, silver, and VIX. They find that oil has a negative and statistically significant association with VIX and that this relationship increases during recessionary periods. Several authors such as Dennis et al. (2006) and Mollick and Assefa (2013) have documented that increases in VIX hurt U.S. stock returns, while other authors use VIX and country-specific volatility indexes to record volatility spillovers to emerging and developed countries (Jiang et al., 2012; Dutta, 2018; Marfatia, 2020). Forbes and Rigobon (2002) define that cross-country financial contagion occurs when cross-country correlations increase considerably compared to non-crisis periods during a financial crisis. Other studies investigate the evolution of comovements between emerging markets and the U.S. stock market, assessing stock return spillovers (Ehrmann et al., 2011; Bekaert et al., 2014; Wang and Choi, 2015).

Another strand of related literature distinguishes demand and supply shocks in the oil market to explore their effects on the U.S. economy and oil prices (Kilian, 2008; Kilian, 2009; Kilian and Park, 2009). These studies use monthly data that includes real-global activity measures to capture demand, global oil production to compute supply, actual oil prices imported by the U.S., and aggregate U.S. stock returns.

Recent studies find evidence of increased comovements amongst Latin American stock returns, however; the speed and magnitude vary between countries, questioning the risk diversification effectiveness of investing in Latin America (Chen, Firth, and Rui, 2002; Araujo, 2009; Lahrech and Sylwester, 2011; Mellado and Escobari, 2015; Chuliá et al., 2017). Rodriguez-Nieto and Mollick (2020) identify that increases in U.S. stock volatility during the U.S. financial crisis contributed to the financial contagion to the major markets in the Americas.

Mollick and Assefa (2013) use GARCH and MGARCH-DCC models to assess the dynamic correlations among several U.S. stock indexes, OilWTI, and macroeconomic and financial variables. They obtain daily data from January 1999 to December 2011 and break it into three subsamples to differentiate these relationships before, during, and after the 2008-2009 financial crisis. They find that during the pre-financial crisis, the conditional correlations between stock returns and OilWTI are slightly negative, switching to positive after the financial crisis.

As an extension to Mollick and Assefa (2013), it is expected that the 2008-2009 financial crisis will have long-lasting effects on the increased relationship between oil prices and stock market returns of the major oil producers in the Americas. Further, due to recent oil production increases in the U.S. aimed at making the country energy sufficient, the DVIX-OilWTI conditional correlations will remain strong beyond the financial crisis.

Data and Empirical Results

The country-specific data used herein consists of daily closing indexes, in U.S. Dollars, from January 1, 2002 through December 31, 2015 for five (5) top oil-producing countries in the Americas. The data set is obtained from DataStream and consists of the primary local stock indexes from Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Colombia (IGBC), Mexico (BOLSA), and the United States (S&P 500 index). The CBOE Volatility Index® (VIX) is used as a proxy of U.S. market volatility and the oil price per barrel of West Texas Intermediate (OilWTI) is used to represent oil price.

Following Mollick and Assefa (2013), the financial crisis period is defined as according to NBER from January 1, 2008 to June 30, 2009. Three sub-periods are analyzed to assess the impact of the financial crisis on the relationship between stock market returns, OilWTI, and DVIX. The first period runs from January 1, 2002 to December 31, 2007 and is referred to as the "pre-crisis period." The "crisis period" begins on January 1, 2008 ending on June 30, 2009 and the "post-crisis period" expands from July 1, 2009 to December 31, 2015.

Figure 1 presents the daily returns for all five stock market indexes, OilWTI, and the first differences for VIX. Increased volatility on all series during the 2008-2009 financial crisis is noted, thus, a GARCH model is used in this study.

Table 1 contains the descriptive statistics in returns/differences. The Shapiro-Wilk test statistic shows non-normality and the results for the Ljung–Box test indicate autocorrelation for all series. The mean returns are all positive, and DVIX is negative.

Colombia has the highest mean returns at 0.048, followed by Mexico at 0.035, with relative standard deviations at 1.646 and 1.584, respectively. Brazil and Canada have similar mean returns at 0.017 and 0.018 in that order, but Brazil has a higher standard deviation of 2.006 with Canada at 1.374. For the U.S., the lowest mean return is 0.016 and standard deviation at 1.228.

Table 1: Descriptive Statistics (Daily Data from Jan. 2002 to Dec. 2015).

	Brazil	Canada	Colombia	Mexico	U.S.	OilWTI	DVIX
Observations	3653	3653	3653	3653	3653	3653	3653
Mean	0.017	0.018	0.048	0.035	0.016	0.017	-0.002
Standard Dev.	2.006	1.374	1.646	1.584	1.228	2.346	1.714
Variance	4.025	1.887	2.708	2.508	1.508	5.504	2.936
Skewness	-0.301	-0.77	-0.431	-0.093	-0.22	0.119	0.659
Kurtosis	9.635	13.892	11.112	10.46	12.776	8.146	22.267
Shapiro-Wilk (Normality)	12.70***	13.95***	13.28***	12.99***	13.98***	12.04***	15.54***
Ljung-Box test (Auto Correlation)	147.41***	210.32***	144.12***	116.25***	121.96***	111.51***	184.75***

Notes: All variables are in returns except DVIX, which is in differences. *, **, and *** represent statistical significance at 10%, 5% and 1% levels, respectively.

Intertemporal Relationship of OilWTI, DVIX, and Stock Returns

A standard vector autoregressive model (VAR) is used to test the intertemporal relationship between stock returns, OilWTI, and DVIX. This method allows for testing of stock returns responses to OilWTI and DVIX innovations (shocks) and captures the short-run dynamics amongst variables. Since the VAR model requires the variables to be of the same order to perform the causality tests, the analysis begins by verifying the order of integration of the variables. Standard ADF, KPSS, and Philips-Perron tests are conducted, and the series are found to be stationary.

The VAR estimation begins by determining the lag length for each variable included in the model. Four selection-order statistics are used: the final prediction error (FPE), Akaike's information criterion (AIC), the Hannan and Quinn information criterion (HQIC), as well as the Schwarz's Bayesian information criterion (SBIC), determining that four lags are appropriate for this model.

The vector autoregressive model is of the following form:

$$(OilWTI)_t = \propto_{2_0} + \sum_{n=1}^{N} \propto_{2_{2n}} (OilWTI)_{t-n} + \sum_{n=1}^{N} \propto_{2_{3n}} (DVIX)_{t-n} + \sum_{n=1}^{N} \propto_{2_{1n}} r_{t-n} + e_{2t} \quad (1)$$

$$(DVIX)_t = \propto_{3_0} + \sum_{n=1}^{N} \propto_{3_{2n}} (OilWTI)_{t-n} + \sum_{n=1}^{N} \propto_{3_{3n}} (DVIX)_{t-n} + \sum_{n=1}^{N} \propto_{3_{1n}} r_{t-n} + e_{3t} \quad (2)$$

$$r_t = \propto_{1_0} + \sum_{n=1}^{N} \propto_{1_{2n}} (OilWTI)_{t-n} + \sum_{n=1}^{N} \propto_{1_{3n}} (DVIX)_{t-n} + \sum_{n=1}^{N} \propto_{1_{1n}} r_{t-n} + e_{1t} \quad (3)$$

With:

$$r_t = \left(r_{Canada,t}, r_{Colombia,t}, r_{Mexico,t}, r_{Peru,t}, r_{US,t} \right)'$$

This model's ordering runs from the most exogenous (OilWTI) to the most endogenous (stock returns) with DVIX in between. In the model, r_t is the vector of stock returns at time *t*, $(OilWTI)_t$ are the oil returns at time *t*, $(DVIX)_t$ are the changes in VIX at time *t*. $(OilWTI)_{t-n}$, $(DVIX)_{t-n}$, and r_{t-n} are lags of oil returns, D*VIX,* and stock returns at time *t-n.* A vector of constant terms is represented by $\propto_{1_0}$, and e_{1t} represents a vector of error terms.

To investigate the effects of shocks to DVIX and OliWTI on stock returns, asymptotic-normal approximations are used to extract the forecasted error variance decompositions and the generalized impulse functions.

Table 2 reports the variance decomposition of the VAR model for Brazil. Results are reported at 1, 3, 5, and 7 days, observing only minor changes after the fifth day. They are unchanged after seven days and this reported as "∞" to represent long-term effects. After seven days, shocks to OilWTI, DVIX, and Brazil stock returns explain 8.54%, 22%, and 69.46%, respectively, of Brazil's variance. Table 3 reports the variance decomposition of the VAR model for Canada. In this case, shocks to OilWTI and DVIX, respectively, account for 17.94% and 30.14% of Canada's stock returns variance. The results for Colombia are in Table 4. Shocks to Colombia's stock returns explain 81.56% of the variance, while shocks to OilWTI and DVIX account for 6.51% and 11.90%, respectively. For Mexico, in Table 5, shocks to stock returns account for 61.69% of the variance, while shocks to DVIX explain 32.06% and shocks on oil returns explain 6.26%.

Table 6 indicates that shocks to U.S. stock returns explain 30.98% of U.S. stock returns variance, while shocks to DVIX explain 63.86%, and shocks to OilWTI 5.16%. These results highlight the impact of shocks on DVIX and OilWTI on the stock returns of all the oil producers, including the U.S. Shocks to oil prices can explain 98% to 99% of the OilWTI variance in all cases, shocks to DVIX only explain about 1%. Shocks to stock returns explain less than 1% of the variance in OilWTI. For the variance in DVIX, shocks on DVIX can explain about 94% to 95% of the variance, while shocks on OilWTI account for about 4.5% and shocks to stock returns account for less than 1%.

Table 2: Variance Decomposition of VAR Model for Brazil

Variance decomposition across days

	Innovation								
	Shock in OilWTI			Shock in DVIX			Shock in Brazil		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	99.08	98.45	99.70	0.85	0.25	1.45	0.08	-0.11	0.26
5	98.84	98.15	99.52	1.05	0.40	1.70	0.11	-0.11	0.34
7	98.84	98.15	99.52	1.05	0.40	1.70	0.11	-0.11	0.34
∞	98.84	98.15	99.52	1.05	0.40	1.70	0.11	-0.11	0.34
DVIX									
1	4.43	3.13	5.74	95.57	94.26	96.87	0.00	0.00	0.00
3	4.59	3.24	5.95	95.39	94.04	96.75	0.01	-0.06	0.08
5	4.64	3.29	5.99	95.34	94.00	96.69	0.02	-0.05	0.09
7	4.63	3.29	5.98	95.35	94.00	96.69	0.02	-0.06	0.09
∞	4.63	3.29	5.98	95.35	94.00	96.69	0.02	-0.06	0.09
Brazil									
1	8.46	6.73	10.19	20.99	18.74	23.25	70.55	68.06	73.03
3	8.40	6.68	10.12	21.98	19.67	24.29	69.62	67.11	72.13
5	8.54	6.81	10.27	21.99	19.68	24.30	69.47	66.95	71.98
7	8.54	6.81	10.27	22.00	19.69	24.31	69.46	66.94	71.97
∞	8.54	6.81	10.27	22.00	19.69	24.31	69.46	66.94	71.97

Table 3: Variance Decomposition of VAR Model for Canada

Variance decomposition across days

	Innovation								
	Shock in OilWTI			Shock in DVIX			Shock in Canada		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	98.69	97.94	99.43	0.80	0.22	1.38	0.51	0.04	0.98
5	98.27	97.42	99.11	1.00	0.37	1.63	0.73	0.16	1.30
7	98.26	97.41	99.11	1.00	0.37	1.64	0.73	0.16	1.31
∞	98.26	97.41	99.11	1.00	0.37	1.64	0.73	0.16	1.31
DVIX									
1	4.51	3.20	5.83	95.49	94.17	96.80	0.00	0.00	0.00
3	4.68	3.31	6.04	95.26	93.89	96.64	0.06	-0.10	0.22
5	4.71	3.35	6.06	94.97	93.59	96.36	0.32	-0.01	0.65
7	4.70	3.35	6.05	94.96	93.57	96.35	0.35	0.00	0.70
∞	4.70	3.35	6.05	94.96	93.57	96.35	0.35	0.00	0.70
Canada									
1	17.95	15.70	20.21	28.96	26.67	31.25	53.09	50.73	55.45
3	17.70	15.46	19.94	30.34	28.00	32.67	51.96	49.61	54.31
5	17.94	15.68	20.20	30.14	27.81	32.47	51.92	49.56	54.28
7	17.94	15.68	20.20	30.14	27.82	32.47	51.92	49.56	54.28
∞	17.94	15.68	20.20	30.14	27.82	32.47	51.92	49.56	54.28

Table 4: Variance Decomposition of VAR Model for Colombia

Variance decomposition across days

	Innovation								
	Shock in OilWTI			Shock in DVIX			Shock in Colombia		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	99.13	98.52	99.74	0.86	0.25	1.46	0.01	-0.06	0.08
5	98.91	98.25	99.57	1.05	0.40	1.70	0.04	-0.08	0.16
7	98.90	98.24	99.57	1.06	0.41	1.71	0.04	-0.08	0.16
∞	98.90	98.23	99.57	1.06	0.41	1.71	0.04	-0.08	0.16
DVIX									
1	4.48	3.16	5.79	95.52	94.21	96.84	0.00	0.00	0.00
3	4.61	3.26	5.97	95.19	93.81	96.57	0.20	-0.08	0.47
5	4.65	3.31	5.99	94.99	93.61	96.37	0.36	0.01	0.71
7	4.64	3.30	5.98	94.99	93.61	96.37	0.37	0.01	0.72
∞	4.64	3.30	5.98	94.99	93.61	96.37	0.37	0.01	0.72
Colombia									
1	6.52	4.97	8.06	9.15	7.42	10.87	84.34	82.17	86.50
3	6.45	4.90	7.99	11.55	9.58	13.52	82.00	79.68	84.32
5	6.51	4.96	8.06	11.92	9.92	13.91	81.57	79.24	83.91
7	6.51	4.96	8.07	11.92	9.93	13.92	81.56	79.22	83.90
∞	6.51	4.96	8.07	11.92	9.93	13.92	81.56	79.22	83.90

Table 5: Variance Decomposition of VAR Model for Mexico

Variance decomposition across days

	Innovation								
	Shock in OilWTI			Shock in DVIX			Shock in Mexico		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	1.00	1.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.99	0.99	1.00	0.01	0.00	0.01	0.00	0.00	0.00
5	0.99	0.98	1.00	0.01	0.00	0.02	0.00	0.00	0.00
7	0.99	0.98	1.00	0.01	0.00	0.02	0.00	0.00	0.00
∞	0.99	0.98	1.00	0.01	0.00	0.02	0.00	0.00	0.00
DVIX									
1	4.46	3.15	5.77	95.54	94.23	96.85	0.00	0.00	0.00
3	4.59	3.24	5.94	94.92	93.51	96.33	0.49	0.06	0.92
5	4.63	3.29	5.98	94.79	93.38	96.20	0.57	0.11	1.04
7	4.63	3.29	5.97	94.79	93.38	96.20	0.58	0.11	1.05
∞	4.63	3.29	5.97	94.79	93.38	96.20	0.58	0.11	1.05
Mexico									
1	6.19	4.67	7.70	31.30	28.87	33.73	62.51	60.03	65.00
3	6.08	4.58	7.57	32.04	29.58	34.50	61.88	59.38	64.38
5	6.26	4.76	7.76	32.05	29.58	34.52	61.69	59.18	64.19
7	6.26	4.75	7.76	32.06	29.59	34.52	61.69	59.18	64.19
∞	6.26	4.75	7.76	32.06	29.59	34.52	61.69	59.18	64.19

Table 6: Variance Decomposition of VAR Model for the U.S.

Variance decomposition across days

	Innovation								
	Shock in OilWTI			Shock in DVIX			Shock in U.S.		
	fevd	Lower	Upper	fevd	Lower	Upper	fevd	Lower	Upper
OilWTI									
1	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00
3	98.94	98.27	99.61	0.85	0.25	1.45	0.21	-0.09	0.52
5	98.74	98.02	99.45	1.05	0.40	1.70	0.21	-0.09	0.52
7	98.74	98.02	99.45	1.05	0.40	1.70	0.22	-0.09	0.52
∞	98.74	98.02	99.45	1.05	0.40	1.70	0.22	-0.09	0.52
DVIX									
1	4.45	3.14	5.76	95.55	94.24	96.86	0.00	0.00	0.00
3	4.61	3.26	5.97	95.37	94.01	96.73	0.02	-0.07	0.10
5	4.66	3.31	6.01	95.30	93.94	96.65	0.05	-0.08	0.18
7	4.65	3.31	6.00	95.30	93.95	96.65	0.05	-0.09	0.19
∞	4.65	3.31	6.00	95.30	93.95	96.65	0.05	-0.09	0.19
U.S.									
1	5.02	3.64	6.40	63.68	61.70	65.65	31.30	29.62	32.99
3	5.05	3.66	6.45	63.89	61.90	65.89	31.05	29.36	32.75
5	5.16	3.76	6.56	63.85	61.85	65.84	30.99	29.30	32.69
7	5.16	3.76	6.56	63.86	61.86	65.85	30.98	29.29	32.68
∞	5.16	3.76	6.56	63.86	61.86	65.85	30.98	29.29	32.68

The impulse response functions (IRFs) are used to obtain the graphical representation of the impacts of shocks on OilWTI and DVIX. Figures 2-6 include the impulse responses to a one standard deviation increase in OilWTI and DVIX. In all cases, stock returns react positively to shocks on stock returns and shocks on OilWTI, while shocks to DVIX have negative effects on stock returns.

Figure 2 includes the impulse responses to one standard deviation increase to Brazil, OilWTI, and DVIX. Brazil reacts positively to shocks on itself with a shock accounting for a 1% increase in stock returns leading to a 1.6% increase on stock returns and this effect disappears after one week. Shocks on OilWTI result in positive stock returns with a 1% shock increase on OilWTI resulting in about 0.7% gains and these effects also disappear after one week. The figure also shows that shocks to changes in VIX reduce stock returns with a 1% shock increase resulting in a 1% decrease in stock returns and the effects disappear after two weeks.

Figure 3 includes the impulse responses to a one standard deviation increase to Canada, OilWTI, and DVIX. A 1% shock in stock returns results in a 1% increase in Canadian stock returns. Results indicate OilWTI shocks will increase stock returns by about 0.6% with similar shocks to DVIX resulting in a drop of about -0.8% on stock returns. The effects of those shocks dissipate after two weeks.

Figure 4 represents the impulse responses to one standard deviation increase to Colombia, OilWTI, and DVIX. Results indicate that shocks on stock returns increase Colombian stock returns by about 1.5%. Similar shocks to OilWTI and VIX changes will improve stock returns by about 0.5% and decrease -0.4%, respectively. Shocks to stock returns and OilWTI will dissipate in one week and shocks to DVIX will disappear in two weeks.

Figure 5 reports the impulse responses to one standard deviation increase to Mexico, OilWTI, and DVIX. Shocks of 1% to stock returns, OilWTI, and DVIX will change stock returns by 1.2%, 0.4%, and -1 %, respectively. Furthermore, these shocks dissipate in 1 week for stock returns and OilWTI, taking two weeks to disappear for DVIX.

Figure 6 reports the impulse responses to one standard deviation increase to U.S., OilWTI, and DVIX. Results indicate that 1% shocks to U.S. stock returns result in positive increases of 0.8% on U.S. stock returns. Similar shocks to OilWTI will increase U.S. stocks by about 0.25% and shocks to DVIX will decrease U.S. stock returns by about -1%.

For the results to be valid, the system VAR equations must be stationary. The model stability conditions, which require the moduli of the dynamic matrix's eigenvalues to lie within the unit circle, must hold. An analysis for all series indicates that the eigenvalues lie inside the unit circle; thus, each VAR model satisfies the stability condition.

These findings contribute to the literature by capturing the short-run effects of shocks to OilWTI and DVIX on the stock returns of the major oil producers in the Americas, warning policymakers and portfolio managers about the diversification effectiveness of a regional portfolio based on the North and Latin American countries.

The DCC-GARCH Model and Estimation Results

Shocks to OilWTI and DVIX are found to influence the stock returns of the major oil producers, thus, there is interest in identifying the dynamic impact of the U.S. financial crisis on the relationship between OilWTI, DVIX, and stock returns. The Dynamic Conditional Correlation - GARCH (DCC-GARCH) model developed by Engle (2002) is used to measure the pairwise dynamic correlations between OilWTI, DVIX, and oil-producing countries.

The model used is as follows:

Mean Equations: $r_{t=}\ \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{OilWTI} + \gamma_3 r_{t-1}^{DVIX} + \varepsilon_t ,$

$$where\ r_t = (r_{Brazil,t}, r_{Canada,t}, r_{Colombia,t}, r_{Mexico,t}, r_{U.S.,t})'$$

$$\varepsilon_t = (\varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{U.S.,t})'\ and\ \ \varepsilon_t \mid I_{(t-1)} \sim N(O, H_t.) \quad (4)$$

Variance Equations: $h_{ii,t} = \omega_i + \alpha_{i,1}\varepsilon_{i,t-1}^2 + \beta_{i,1}h_{ii,t-1}, \quad for\ i = 1,2, \ldots, n.$

$$q_{ij,t} = \bar{\rho}_{ij}(1 - a - b) + bq_{ij,t-1} + a\eta_{i,t-1}\eta_{j,t-1} \quad (5)$$

DCC equation: $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}\ , \quad where\ i,j = 1,2, \ldots, 6.\ and\ i \neq j$ (6)

The described DCC–GARCH is applied to the pooled data, expanding from January 2002 to December 2015, and the results are presented in Table 7. Results for the mean and variance equations (4) and (5) are as follows: for the mean equation, the constant term γ_0, is positive and statistically significant for all markets, varying from a high of 0.1274 for Brazil to a low of 0.0881 for the U.S.

Table 7: DCC Estimations for Stock Returns, OilWTI, and DVIX (Daily Data from Jan. 2002 to Dec. 2015).

Mean Equations	Brazil	Canada	Colombia	Mexico	U.S.
ϒ0	0.1274***	0.0935***	0.0988***	0.1269***	0.0881***
	(0.0235)	(0.0142)	(0.02)	(0.0181)	(0.0118)
ϒ1	0.0007	-0.0385***	0.0803***	-0.006	-0.1028***
	(0.0141)	(0.0136)	(0.0163)	(0.0136)	(0.0144)
ϒ2 (OilWTI)	0.0306***	0.03***	0.0209**	0.0129	0.0081**
	(0.0108)	(0.0064)	(0.0093)	(0.0079)	(0.0038)
ϒ3 (ΔVIX)	-0.1226***	-0.1281***	-0.1121***	-0.135***	-0.0632***
	(0.0183)	(0.011)	(0.0145)	(0.0144)	(0.0107)
Variance Equations					
Constant	0.0835***	0.0189***	0.1348***	0.0505***	0.0166***
	(0.0133)	(0.0032)	(0.0233)	(0.0078)	(0.0022)
Arch	0.0747***	0.0654***	0.131***	0.079***	0.081***
	(0.0067)	(0.0056)	(0.0128)	(0.0072)	(0.0052)
Garch	0.9043***	0.9226***	0.8158***	0.9011***	0.9058***
	(0.0086)	(0.0065)	(0.0193)	(0.0089)	(0.0058)
Persistence	0.980	0.9880	0.9469	0.9802	0.9869
Multivariate DCC Equation					
Lambda1	0.014***				
	(0.0009)				
Lambda2	0.9764***				
	(0.0016)				
Observations	3652				
χ2	361.85				
χ2 (p-value)	0				

Notes: Robust standard errors are in parentheses. *, **, and *** represent statistical significance at 10%, 5% and 1% levels, respectively.
The mean equation is $r_t = \gamma_0 + \gamma_1 r_{t-1} + \gamma_2 r_{t-1}^{WTI} + \gamma_3 r_{t-1}^{DVIX} + \varepsilon_t$
where $r_t = (r_{Brazil,t}, r_{Canada,t}, r_{Colombia,t}, r_{Mexico,t}, r_{U.S.,t})'$; $\varepsilon_t = (\varepsilon_{Brazil,t}, \varepsilon_{Canada,t}, \varepsilon_{Colombia,t}, \varepsilon_{Mexico,t}, \varepsilon_{U.S.,t})'$
and $\varepsilon_t \mid I\Omega_{(t-1)} \sim N(O, H_t.)$. The variance equations are $h_{ii,t} = c_i + a_i\varepsilon_{i,t-1}^2 + b_i h_{ii,t-1}\ for\ i = 1,2, \ldots, n.$
The null for the x^2 test is $H_0: \alpha = \beta = 0$. Persistence is calculated as (Arch + Garch).

The AR(1) term, γ1, shows mixed results, being positive and statistically significant for Colombia at 0.0803, and negative and statistically significant for the U.S. at -0.1028 and Canada at -0.0385. The effect γ2, representing the impact of OilWTI returns on each market return, is positive and statistically significant for all except Mexico. With coefficients for Brazil at 0.0306, Canada at 0.3, Colombia at 0.0209, and the U.S. at 0.0081. The effect of γ3, representing DVIX, is negative and significant for all countries, confirming the influence of the U.S. market volatility on these oil producers. The γ3 coefficients range from a high of -0.135 for Mexico, Canada at -0.1281, Brazil at -0.1226, Colombia at -0.1121 to a low of -0.0632 for the U.S.

The table also includes parameter estimates of the mean and conditional variance equations; the coefficients are all positive and significant, confirming the appropriate use of the GARCH (1,1) specification. The volatility persistence (Arch + Garch coefficients) is consistently near one (1) in all cases, indicating increased volatility persistence in the GARCH model.

Table 7 also includes the estimates for the DCC-GARCH estimates Lambda 1 and Lambda 2. Both parameters statistically significant, indicating that the DCC-GARCH model is appropriate for the sample. The sum of these parameters is higher than 0.94 and less than 0.99, which means strong comovement over time and a high level of persistence.

The impact of OilWTI on the oil producers' stock returns is identified and the adverse effects of increased volatility shocks on the same stock markets is verified. The pooled data incorporated the financial crisis, so long-term dynamics between DVIX, OilWTI, and each of the stock markets are assessed in the next section.

Explaining the Conditional Correlation Coefficients

The impact of the U.S. financial crisis on the dynamic conditional correlations between OilWTI, DVIX, and the five oil-producing countries' stock returns is considered next. OilWTI (γ2) has positive effects on the oil producers and DVIX has an adverse impact on the same. In this section, the effects of the financial crisis on these pairwise correlations is explored as well as the pairwise correlations between these oil producers and DVIX.

One of the advantages of using the DDC-GARCH model is to obtain all possible dynamic pairwise correlations between DVIX, OilWTI, and each of the stock markets, in addition to all possible pairwise correlations between the individual stock market returns. An empirical regression model is built, presented in Equation 7 to analyze the conditional correlation dynamics.

$$\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t, \text{ for } i \neq j \qquad (7)$$

The dependent variable $\hat{\rho}_{ij,t}$ represents the predicted conditional correlation by the DCC-GARCH between markets *i* and *j* at time *t*. Two dummy variables are then included; $DV1_t$ is the dummy variable for the financial crisis (January 1, 2008 to June 30, 2009), and $DV2_t$ is the dummy variable for the post-crisis period (July 1, 2009 to December 31, 2015). Each dummy variable is set equal to one for each period and zero otherwise.

The dynamic conditional correlation coefficients are regressed on the dummy variables, capturing the effect of each period relative to the pre-financial crisis. The estimation results of the regressions for all possible pairwise correlations are included in Table 8.

Table 8A contains the regression coefficients for the pairwise correlations between the U.S. stock returns and each oil producer. The constant term or intercept λ_0 captures the pre-crisis period, and it is positive and significant in all cases. The coefficients range from 0.2279 for Colombia, 0.4897 for Brazil, 0.6045 for Canada, and 0.6176 for Mexico, indicating high correlations during the pre-crisis period. The estimates of λ_1 capture the effects of the financial crisis period, indicating that the comovements increased significantly for each pair, evidence of contagion. The λ_1 estimates are all positive and significant and range from 0.0577 for Canada, 0.1113 for Brazil, 0.1144 for Mexico, to 0.1382 for Colombia. The effect of the post-financial crisis λ_2 is also positive and significant, indicating that all pairwise correlations are significantly higher during the post-crisis period than the pre-crisis period. The λ_2 coefficients are greater than those from the financial crisis in two cases, with Canada at 0.1127 and Colombia at 0.1671. The coefficients are lower for Brazil-U.S. at 0.085, as well as Mexico-U.S. at 0.599. The positive and significant λ_1 estimates indicate contagion during the U.S. financial crisis and observe through the λ_2 coefficients that the contagion persists during the post-crisis period for Canada and Colombia.

After identifying evidence of contagion from the U.S. to the four oil producers, oil prices are investigated as a contagion source. Table 8B reports the regression analysis of the dynamic conditional correlations between OilWTI and each country, observing that the constant term λ_0 is positive and significant, indicating that all stock markets move in the same direction as oil prices during the pre-crisis period. The coefficients range from 0.1255 for Colombia, 0.1283 for Mexico, 0.1618 for Brazil, to 0.3135 for Canada. In the case of the U.S., λ_0 is also positive and significant, with a coefficient of 0.0772. The effect of the financial crisis, λ_1, is positive and significant for all countries, reporting coefficients ranging from 0.0309 for Mexico, 0.0635 for the U.S., 0.1139 for Canada, 0.1623 for Brazil, and 0.176 for Colombia.

Table 8A: Regression Analysis of Conditional Correlations Coefficients between U.S. and oil producers

Country/Index i:	U.S.	U.S.	U.S.	U.S.
Country j:	Brazil	Canada	Colombia	Mexico
λ_0	0.4897***	0.6045***	0.2279***	0.6176***
	(0.0027)	(0.0022)	(0.0025)	(0.0021)
λ1 (Financial Crisis)	0.1113***	0.0577***	0.1382***	0.1144***
	(0.006)	(0.0048)	(0.0055)	(0.0047)
λ2 (Post- Financial Crisis)	0.085***	0.1127***	0.1671***	0.0599***
	(0.0037)	(0.003)	(0.0034)	(0.0029)
Observations	3652	3652	3652	3652
F	326.64	710.44	1228.55	386.23
F (p-value)	0.000	0.000	0.000	0.000
Adjusted R^2	0.1514	0.2799	0.4021	0.1743

Notes: *** Represent statistical significance at the 1% level. Standard errors are in the parenthesis. The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t$, for $i \neq j$, where $\hat{\rho}_{ij,t}$, represents the predicted conditional correlation by the DCC-GARCH in Table 7 between markets *i* and *j* at time *t*.

Table 8B: Regression Analysis of Conditional Correlations between OilWTI and oil Producers.

Country/Index i:	OilWTI	OilWTI	OilWTI	OilWTI	OilWTI	OilWTI
Country j:	Brazil	Canada	Colombia	Mexico	U.S.	DVIX
λ_0	0.1618***	0.3135***	0.1255***	0.1283***	0.0772***	-0.085***
	(0.0023)	(0.0024)	(0.0022)	(0.0027)	(0.0029)	(0.0026)
λ1 (Financial Crisis)	0.1623***	0.1139***	0.176***	0.0309***	0.0635***	-0.058***
	(0.0052)	(0.0053)	(0.0048)	(0.006)	(0.0066)	(0.0058)
λ2 (Post- Financial Crisis)	0.1961***	0.162***	0.1998***	0.2009***	0.245***	-0.180***
	(0.0032)	(0.0033)	(0.003)	(0.0037)	(0.0041)	(0.0036)
Observations	3652	3652	3652	3652.00	3652.00	3652.00
F	1924.71	1253.25	2338.13	1559.05	1849.39	1231.02
F (p-value)	0.000	0.000	0.000	0.00	0.00	0.00
Adjusted R^2	0.5131	0.4069	0.5615	0.46	0.50	0.40

Notes: *** Represent statistical significance at the 1% level. Standard errors are in the parenthesis. The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t$, for $i \neq j$, where $\hat{\rho}_{ij,t}$, represents the predicted conditional correlation by the DCC-GARCH in Table 7 between markets *i* and *j* at time *t*.

Table 8C: Regression analysis of conditional correlations between DVIX and oil producers.

Country/Index i:	DVIX	DVIX	DVIX	DVIX	DVIX
Country j:	Brazil	Canada	Colombia	Mexico	U.S.
λ_0	-0.4303***	-0.4976***	-0.2461***	-0.5249***	-0.7831***
	(0.0024)	(0.0021)	(0.0024)	(0.002)	(0.0017)
λ1 (Financial Crisis)	-0.1063***	-0.0772***	-0.0949***	-0.1097***	-0.0695***
	(0.0054)	(0.0047)	(0.0053)	(0.0045)	(0.0039)
λ2 (Post- Financial Crisis)	-0.0598***	-0.1108***	-0.1264***	-0.0552***	-0.0492***
	(0.0033)	(0.0029)	(0.0033)	(0.0028)	(0.0024)
Observations	3652.00	3652.00	3652.00	3652.00	3652.00
F	270.48	746.78	766.81	369.77	277.92
F (p-value)	0.00	0.00	0.00	0.00	0.00
Adjusted R^2	0.16	0.29	0.30	0.17	0.13

Notes: *** Represent statistical significance at the 1% level. Standard errors are in the parenthesis. The regression equation is $\hat{\rho}_{ij,t} = \lambda_0 + \lambda_1 DV1_t + \lambda_2 DV2_t + \epsilon_t$, for $i \neq j$, where $\hat{\rho}_{ij,t}$, represents the predicted conditional correlation by the DCC-GARCH in Table 7 between markets *i* and *j* at time *t*.

The increased correlations during the U.S. financial crisis indicate contagion from OilWTI to each of the oil producers' returns. The effects of the post-financial crisis λ_2 are positive and significant in all cases and with higher coefficients than those observed during the crisis. The coefficients for λ_2 range from 0.162 for Canada, 0.1961 for Brazil, 0.1998 for Colombia, 0.2009 for Mexico, and 0.245 for the U.S. These estimates reveal that the relationship between OilWTI and stock markets continues to strengthen beyond the U.S. financial crisis, highlighting the importance of oil prices during the crisis and the subsequent economic recovery of these stock producers.

The coefficients for the OilWTI –DVIX relationship are negative and significant for the constant term, λ_0, at -0.0852, and note that the financial crisis term, λ_1, is also significant at -0.0575, and that the post-crisis term, λ_2, is higher than the crisis term at -0.1795. This increased relationship with OilWTI-DVIX is interpreted as indicating the critical role oil has taken for the U.S. economic recovery as it becomes energy independent.

The last pairwise correlations are posted in Table 8C and include DVIX *and* stock market returns. The constant term, λ_0, is negative and significant for all pairs indicating robust negative correlation during the pre-crisis period, ranging from -0.2461 for Colombia, -0.4303 for Brazil, -0.4976 for Canada, -0.5249 for Mexico, and -0.7831 for the U.S. The effect of the financial crisis, λ_1, is negative and significant for all pairs, indicating contagion, with coefficients ranging from -0.0695 for U.S., -0.0772 for Canada, -0.0949 for Colombia, -0.1063 for Brazil, and -0.1097 for Mexico.

The effect of the post-financial crisis, λ_2, is also negative and significant in all cases, reporting that the inverse relationship between DVIX and each stock returns is stronger during the post-crisis relative to the pre-crisis period. In two cases, Canada at -0.1108 and Colombia at -0.1264, the post-crisis coefficients are higher than the corresponding coefficients for the financial crisis period. For Mexico and the U.S., the coefficients are smaller than during the crisis period, at -0.0552 and -0.0492, respectively, but they remain significantly higher than the pre-crisis period. These results indicate that even when the financial crisis was over, the markets in these countries remained vigilant of the U.S. market volatility and oil prices.

In summary, the DCC-GARCH model is used to identify the long-lasting effects of the financial crisis on the conditional correlations between OilWTI, DVIX, and the stock market returns. The estimation results in Table 8 indicate contagion from the U.S. to the oil-producing countries. Two contagion factors are considered: changes in market volatility represented by DVIX and Oil price returns represented by OilWTI. The long-lasting effects of the U.S. volatility on stock markets during and beyond the U.S. financial crisis are confirmed. The contribution to the literature is establishing the strengthening relationship between OilWTI and the producers' stock returns during the financial crisis, which strengthens even after the crisis is officially over.

Robustness Check and U.S. Energy Independence Efforts

The pooled sample is broken into sub-samples to assess the impact of the financial crisis on the relationship between stock market returns, OilWTI, and the DVIX. First, the pooled sample is split into the periods described before, namely the pre-crisis, crisis, and post-crisis periods, and then the DCC-GARCH model described in section 5 is applied to each subsample. Since the model does not converge for the crisis period, the crisis and post-crisis periods are consolidated, leaving two sample periods. Sample I is from January 1, 2002 to December 31, 2007 covering the pre-crisis period. Sample II begins on January 1, 2008 and continues until December 31, 2015 covering the crisis and post-crisis periods.

The DCC-GARCH model described in Equations 4, 5, and 6 are replicated for each period and the specific dynamic conditional correlations are obtained; next, a comparison of the conditional correlation coefficients for each period is performed and results are interpreted. Table 9 includes the DCC-GARCH based relationships between OilWTI, DVIX, and the stock market returns. The table consists of results for the Pooled Sample, Sample I (pre-crisis period), and Sample II (crisis and post-crisis periods).

For the Pooled Sample, the correlation coefficients between OilWTI and oil producers are positive and significant, ranging in descending order from 0.4184 for Canada, followed by Brazil at 0.3279, Colombia at 0.2808, Mexico at 0.2799, and the U.S. at 0.2675. The correlation between OilWTI and DVIX is negative and significant at -0.2115, indicating an inverse relationship between oil prices and market volatility changes. As expected, the correlation between DVIX and the country-specific stock markets is negative and significant in all cases, and not surprising; the highest relationship is observed between DVIX and the U.S. at -0.8349. The other countries report correlations from -0.5865 for Canada, -0.5774 for Mexico, -0.5096 for Brazil, and -0.3542 for Colombia. The cross-country conditional correlations between the U.S. and each of the other oil producers are analyzed, and the highest coefficients are for Canada, Mexico, and Brazil at 0.6954, 0.6752, and 0.6031, respectively, trailing by Colombia at 0.392. The pairwise correlations for both sub-samples are then compared.

Analyzing Sample I, the pairwise correlations between OilWTI and the stock markets are only significant for Brazil at 0.1648 and Canada at 0.3472. The pairwise correlations between DVIX and stock indices are negative and significant in all cases, ranging from -0.8677 for the U.S., -0.6975 for Mexico, -0.6033 for Brazil, -0.566 for Canada, and -0.3458 for Colombia. The cross-country correlations with the U.S. are positive and significant in all cases, ranging from 0.7642 for Mexico, 0.6962 for Brazil, 0.65 for Canada, and 0.3713 for Colombia. These results shed light on the strong relationship between oil producers and the U.S. stock returns before the financial crisis.

The last section of Table 9 includes the correlation coefficients for Sample II, reporting that the correlation coefficients between OilWTI and each oil producer are positive and significant. For the U.S., the correlation is significant at 0.4282. These results align with Mollick and Asseffa (2013) since it is also found that the correlations between the OilWTI and the U.S. have negative and not statistically significant relationships during the pre-crisis period. They change to positive and significant due to the financial crisis. This study expands their work by identifying similar results for Canada (0.533), Brazil (0.4526), Mexico (0.4194), and Colombia (0.4058), highlighting the substantial influence of the financial crisis on the correlations between OilWTI and each of the oil producing countries, hinting contagion between OilWTI and stock market returns.

The coefficients are negative and significant for the pairwise correlations between DVIX and each stock market. When contrasting them from Sample II and Sample I, Canada (-0.648) and Colombia (-0.4423) are higher during Sample II but are smaller for the U.S. (-0.8492), Brazil (-0.5466), and Mexico (-0.6118). The pairwise correlations between the U.S. and each stock market are reviewed with the finding that the coefficients increase for Canada (0.7564) and Colombia (0.4927). Still, for Brazil (0.6497) and Mexico (0.7125), they decreased.

U.S. efforts to becoming a net exporter of oil have changed the relationship between OilWTI and stock returns from negative and insignificant to positive and significant. These findings are essential for policymakers and practitioners because they highlight the importance of oil price returns on the economic recovery of these oil-producing countries during and beyond the U.S. financial crisis.

Table 9: Conditional correlation coefficients of daily stock index returns, OilWTI and DVIX

	Pooled Data	Sample I	Sample II
OilWTI, DVIX	-0.2115***	0.021	-0.3454***
	0.0387	0.072	0.0331
OilWTI, U.S.	0.2675***	-0.0036	0.4282***
	0.0386	0.0759	0.0316
OilWTI, Brazil	0.3279***	0.1648**	0.4526***
	0.0371	0.0752	0.0301
OilWTI, Canada	0.4184***	0.3472***	0.5333***
	0.0336	0.0658	0.0268
OilWTI, Colombia	0.2808***	0.104	0.4058***
	0.0379	0.0736	0.031
OilWTI, Mexico	0.2799***	0.0493	0.4194***
	0.0381	0.0738	0.0313
DVIX, U.S.	-0.8349***	-0.8677***	-0.8492***
	0.0122	0.017	0.0102
DVIX, Brazil	-0.5096***	-0.6033***	-0.5466***
	0.0297	0.0462	0.0258
DVIX, Canada	-0.5865***	-0.566***	-0.648***
	0.0264	0.0491	0.0216
DVIX, Colombia	-0.3542***	-0.3458***	-0.4423***
	0.0353	0.0654	0.0302
DVIX, Mexico	-0.5774***	-0.6975***	-0.6118***
	0.0265	0.0419	0.0229
U.S., Brazil	0.6061***	0.6962***	0.6497***
	0.0259	0.0435	0.0219
U.S., Canada	0.6954***	0.65***	0.7564***
	0.0212	0.0447	0.0164
U.S., Colombia	0.392***	0.3713***	0.4927***
	0.0348	0.0693	0.0289
U.S., Mexico	0.6752***	0.7642***	0.7125***
	0.0218	0.0375	0.0183

Note: Robust standard errors are in parentheses. *, **, and *** represent statistical significance at 10%, 5% and 1% levels, respectively.

Summary and Conclusions

VAR and DCC-GARCH models are used to study the influence of the 2008-2009 financial crisis on the relationship between OilWTI, U.S., DVIX, and the stock market returns of the five largest oil-producing countries in the Americas.

The sample includes daily closing prices from January 1, 2002 through December 31, 2015 of five major oil-producing countries in the Americas, including Brazil (BOVESPA), Canada (S&P/TSX Composite Index), Colombia (IGBC), Mexico (BOLSA), and the United States (S&P 500 index). To measure the U.S. implied market volatility, the CBOE Volatility Index® (VIX) is used while the oil price per barrel of West Texas Intermediate (OilWTI) represents oil prices.

Using VAR models, the effects of shocks on DVIX and OilWTI on stock returns from the Americas' principal oil producers is tested. Shocks to DVIX have short-run adverse effects on stock returns, followed by a reversal and eventual dissipation of the impact by the fifth day. Shocks to OilWTI have short-sun positive effects on all oil producers' stock returns. Overall, there is confirmation of the influence of DVIX and OilWTI shocks on the stock returns of these major oil producers.

To assess the dynamic relationship between OilWTI, DVIX, and stock returns, the DCC-GARCH for the pooled data is used and the pairwise dynamic conditional correlations between OilWTI, DVIX, the U.S., Brazil, Canada, Colombia, and Mexico are obtained. These pairwise dynamic-conditional correlation coefficients with two dummy variables representing the financial crisis and post-financial crisis periods are regressed. Each period's effects relative to the pre-financial crisis are captured, identifying the positive and long-lasting impact of the U.S. financial crisis on the correlation between OilWTI and the oil producers' stock returns. These results highlight the importance of oil prices on the post-crisis economic recovery of all countries. For the U.S., these long-lasting effects on the latest efforts to become a net oil exporter are inferred.

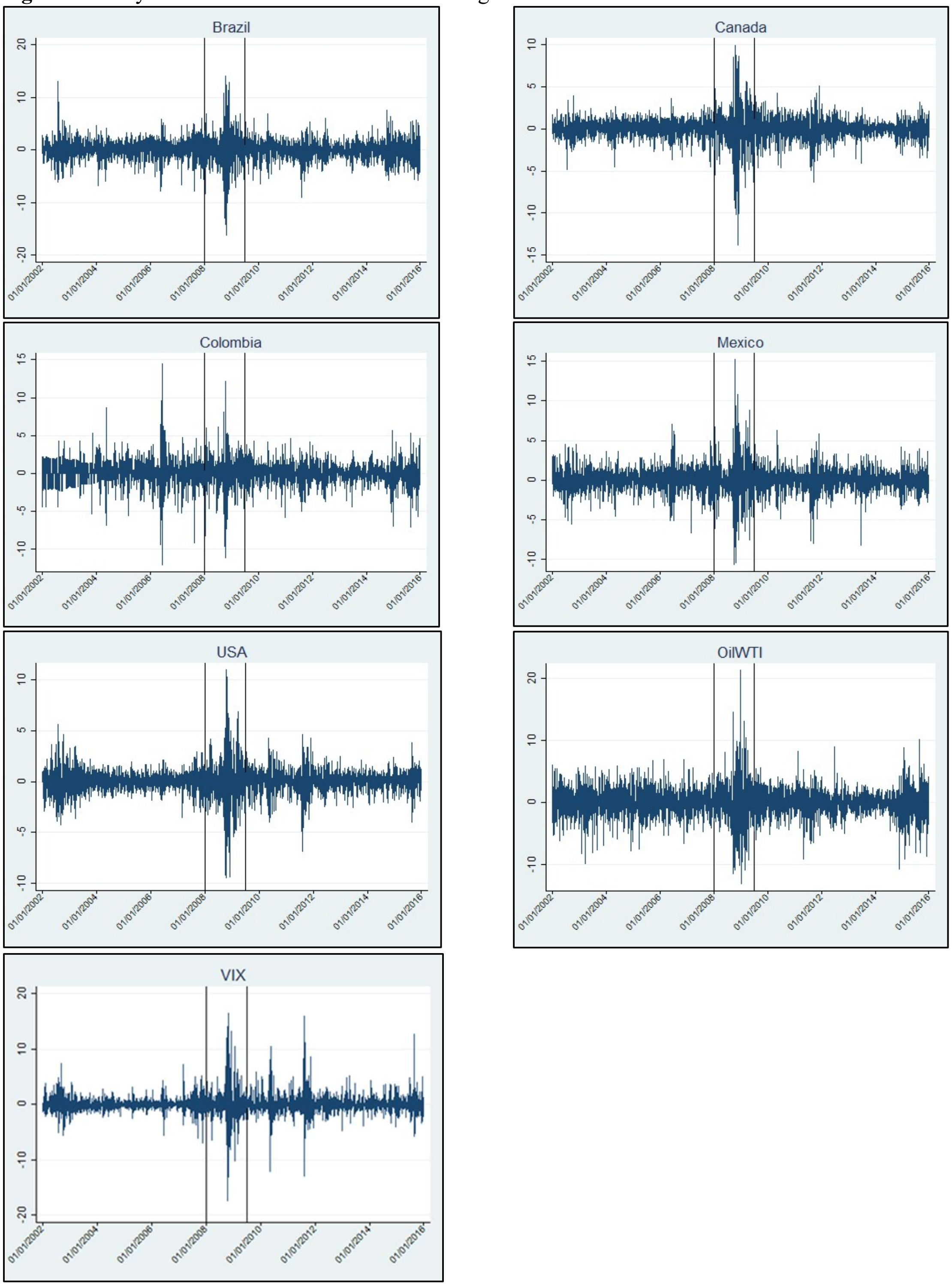
The existence of contagion is identified through the increased correlation coefficients between the U.S. and the other oil producers due to the financial crisis. A similar pattern is found, but with a negative sign, for the pairwise correlations between the DVIX and the stock markets, confirming financial contagion from the U.S. to the other countries.

Robustness checks are conducted by breaking the pooled data into two samples; Sample I includes the pre-crisis and Sample II consists of both crisis and post-crisis periods. The DCC-GARCH model is applied for each period, and a comparison of the generated conditional correlations for each sample is conducted, with the results indicating evidence of contagion. The relationship between the OilWTI and the stock returns is positive and significant only for Brazil and Canada during the pre-financial crisis period. The relationship between OilWTI and the U.S has a negative and not significant coefficient. The correlation coefficients between OilWTI, Colombia, and Mexico are positive but not significant. For the post-crisis period, all pairwise correlations between OilWTI and the oil producers are positive and significant, changing the relationship between OilWTI and the U.S. and increasing the influence of oil price changes on all stock returns after the financial crisis.

The contribution to the literature is the identification of how the U.S. financial crisis significantly changed the relationship between OilWTI and the major oil producers' stock returns in the Americas. Before the U.S. financial crisis, the oil producers are influenced by the U.S. financial markets' performance and volatility, and these relationships strengthened during the financial crisis and beyond. Except for Brazil and Canada, the relationship between OilWTI and the oil producers' stock returns is insignificant before the financial crisis. Still, these relationships shift to being statistically significant during the financial crisis, continuing after the crisis ends. A radical change of conditional correlations between OilWTI and the U.S. is identified, shifting from negative and insignificant before the U.S. financial crisis to positive and significant after the start of the crisis. This is attributed to the recent U.S. efforts of becoming energy independent and a net exporter of oil. Since oil is also an important revenue source for other countries, low oil prices accentuated the financial contagion and continue to be crucial during the economic recovery.

This contribution provides tools for policymakers when seeking alternative energy sources and financial professionals seeking diversification strategies since oil producers are more oil-dependent since the U.S. financial crisis. Any shocks to oil prices are likely to affect all oil producers in unison.

Figure 1: Daily Stock Returns and Calculated Changes or Differences.



Note: Vertical lines represent the beginning and end of the 2008-2009 financial crisis, according to NBER.

Figure 2: Impulse Responses to Shocks on Brazil, OilWTI, and DVIX.

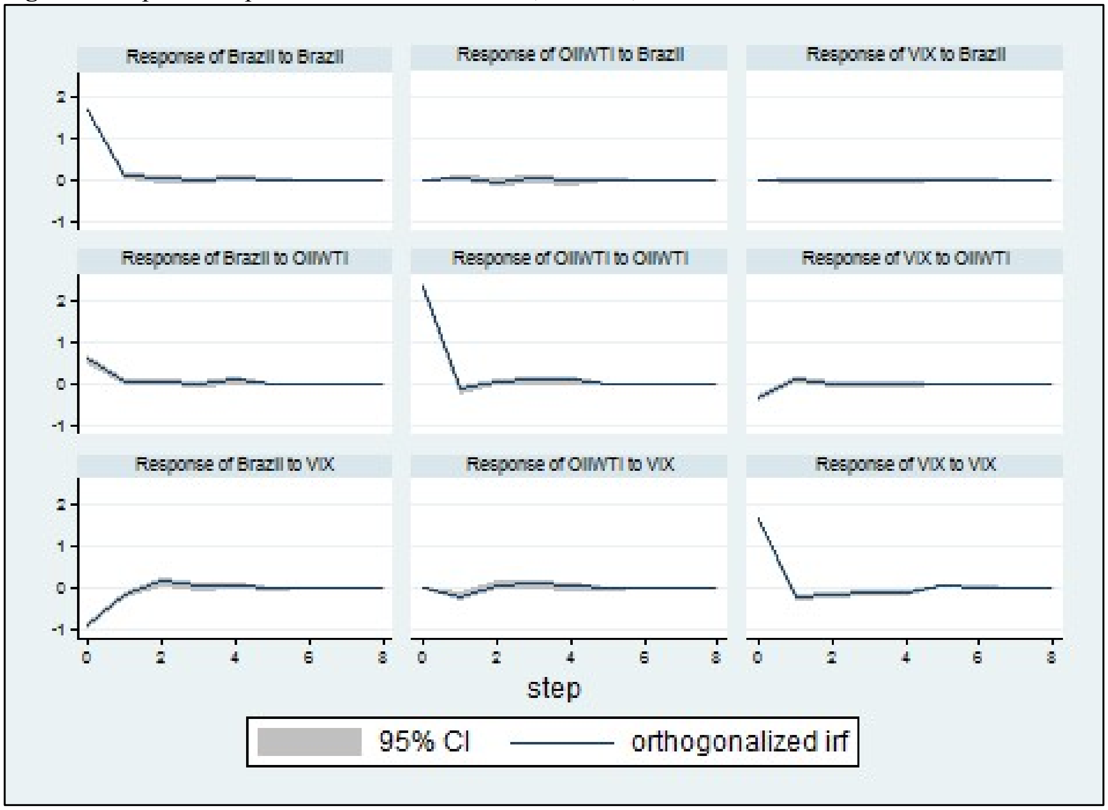


Figure 3: Impulse Responses to Shocks on Canada, OilWTI, and DVIX.

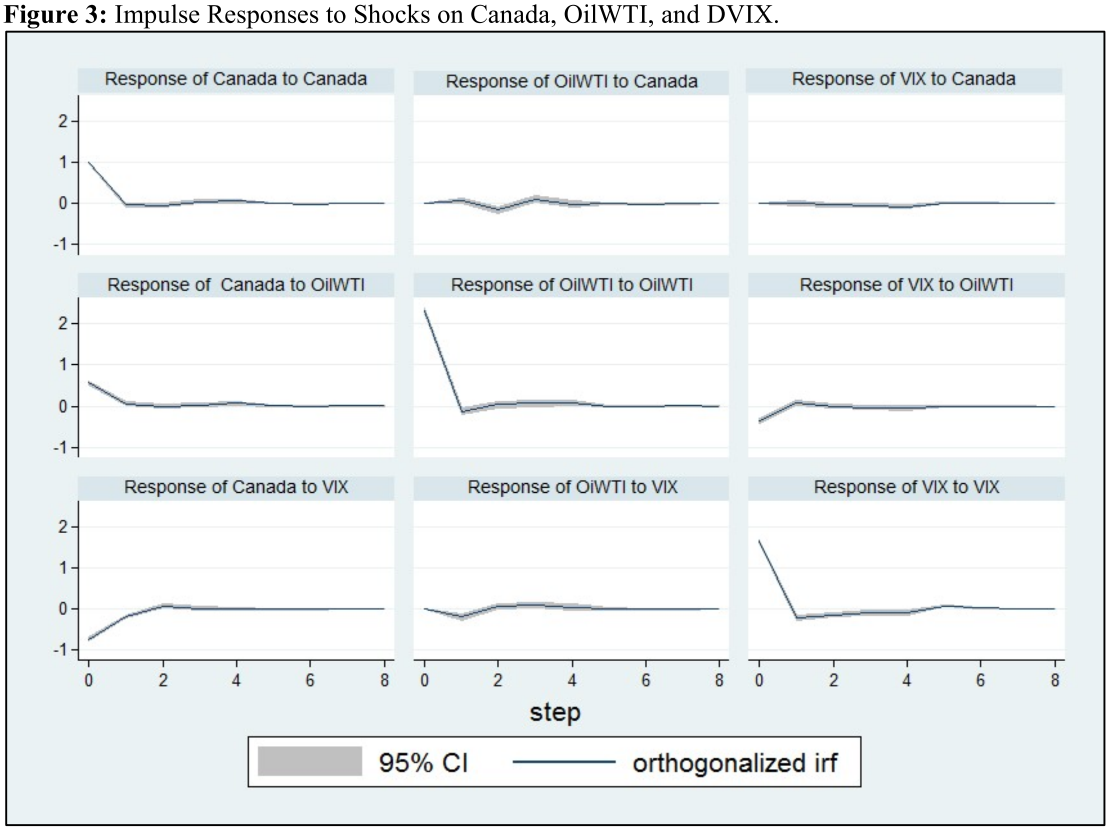


Figure 4: Impulse Responses to Shocks on Colombia, OilWTI, and DVIX.

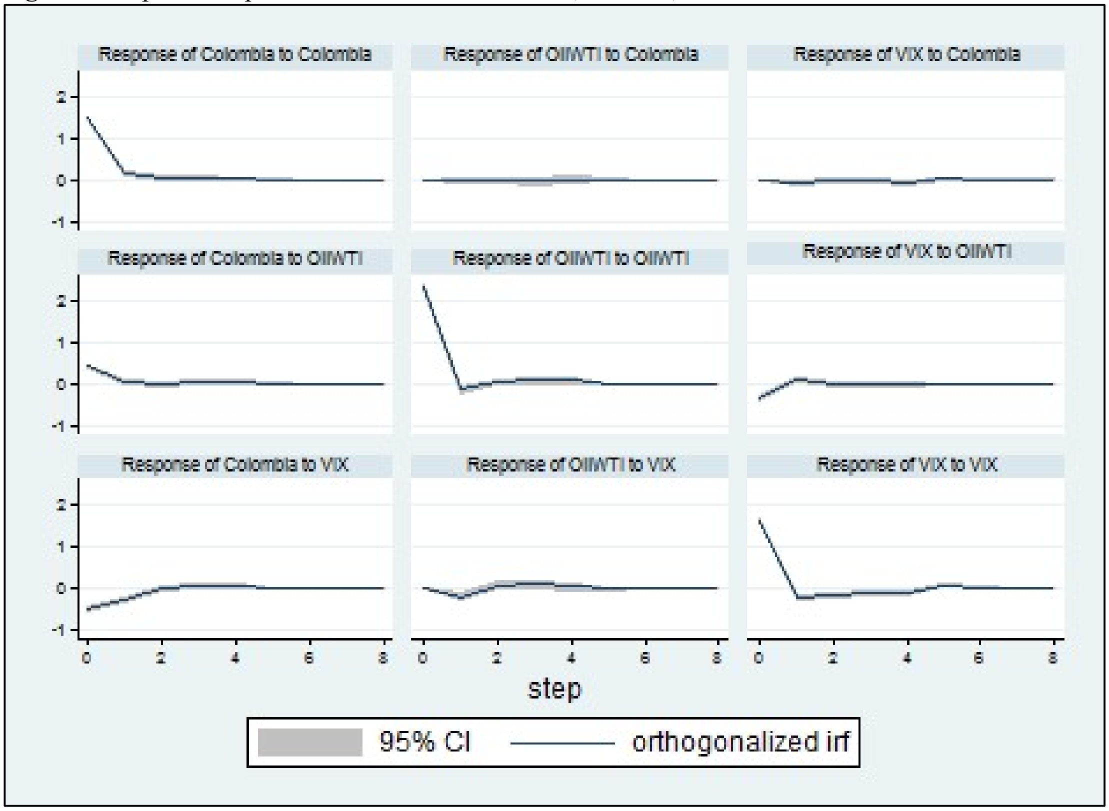


Figure 5: Impulse Responses to Shocks on Mexico, OilWTI, and DVIX.

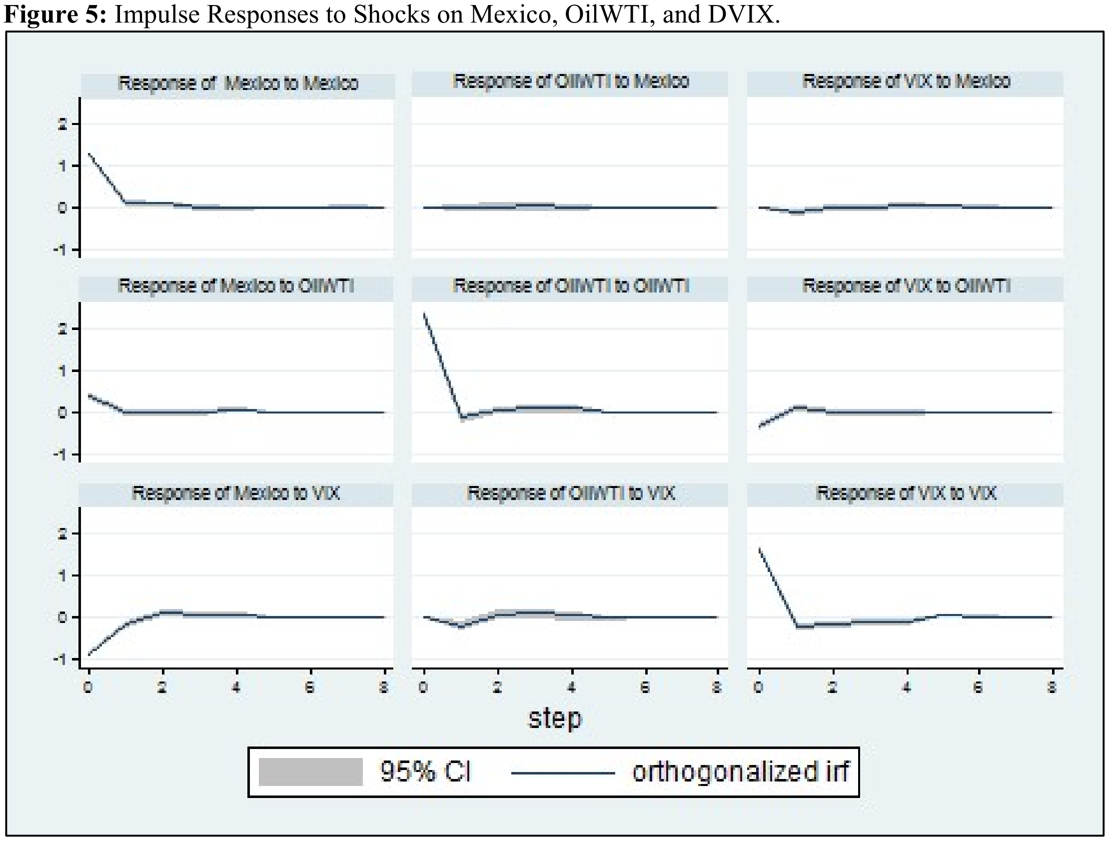
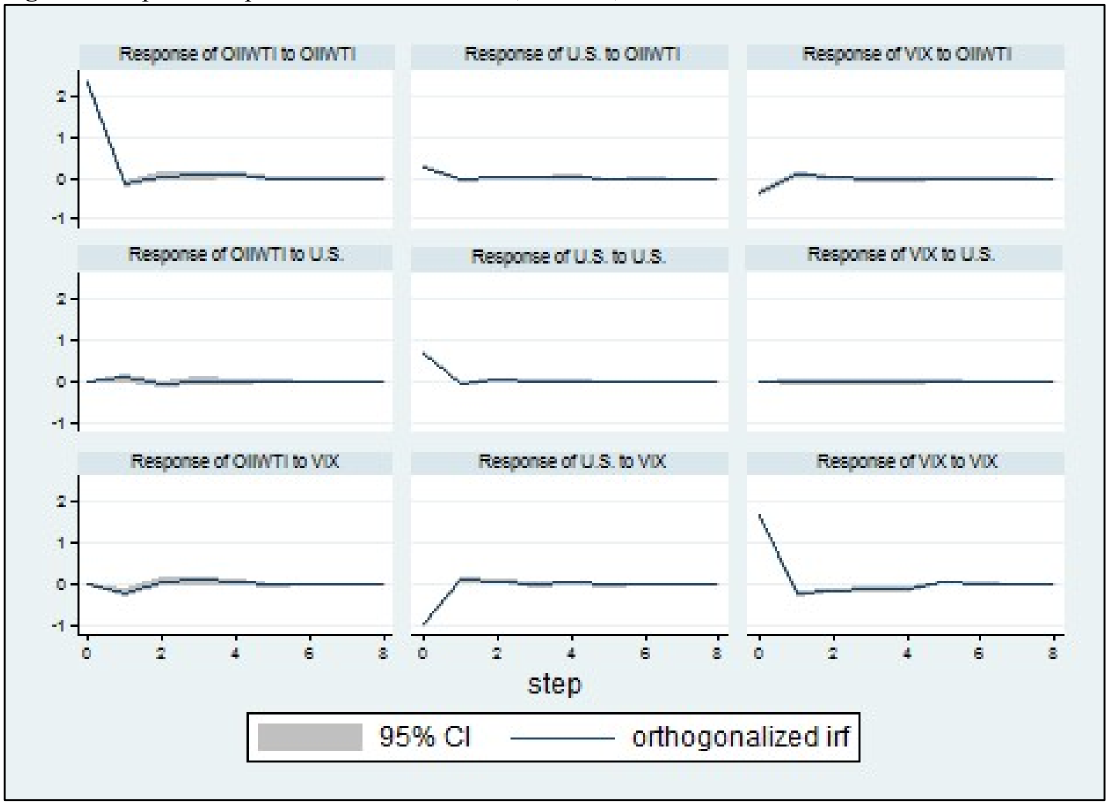


Figure 6: Impulse Responses to Shocks on U.S., OilWTI, and DVIX.



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Recreational Marijuana in New York State: Local Community Choice to Opt Out

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Abstract

New York's Marijuana Regulation and Taxation Act (MRTA) legalized recreational marijuana in New York State. The MRTA allowed municipalities to opt out of allowing dispensaries and public consumption sites within their borders. An empirical median voter model is used to better understand community opposition to participating in the legal recreational retail market for marijuana. The analysis finds a positive and significant relationship between income, political affiliation (Republican), crime rates, and the percent of the population under 18 leading communities to be more likely to opt out. Further, older and more diverse communities are more likely to allow retail dispensaries to operate.

JEL Codes: H80, R59
Keywords: Cannabis Policy, Recreational Marijuana Markets, Community Choice

Introduction

With the passage of Marijuana Regulation and Taxation Act (MRTA) in the spring of 2021, New York joined the ranks of 18 other states to legalize the sale, possession, and use of recreational marijuana. Chapter 7A of the law includes three important components, 1) the creation of the Office of Cannabis Management to establish a regulatory framework and oversee the production, processing and sale of marijuana, 2) a licensing mechanism including minimum mandatory orientation and training for licensing operators of retail, processing, and production facilities as well as individuals interested in working in the field, and 3) a mandate to address individual and community social justice and inequities that arose from the enforcement of drug (marijuana related) laws (Senate Bill 854-A).

One important aspect of the bill is that it offered communities the option to opt out of the retail market. In other words, while a community could not prevent the consumption and cultivation of cannabis for personal use by adults over the age of 21, they could choose to prevent recreational dispensaries or on-site consumption facilities (lounges in which individuals would be able to purchase and smoke or vape marijuana on the premises) from opening within their borders. The process to opt out required the local municipality to pass a law prohibiting the operation of either retail dispensary sales, consumption sites, or both by December 31, 2021 (New York State Office of Marijuana 2021). Voters in communities in which elected town and village boards had passed an opt-out law could petition to hold a referendum on whether to allow the law to stand or not. Communities that opted out could later decide to allow dispensaries in the future.

Opting out would not prevent anyone from consuming or purchasing marijuana. Dispensaries in communities where they were allowed would be able to offer delivery service to non-participating communities and individuals are allowed to transport their legal purchases across community borders (within the state) with no restrictions. Non-participating towns and communities would simply not share in the tax revenues generated by legal marijuana sales. The decision to opt out only applied to recreational retail dispensaries and on-site consumption facilities. Communities could not prohibit medical marijuana dispensaries or cultivation, production, and processing operations for either medical or recreational use from opening within their borders. Marijuana is still classified as a Schedule 1 drug at the federal level, thus, its cultivation, processing and distribution for either medical or recreational use is bounded by New York state borders.

Legal marijuana in the United States, whether for medical or recreational use is a relatively recent phenomena and there is a small but growing body of literature analyzing the factors underlying legalization in the various states. Building upon the previous literature, this paper adds to this area of inquiry with the aim to identify factors that may have led individual New York State communities to opt out of the legal recreational market.

Studies such as those by Hall and Schiefelbein (2011), Bradford and Bradford (2017), and Calkins et al. (2021) focus upon state choices to allow medical marijuana. Hall and Shiefelbein modeled the decision to allow medical marijuana using a probit analysis that included key political, demographic, and economic variables across 48 states of the United States. Only 14 states had legalized medical marijuana at the time of their analysis. Hall and Shiefelbein found a negative relationship between the choice to legalize medical marijuana and economic freedom, church attendance, and political affiliation (voted republican in the 2008 presidential election). Subsequent studies by Bradford and Bradford (2017), Bock (2021) and Calkins et al. (2021) root their analysis in median voter theory identifying various economic and demographic factors likely to influence voter behavior. Following Congelton (2004) these studies suggest that legislators/politicians will adopt policies that appeal to the median voter.

Bradford and Bradford (2017) analyzed the process of policy diffusion across the country as the number of states allowing medical marijuana grew from 1 in 1996 to 23 by 2015. Based in part upon median voter theory, Bradford and Bradford develop a probit model in which a combination of diffusion variables measuring policy and ideological differences between neighboring states and political and economic variables representative of each state's own motivational factors to estimate the adoption of legal medical marijuana over time. They found that proximity to neighboring states that legalized medical marijuana increased the probability that a state may legalize medical marijuana, countervailing in-state median voter factors such as political beliefs, and economic variables were however more likely to determine the outcomes. More conservative states were less likely to adopt legal medical marijuana than more liberal states were.

Calkins et al.'s (2021) analysis of the adoption of legalized medical marijuana updates Hall and Schiefelbein's (2011) model, supplementing it with additional demographic and economic variables and a spatially weighted variable to capture proximity effects between neighboring states that may have already legalized medical marijuana. The original model specification included only medical marijuana, economic freedom index, the percentage of the population over age 65, state per capita income, the percentage of the population with a bachelor's degree, the percentage of the population residing in urban areas, average weekly church attendance, and the percentage of the population that had voted Republican in the 2008 Presidential election. Calkin et al. include additional demographic variables for gender (percentage of the population identifying as female), racial composition (percentage of the population that is Black), the percentage of the population that is under 24, variables for tobacco and cigarette use, and a spatial lag variable. Estimates from the updated specification are similar to Hall and Shiefelbein in that economic freedom and Republican are both inversely related to legalization, and urban and over 65 are directly related to legalization. Contrary to Bradford and Bradford (2017), Calkins et al. does not find direct spatial dependence between states for the adoption of legal medical marijuana.

Two other recent studies, one by Bock (2021) and the other by Cruz et al. (2016) focus attention directly upon the legalization of recreational marijuana. Bock's analysis focuses on the approval of Amendment 64 legalizing marijuana in Colorado in 2012 only six years after a similar referendum had failed to gain voter approval. Following the earlier literature, Bock roots the analysis to the median voter framework and includes a spatial component to capture the influence of geographic proximity of Colorado counties to neighboring states. Bock includes in the analysis variables for political affiliation, education, gender, income and poverty, rural population, and whether an individual is a native-born Coloradan or not. The analysis was conducted using OLS, a probit specification and a spatial autoregressive model. Under the probit analysis (dependent variable, vote yes for approval), Bock found the estimated coefficients for political affiliation (Democrat) to be positive and significant, with both the native-born and rural population coefficients to be negative and significant. The spatial component was not found to be significant.

As opposed to the probit analysis used in most of the other studies, Cruz et al. (2016) use a logistic function to analyze the factors associated with cannabis legalization from cross-cultural survey data for three countries, Uruguay, El Salvador, and the United States. Uruguay legalized marijuana for personal use in 2013 through a legislative process. In the United States, legal marijuana and the process used to legalize it (i.e., public referendum or legislative action) varies state by state, and marijuana is illegal in El Salvador. The data used included both demographic and economic (age, family income, years or level of education, families with children), social and behavioral variables (political viewpoints, crime victimization, beliefs in the role of the state, marijuana usage by individuals and friends and family). Instead of rooting their analysis in median voter theory, Cruz et al. explain the outcomes of their analysis in terms of socialization and trust in government, especially as it relates to the case of Uruguay. Factors that appear to be strong indicators of support for legalization in the Latin American countries include years of education, prior marijuana use, the President's job approval rating, and left of center political beliefs. For the United States and El Salvador, the estimated logistic coefficients indicate that families with children did not support legalization, and for Uruguay and El Salvador, religion was negatively associated with support for legalization.

This paper is organized as follows. Section 2 presents an overview of some of the recent literature on individual state experiences with the legalization of marijuana. In Section 3, a preliminary analysis of New York's potential marijuana market is presented. Section 4 presents an evaluation of the factors that led communities in New York to either allow dispensaries and consumption sites within their borders or to opt out of the retail marijuana market. The conclusions of this study are presented in Section 5.

Individual State Experiences with Legalization

Similar to alcohol during Prohibition, the criminalization of marijuana over the twentieth century did not result in its disappearance from the social and economic landscape. Miron and Zwibel (1991) pointed out in their study of alcohol consumption following the imposition of Prohibition, alcohol consumption initially declined by 70 percent, however by the early 1930s, its use approached pre-Prohibition levels.

Arrests for marijuana possession in New York City ranged between 1038 in 1991 to a high of 51,589 in 2011, and as of 2017 stood at 18,241 (Bond et al., 2019). Estimates by the New York State Department of Health (2018, pages 16-20) found that the state's illegal marijuana market ranged from $1.74 billion to $3.5 billion annually and estimated that 1.27 million individuals (8.5 percent of the state's population) used marijuana. Using these figures to drive revenue projections for a legal recreational marijuana market and depending on specific tax rates used, the New York Department of State estimated annual potential sales tax revenues between $297 million to $677 million. A recent study by Parrot and Mattingly (2021) estimated that recreational marijuana would generate approximately $276 million annually in state and local taxes and 40 to 50 thousand new jobs. The potential gain to state revenues from legalized recreational marijuana served as one of the underlying arguments used to pass the MRTA in New York.

However recent analysis by Miller and Seo (2021) and Amlung and MacKillop (2019) suggests that there may be some substitutability between marijuana and other products. In their analysis of Washington State's tax revenues following legalization, Miller and Seo (2021) found significant substitution between cannabis, alcohol and tobacco sales leading to a decrease in the demand for alcohol by as much as fifteen percent and a drop in cigarette demand by up to 5 percent that would decrease tax revenues from those products. Amlung and MacKillop (2019) focused upon substitution between legal and illegal markets for recreational marijuana and suggested that pricing policy for legal markets was an important factor. For their analysis, Amlung and MacKillop conducted a behavioral study of 276 individuals in which participants were tasked with identifying their willingness to purchase one gram of marijuana at various price points and from both the legal and illegal market. Using the collected data, they created demand functions for both markets which were in turn used to estimate elasticities with the conclusion that marijuana consumers would prefer to purchase from the legal market when prices were equivalent to or just slightly higher than illicit market prices. Study participants were price sensitive and would switch back to the illegal market if prices rose above this range.

Sen and Wyonch (2018) also found that the persistence of illegal markets for marijuana in Canada impacted legal sales and tax revenue. Two factors drive this conclusion, the relative infancy of the legal supply chain for the period that Sen and Wyonch evaluated which by their estimation was only able to meet approximately 30 to 60 percent of market demand, and the existence of a well-developed black-market supply. Sen and Wyonch advocate for the streamlining of regulations to ensure the legal supply of marijuana into Canadian markets to improve overall tax revenue collections from an estimate of between 300 to 600 million Canadian dollars to a potential of 1.3 billion Canadian dollars annually, and to reduce the overall size of the black market (2018, p. 3). Irvine and Light (2020), using a nested demand model of Canadian cannabis markets, found substantial substitution effects leading to a reallocation of excise tax revenues across alcohol, marijuana, and tobacco. As part of their analysis, Irvine and Light conducted market revenue simulations to estimate overall revenues and tax revenues for recreational goods (comprised of alcohol, tobacco, and marijuana) and a second good "z" (all other goods) under alternate elasticity levels and find that increased revenues for legal marijuana would lead to decreases in revenue from both alcohol and tobacco. In addition, they find that personal and corporate tax revenues would increase from new employment and corporate profits generated in the recreational cannabis industry (Irvine and Light, 2020).

It is evident from the literature that tax policies and the appropriate level of taxation on recreational cannabis are an important consideration for the market. Jacobi and Sovinsky (2016), using a utility framework to analyze legalization, found that excise taxes will impact both legal use of recreational cannabis as well as purchases from the illicit market and suggest that taxing marijuana at 25 percent of the current market price would increase its probability of use after legalization by just 40 percent. Mace et al. (2020) with a focus on market structure and tax incidence, found significant deadweight loss by as much as 48 percent as market structure became more concentrated (monopolistic) with consumers paying more of the sales and excise taxes than sellers. In addition, Mace et al. found significant cross-border sales issues with neighboring states that had legalized recreational marijuana. Khan et al.'s (2020) analysis focuses directly on the cross-border sales issue (Washington and Oregon) and the taxes leveled on marijuana sales. Using several techniques including difference-in-differences, they found that the imposition of a 25 percent sales tax on recreational marijuana in Oregon led to a decrease in marijuana sales in border communities with Washington of 19.7 to 26.8 percent (Khan et al, 2020, p. 121).

As reported in the news media, the legalization of recreational marijuana in New York state was not without controversy. Ferre-Sadurni (2021) for example cites opposition legislators concerns with health and safety issues stemming from the MRTA. The cannabis literature reflects some of the potential issues that may arise from the location of dispensaries including possible impacts on home prices and sales, crime, and level of personal usage. Ambrose et al. (2021) using a linear probability model and data from the Behavioral Risk Factor Surveillance System for the State of Washington, found that individual proximity to a dispensary measured by travel time resulted in increased usage and intensity of use of marijuana. They estimated that a 33 percent reduction in travel time to a dispensary led to increased recreational usage by 0.082 day in past month use, and a 0.54 percent increase in the probability of having used marijuana in the past month (Ambrose et al., 2021, p. 2).

In their analysis of Denver's housing market, Burkhardt and Flyr (2019) found a positive relationship between home prices and new retail dispensary locations with home prices within .25 of a mile increasing by 7.7 percent on average and from .25 to .5 miles increasing by 4.7 percent. Burkhardt and Goemans (2019), using a difference-in-differences methodology, found that drug-related crime rates fell by as much as 13 percent in above median income neighborhoods within a half-mile of a new dispensary. Along a similar vein, Prestemon et al. (2019) found a reduction in the illegal growing of marijuana by 20 to 29 percent in national forests in states with legal recreational marijuana. A recent study by Meehan et al. (2020) of both Colorado and Washington found evidence that legal marijuana led to an increase in the number of tourists visiting as measured by hotel rooms rented per month and hotel occupancy rates with monthly hotel room rentals rising by 4 percent and increased occupancy by 7 percent in Colorado and 1 percent increase in room rentals and 3.5 percent increase in occupancy rates for Washington. Zambiasi and Stillman (2020), using a synthetic control model, found evidence that legal marijuana was a positive amenity for Colorado attracting in-migration resulting in a 3.2 percent increase in population by 2015.

The New York Market

New York's Office of Cannabis Management (OCM) and the Cannabis Management Board were established in October 2021. Since their establishment, they have overseen the process of developing the regulatory processes for licensing and certifying firms and workers, and the establishment of dispensaries and the state supply chain for marijuana. The first legal recreational dispensary opened in New York City in late December 2022 with more slated to open throughout the state within the first few months of 2023. The MRTA (except for legacy medical marijuana companies already in operation) limits the amount of vertical integration between growers (cultivation), processors, distributors, and dispensaries. It does carve out exceptions for a microbusiness license and a small business cooperative license that will allow small businesses/licensees to operate in all stages of the market. This license is aimed at promoting social equity. Other forms of licenses available include adult use cultivator, adult use processor, adult use distributor, adult use retail, New York delivery license, and New York nursery license.

In general, licensing falls on individuals and firms interested in owning and operating a cannabis related business, not employees of these businesses. Licensing of any industry or occupation inherently creates entry barriers limiting the number of firms or individuals in the industry/occupation and may impact the quality and pricing of services (Kleiner, 2000). While the OCM has no set limits on the number of licenses for retail dispensaries or consumption sites that will be issued, it has not granted many licenses at this time. The initial set of licenses granted in Spring 2022 by the OCM were for provisional cultivators and processors to allow for the provision of legal cannabis into the market. Provisional dispensary licenses were granted in November 2022 primarily to individuals (or closely related family members) that had been impacted by past enforcement of anti-marijuana drug laws. Forty percent of the tax revenues generated by the sale of marijuana in the state are reserved for the New York State Community Reinvestment Fund for use in revitalization in areas most affected by the past enforcement of New York drug (cannabis) laws.

Marijuana in the state will be taxed through several methods. At the retail level, there is a 13 percent tax rate, with the state receiving 9 percent and the additional 4 percent directed towards the community in which the sale took place. Communities that have opted out will not receive the additional 4 percent of the tax. Distributors and producers will pay a per milligram tax per unit based upon type of product and the potency of the product.

Under New York's medical marijuana program, there are currently 10 firms licensed to both produce and dispense marijuana in the state with a total of 40 dispensaries in operation dispersed geographically across the state, with 21 located in New York City and surrounding counties (12 in New York City, 6 on Long Island, 2 in Westchester, and 1 in Rockland). Under the MRTA, these firms will continue to operate in the medical marijuana market. They will also be eligible to enter the recreational market as wholesalers by paying $5 million to the OCM and the direct retail level of the market (with a 3-year waiting period) by paying $3 million (Southall, 2022).

The 2018 study from New York State Department of Health concluded that a regulated recreational market would provide quality control in the cannabis market, reducing the risk from consumption by users. It also suggested that adult cannabis usage would not increase substantially, nor would underage use. Studies conducted by Barcott and Whitney (2019), and Barcott, Whitney and Bailey (2021) found that the number of individuals employed in the legal medical and recreational cannabis industry in the U.S. grew by over one hundred thousand from 211,000 to 321,000 full-time equivalent. Schulz (2019), using an Input-Output model, forecast potential employment gains in New York state of approximately 30,000 people.

The Choice to Opt-Out

With the adoption of the MRTA, New York towns and communities faced a choice of 1) whether to do nothing, in which case state licensed marijuana dispensaries and consumption sites would be allowed to operate within their borders, or 2) pass a law to opt out and not allow either one or the other type of retail operation. New York's approach to legalizing marijuana was primarily driven by the Governor's office and the legislative leadership. How much this choice fully represents the view of the general populace and individual communities is an open question.

Following studies such as Hall and Schiefelbein (2011), Bock (2021), Calkins et al. (2021), and Cruz et al. (2016), the community choice to opt out of the retail cannabis market Is modeled using a discrete choice model (probit and logit). Bock (2021) and Calkins et al. (2021) use a probit function and root their analysis as an empirical median voter model, in which the dependent variable (the adoption of legal marijuana) is a function of a combination of demographic and economic variables representative of the median voter. While Cruz et al. (2016) use a similar structure as these other studies, they approach the issue more from a sociological and political perspective and use a logistic function. There are several key variables common across these four previous studies including indicators for community political leanings, educational attainment, income, and community age distribution. Cruz et al. (2016) include in their analysis additional variables related to marijuana use by individuals and crime.

The data used in the analysis include community level per capita personal income the percentage of the population that is white, and percentage of the population that is black, the percentage of the population 65 and older, the percentage of the population 18 and under, and the percentage of the population holding a bachelor's degree or higher collected from the 2020 decennial census. Local political viewpoints were proxied by using the percentages of the population by county that voted Republican and Democrat in the 2020 Presidential election (from Politico).

Data on crime was collected from New York State Division of Criminal Justice Services including total arrests by county, and total arrests reported by individual towns and villages (only available for 222 communities) for 2021. Marijuana use by county for 2018 was collected from the National Survey on Drug Use and Health. Other drug use within the community is proxied using county level opioid death rates per 100,000 for the year 2018 as reported by the New York State Department of Health annual report. Community opt-out data was collected from the New York State Rockefeller Institute that has assembled city, town and village actions on whether to participate in the legal marijuana market by allowing either dispensaries or consumption sites or both to operate within their boundaries. While there are a total of 1400 separate communities identified in the Rockefeller Institute data, many of these communities do not directly align with available census data. Matching individual cities, towns and villages to the Census Bureau data resulted in 463 communities that are included in the analysis. Given that communities had to actively pass a law to opt out of the retail cannabis market, this variable is coded as a dichotomous choice with '0' representing the base state in which retail sales and consumption sites are allowed and '1' the case where the community chooses to opt out. This coding differs from the previous studies (Hall and Schiefelbein, 2011; Bock, 2021, Cruz et al., 2016; Calkins et al., 2021) where the choice is whether to legalize recreational marijuana, but better fits the situation that New York communities faced. The full list of variable names and dummy coding is presented in Table 1.

From the summary statistics reported in Table 2, 51 percent of the reported communities had opted out of allowing dispensaries to operate within their borders. Additionally, 63 percent of the communities had chosen not to allow consumption sites within their borders. The decision to opt out can be rescinded at any time by a community, however, communities only had until December 31, 2021 to opt out. There are any number of reasons why a community may choose to opt out and as reported in the popular press these included concerns over drug use in general, the ability of law enforcement to test individuals for marijuana in DWI related traffic stops, possible increases in local crime rates, and the fact that the rules and regulations for the sale of legal marijuana were not fully developed.

The summary statistics reveal that most of the communities included in the analysis voted Democrat at 51 percent in the 2020 elections, and only 47 percent voted Republican. Per capita income varied significantly across the communities ranging from a minimum of $7,467 annually to a high of $137,352 with a mean of $40,579. The mean for percentage of the population that was white was 84 percent, with a range of 13.4 percent to 99 percent white. The age range for the population varied significantly across the various communities, with the population 65 and above as high as almost 40 percent and a mean of 18 percent across the sample. Similarly, the percentage of the population under 18 ranged from 8 to 59 percent with a mean of almost 20 percent. One statistic of particular interest, the percentage of the population that had used marijuana, ranged from 11 to 19 percent with a mean of 15 percent.

Two models were estimated in both probit and logit forms:

$$\begin{aligned} OptOutDispensary_j = {} & C + \beta_1 PC\_Income_j + \beta_2 Percent\_B_j + \beta_3 Republican_j + \beta_4 CountyCrime_j + \beta_5 Percent65_j + \\ & \beta_6 Percent18 + \beta_7 Bachelors_j + \beta_8 Opioid_j + \beta_9 Marijuana_j + \varepsilon, \end{aligned} \tag{1}$$

and

$$\begin{aligned} OptOutConsumsite_j = {} & C + \beta_1 PC\_Income_j + \beta_2 Percent\_B_j + \beta_3 Republican_j + \beta_4 CountyCrime_j + \beta_5 Percent65_j + \\ & \beta_6 Percent18 + \beta_7 Bachelors_j + \beta_8 Opioid_j + \beta_9 Marijuana_j + \varepsilon, \end{aligned} \tag{2}$$

Results for the analysis are reported in Table 3.

The regression results (reported in Table 3) for both OptOut Dispensary and OptOutConsumsite are very similar. Coefficients for income, Republican, crime rate, and the percent of the population that is under 18 are all positive and significant in both probit and logit estimations. Communities with higher income, a larger percentage of the population that is more conservative (voted Republican), or with greater perceived crime rates were more likely to opt out of retail dispensaries. The result for conservative communities is consistent with the previous literature, in particular Hall and Schiefelbein (2011), Calkins et al. (2021), and Cruz et al. (2016), which all found that more conservative voters and individuals were less likely to support legal marijuana. The estimated coefficient on the percent of the population below the age of 18 is also consistent with Cruz et al., indicative that communities with more under-age children are less likely to support legal retail dispensaries or consumption sites.

Table 1: Variable Names and Sources

Variable name	Definition	Year of data	Source
OptoutDispensary	Community choice to allow dispensaries. Equal to 0 if a dispensary is allowed, and 1 if the community opted out	2022	https://rockinst.org/issue-areas/state-local-government/municipal-opt-out-tracker/
OptoutConsume	Community choice to allow public and commercial consumption sites. Equal to 0 if a consumption site dispensary is allowed, and 1 if the community opted out	2022	https://rockinst.org/issue-areas/state-local-government/municipal-opt-out-tracker/
PC_Income	Per capita income	2020	United States Census Bureau
Population	Population	2020	United States Census Bureau
Percent-W	Percent of the population that is white	2020	United State Census Bureau
Percent-B	Percent of the population that is Black or African-American	2020	United States Census Bureau
Democrat	Percent of voters that voted Democratic in 2020 election	2020	Politico
Republican	Percent of voters that voted Republican in the 2020 election	2020	Politico
Percent-65	Percent of the population that is 65 or older	2020	United States Census Bureau
Percent-18	Percent of the population 18 and under	2020	United States Census Bureau
Crime	Crime Index for individual towns and villages	2021	New York State Almanac, New York State Division of Criminal Justice Services
CountyCrime	Total arrests by county, all crime	2021	New York State Almanac, New York State division of Criminal Justice Services
Opioid	County death rate per 100,000	2018	New York State Department of Health, New York State Opioid Annual Report 2019
Marijuana	Percent of the population (county) 18 or older that used marijuana in the past year	2018	2016, 2017, 2018 National Surveys on Drug Use and Health
Bachelors	Percent of the population with a Bachelor's degree or higher	2020	United States Census Bureau

Table 2: Summary Statistics

Variable Name	Mean	Median	Maximum	Minimum	Std. Dev.	Observations
OptOutdispensary	0.510204	1	1	0	0.500464	441
OptOutconsumsite	0.639013	1	1	0	0.480826	446
Pcincome	40579.59	36881	137352	7367	17696.3	463
Population	24261.85	10329	793409	5056	55460.84	463
White	0.840716	0.8795	0.992	0.134	0.134017	462
Black	0.054969	0.029	0.627	0	0.071388	463
Democrat	0.512313	0.516	0.736	0.262	0.098244	463
Republican	0.470164	0.466	0.717	0.243	0.096447	463
Percent-65	0.180108	0.181	0.399	0.024	0.043635	462
Percent-18	0.209117	0.203	0.595	0.083	0.054095	463
Crime	418.787	131	10622	1	1030.326	230
CountyCrime	6179.838	3573	20441	257	5998.07	463
Opioid	16.80319	14.7	45	0.182159	7.942584	463
Marijuana	0.153378	0.159901	0.191729	0.115177	0.027223	463
Bachelors	0.478311	0.339	54	0.031	2.497995	463

Table 3: Regression Results

Variable	OptOut Dispensary (Probit)	OptOut Dispensary (Logit)	Odds Ratio	Mean Marg. Effect	OptOut Consumsite (Probit	OptOut Consumsite (Logit)	Odds Ratio	Mean Marg. Effect
C	-1.08215	-1.86040		-0.7341	-0.01623	-0.08398		-0.0231
	(-1.03505)	(1.70188)			(1.07409)	(1.78780)		
PCINCOME	0.00003***	0.00005***	1.00005	0.00002	0.00003***	0.00006***	1.00005	0.00002
	(7.31515)	(0.00001)			(0.00001)	(0.00001)		
Percent-B	-2.51128**	-4.05794**	0.01728	-1.6013	-3.0188***	-5.0633***	0.00632	-1.3938
	(1.11675)	(1.86714)			(1.11137)	(1.87580)		
Republican	2.83445***	4.65492***	105.10	1.8368	0.92953	1.52415	4.59124	0.41957
	(0.87402)	(1.48275)			(0.86583)	(1.45071)		
CountyCrime	0.00004***	0.00006***	1.00006	0.00002	0.00003**	0.00004**	1.00004	0.00001
	(0.00001)	(0.00002)			(0.00001)	(0.00002)		
Percent-65	-6.5800***	-10.7651***	0.00002	-4.2480	-2.85822	-5.02240*	0.00658	-1.3825
	(1.8996)	(3.15069)			(1.86897)	(3.10971)		
Percent-18	2.76778*	4.6543*	105.03	1.8366	3.09260*	5.54900**	256.97	1.52754
	(1.65664)	(2.76765)			(1.70321)	(2.90315)		
Bachelors	0.02159	0.04133	1.042	0.0163	0.02314	0.04691	1.0480	0.01291
	(0.07746)	(0.15633)			(0.12557)	(0.24777)		
Opioid	0.00278	0.00469	1.005	0.0018	-0.00608	-0.01139	0.988	-0.0031
	(0.00911)	(0.01501)			(0.00933)	(0.01556)		
Marijuana	-6.16254*	-10.0339***	0.00004	-3.9594	-8.42514**	-14.1489**	0.0000007	-3.8949
	(3.45073)	(5.68511)			(3.55652)	(5.92940)		
McFadden R^2	0.14905	0.14852			0.15590	0.15660		
Observations	440	440			445	445		

* 0.10, **0.05, and ***0.01 levels of significance respectively. Odds ratios and Mean Marginal effects are from logit functions.

The coefficients for Percent-B, Percent-65, and marijuana use in the community were all found to be negative and significant, indicative that the greater the diversity of the population, percentage of the population that had previously used marijuana, and the older the community, the more likely they were to support both retail dispensaries and consumption sites.

The previous literature, in particular Cruz et al. (2016), also found a strong link between support for legal marijuana and prior use. The coefficients on opioid deaths and percentage of the population with a bachelor's degree or higher were not statistically significant.

The analysis does find a significant positive relationship between income and a community's choice to opt out of the retail market. While most of the previous studies tended to find mixed results (related to overall legalization) on this relationship, they tended not to be significant (Hall and Schiefelmein, 2011; Calkins et al., 2021; Cruz et al., 2016). For communities in New York, the question is not legalization, but whether to allow the operation of retail sales and consumption sites. Opting out of the legal market also means that a community will forgo a potential new source of tax revenues. That does raise the possibility that higher income communities may be in less need of the additional revenues.

Odds ratios and mean marginal effects estimates provide additional support to the strength and direction of the relationships between the choice to opt out and variables such as Republican, percent of the population under 18. Similarly, older and more diverse communities were more likely to allow dispensaries and consumption sites to operate. Overall, the analysis is indicative that there is significant concern in many New York communities towards allowing legal retail marijuana dispensaries or consumption sites.

Conclusions

New York's retail recreational marijuana market is still in its early stages of formation. Local political affiliation, income level, community size, and several demographic and behavioral characteristics impact a community's decision on whether to participate in the legal cannabis market. It is quite possible that in passing the MRTA, the state's more liberal legislative body, dominated by New York City and metropolitan legislators moved more quickly than many of the more conservative suburban and upstate communities were ready to fully accept. This suggests that there are additional questions to be addressed in the future such as how the urban-rural divisions in the state, or proximity to other states with legal markets, particularly Massachusetts, Connecticut, and New Jersey, may have impacted local community decisions. The relationship between higher income communities and the possible need for additional tax revenues is another area ripe for analysis, especially given how much attention was focused on the potential new source of revenues in the political debate leading to legalization.

It is anticipated that once the recreational market becomes fully operational and the forecast stream of tax revenues is realized, some communities that chose to opt out will reconsider their choice. Local communities cannot restrict the consumption of recreational marijuana, just whether it can be sold or used in public venues.

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No Hospitality Service For You! (or 'Housekeeping…Only On Request')

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Abstract

Historically the hospitality industry required a consistently high level of service staged to exceed guest expectations. The effects of COVID-19 forced a radically new guest experience to emerge to minimize risks of transmission. The delivery of service thus evolved and has been reworked, such that a new characterization of what drives customer satisfaction has become enshrined. Empirical evidence is provided indicating ways in which customer service experience has altered. In addition to the expectations of delivery changing, fundamental dynamics in the hospitality labor force model are identified, as hoteliers and housekeeping grapple with the impacts of recalibrated daily service levels.

JEL Codes: L83, Z31
Keywords: Hospitality, COVID-19, Workforce, Precarity

Introduction

The hospitality industry consistently requires a high level of service staged to meet, and ideally exceed, its guests' expectations. The effects of COVID-19 compelled such companies to carefully rework many aspects of the guest experience through the ostensible lens of safety. For example, the reservation process was revised to include messaging on vaccination and mask requirements, the point of arrival was replaced with touchless and digital entry systems, and the service environment, whether it be a hotel room, airplane or restaurant table was sanitized and redesigned for the guest's safety and the safety of employees. The result has been a new characterization of what exactly drives customer satisfaction.

"No Hospitality Service for You" or at least what service hospitality used to be prior to the COVID-19 pandemic, was characterized with closed, or capacity restricted, social areas from restaurants, pool decks, gyms, bars, and event space. Free and readily available condiments in fast food restaurants were put behind counters, along with the 'free' hotel breakfast, free samples at retail outlets, and the quickly disappearing daily housekeeping – all in the name of COVID-19 protocols. New construction and rehabilitation of communal spaces generally looked to incorporate hard surfaces versus soft finishes throughout hotel lobbies, as updated guidance to maintaining COVID-19 cleanliness protocols. Also absent from the service stage were the employees who remain behind plastic shields, masks or were only present via text, chat, or via Facetime or Zoom.

Researchers now feel that COVID-19 has shifted the emphasis from service to a product model (Youssef, Redzepagic, and Zeqiri, 2022). That is to say that product (rather than service) now bears almost all the weight, at least in terms of the delivery of an experience to meet, or ideally exceed, guest expectations. Customer touchpoints are largely absent of the human touch, smile, warm greeting or even a more distant handshake. The classic 10-5 Rule of Hospitality - visibly acknowledge the guest within 10 feet and provide a positive and upbeat greeting at 5 feet - has been replaced with the 10-0 Rule – visibly acknowledge the guest within 10 feet and have no physical or close contact with the guest whatsoever after 10 feet. Frontline employees are now more reserved, fearful and restricted in the delivery of the guest experience (Xiao et al., 2022). The new drivers of customer satisfaction appear characterized by an absence of employees, replaced with their digital equivalents, and products that must now bear the burden of responsibility in meeting and exceeding guest expectations.

According to analysis by McKinsey & Co in 2021, the response to COVID-19 has been shaped by a technological shift away from service to product, even though research suggests a clear imperative of service level in actually retaining repeat customers. As recently as 2018 an industry study of 10,000 resort travelers, safety of the accommodations and the safety of the public areas (e.g., pools, grounds, gyms, restaurants and public spaces) were found to be statically significant in the delivering of outstanding hospitality experiences (see Salazar, 2018). This study also found that friendly and helpful staff were statistically significant in bringing guests back to the venue and leading to higher levels of recommendation to third parties. Supporting the industry premise: Guests comes in for the product (i.e. what the customer values) but return for the service (i.e. how the customer was emotionally involved and treated).

It can be argued that the traditional style service models that are being rapidly replaced, rather than gradually phased out on grounds of safety, are largely for economic, technological and generational expectations, rather than as an evolution in service levels per se as driven by underlying customer demand. Customer experience is being redefined to be less dependent on face-to-face service and more on delivering customer expectations via technology and streamlined processes. The question posited is whether this approach is structurally sound.

Most of the inherent profitability in the hospitality sector is driven by the repeat customer base and in the absence of these traditional metrics to generate and capture repeat revenue, greater volatility may be introduced into the sector, potentially driving a bifurcation between minimalist service levels, scaled through technology for the mass population, and the more personal approach of the remaining ‘traditionalist’ institutions. It appears likely that the rise of Airbnb, among others, has backfilled this missing middle segment to some extent, where personal service levels are more easily retained in combination with much lower utilization rates that appear much more COVID-19 sustainable.

This paper sets out to contribute to the discussion of industry costs and changes in the value proposition across hotels and resorts. Empirical evidence is therefore reviewed indicating that the customer experience has been altered accordingly. In addition to expectations of modes of delivery changing, fundamental changes in the model of the hospitality labor/workforce are reviewed. Due to COVID-19, hotels seeking cost-cutting moves, are now working with far less people with far fewer customers staying. After the initial return to work in early 2021, most hotels did not entirely recall their staff leaving many to find jobs in other industries preempting a future employment crisis in the sector. Now, one may expect to just see a minimum of a single staff member handling service instead of multiple staff. The front desk has typically just one attendant, who is not only in charge of checking in/out guests, but also alerting guests to convenience store sundries available in close proximity to the front desk. The buffet is handled by perhaps two people, with one serving as hostess/wait staff with another handling the buffet and clearing the tables, etc. This is almost the same across other departments, leaving no backup operatives should someone call in sick. The trend of having to ‘ask’ for housekeeping service started even before the pandemic. These types of manual jobs may eventually be going away, to be replaced by automation, although cleaning and making beds is technically quite challenging even for state-of-the-art artificial intelligence.

COVID-19 also accelerated these changes in the guise of “going green" by reusing towels and keeping the room temp up for example, which was already in place. This is certainly one way that a hotel might prospectively operate with minimum staffing, but will guests notice non-union replaced switchboard operators, who were eliminated and replaced with an outside contractor via outsourcing. Daily housekeeping ‘only on request’ is another example of productivity and efficiency measures; although forcing rooms to be "cleaned" daily, without guest changes is probably akin to modern "featherbedding". Some customers prefer them to skip the cleaning altogether anyway and just obtain fresh towels and coffee pods at reception to save them from having to lock up their belongings. Leaving a compact electric rechargeable vacuum cleaner in the room for example, alongside the standard iron and ironing board could also alleviate some of the more basic cleaning needs. Not offering housekeeping to any of the rooms unless checking out is also probably here to stay except for very high-end establishments.

‘Skimpflation’ appears to be a new term coined for services rather than goods, when paying the same rate (or higher) and essentially getting less ‘service’. While corporate travel has not fully recovered, pleasure travelers are already booking rooms whilst appear willing to pay higher rates so leisure hotels are concomitantly already increasing staff wages to attract additional workers. This cost-push inflation is now likely to pervade the rest of the hospitality sector, once any recovery gets properly underway. It could be argued that sector-wide furloughs have inadvertently sown the seeds for prospective hiring challenges, with only the more enlightened operators incentivizing retained staff to remain on the payroll throughout the pandemic.

This paper proceeds with a literature review, illustrating key areas of enquiry within the hospitality sector, the presentation of data and findings, alongside concluding remarks and an outline of areas for further research.

Literature Review

The global onset of COVID-19 in 2020 compromised numerous industries worldwide, creating a myriad of difficulties and challenges across the business spectrum. Three sectors in particular bore the brunt of the initial economic wave of devastation - aviation, hospitality, and tourism. Multiple countries implemented immediate restrictions via stringent border control practices to mitigate the worst health impacts of the pandemic, typically preventing tourists even entering foreign countries. In combination these measures ultimately devastated much of the hospitality and tourism industries, alongside the burgeoning international aviation sector, with US employment across these sectors dropping by almost half at one point or another (see Chen and Chen, 2021). Ntounis et al. (2022) perceived numerous temporal contextual factors also affecting tourism-dependent businesses including specific vulnerabilities such as seasonality in underlying demand, inherent unpredictability in lockdown duration, and more uncertain reopening schedules due to latent hesitancy across different constituents to resume travel, all of which imply a far greater risk premium should be attached to tourism-dependent businesses.

Regarding the hospitality industry specifically, in the immediate term, as well as in any post-COVID recovery, the imperative was to urgently restructure the business to accord with far lower levels of patronage, initially as a survival mechanism, but more strategically to accommodate changes inherent in a post-Covid world. According to Nair et al. (2021), customer expectations and perceptions led to a greater focus on incorporating hygiene and safety as an essential part of welcoming guests, and thus redefining the hospitality term “people-friendly” service provision.

Recruitment, Training and Development

The devastating effect that the global COVID-19 pandemic had on hospitality and tourism industries left many smaller companies out of business altogether, with even larger companies forced to furlough their employees and many reliant on state intervention. Long periods of unpaid leave were one of the greatest contributors to the loss of experienced employees across the various leisure sectors and according to Chen and Chen (2021) there was a type of mutiny in the hospitality workforce. If the much higher levels of pay across the industry, required to win back those previously discharged from the workforce, which have averaged over 12% according to the Federal Reserve, are anything to go by, then the answer globally must be yes. The war for talent in the hospitality sector, as workers increasingly fail to resume work in their sector of origin, appeared to have created something of a paradox given many previous initiatives to partner with other seasonal sectors such as agriculture, healthcare, and retail. Despite their shared seasonality for labor requirements, where the much-publicized vulnerable workers are typically left with limited options, many operatives discovered more secure and favorable opportunities in related sectors.

According to Baum et al. (2020), in the aftermath of the 'Great Resignation', a much more competitive and reimagined approach to the labor market must be pursued by the hospitality industry. The amplification of workplace exploitation, precarity and disadvantage that subsisted for generations is already documented within the hospitality/travel industry (see Chen and Chen, 2021 for a review). Concerns remain that even as some form of 'normality' returns to the hospitality sector, insecurity at work pervades especially given the Rubicon of lost employee psychological/organizational contracts, which remains problematic prospectively according to Baum et al. (2020).

Bar Am et al. (2020) pointed out that a company's environment and management are made more explicit at times of severe crisis; what differed from previous crises was that employees' thought processes also diverged. According to Chen and Chen (2021) employees were most likely to perceive signs of job insecurity whenever employees' working hours are decreased by hospitality firms. To mitigate these disincentives and normalize the inherent seasonality in these vocations, firms ought to preplan different work patterns for peak and off season as part of their regular work practices and announcing these well in advance at regular work training sessions, thus allowing employees to make arrangements and prepare accordingly. In addition, given the relatively high turnover rates within the hospitality sector, training and recruitment operations should be devised and enhanced to respond to such varied scenarios and even to map out responses to prospective pandemics type scenarios.

Social exchange theory, at least from a theoretical perspective, is often used to understand the relationship between organizations and employees or employees and supervisors. Chen and Chen (2021) indicated that organizational identification among staff was critical to recover from the hiring and staffing concerns facing the hospitality industry. Historically, and especially during COVID-19, hospitality employees were confronted with perceived job insecurity. According to Chen and Chen, organizational identification and job insecurity were significantly linked, meaning intentions by employees to remain in positions within the hospitality industry were significantly affected by both organizational identification and job insecurity. The implication being that retention policies may well be more effective by promoting and resourcing organizational identification among staff.

Regarding training and development constraints in the hospitality industry, the lack of in-person training due to social distancing and operational shutdown requirements was acknowledged. In terms of the post-pandemic situation many hotel firms discovered that online development and training were key in adapting their workforces to the "new normal". Despite working from home being prevalent across many industries, in most cases hospitality employees could not work from home. Due to operational and logistical challenges, the service job from home concept could not be readily applied within hospitality. In addition, industry operators considered ways of relieving anxieties in their employees, notwithstanding economic turmoil for COVID-19. Examples included housing employees in hotels directly, supplying essentials to their home, providing 24-hour tele-counselling services to diffuse psychological distress, and enrolling them in e-learning programs during furlough to retain workplace readiness (Nair et al., 2021).

Inevitably, many employees have not and may not return to the hospitality sector. Relative to layoffs and career changes, a pervasive critical shortage in staffing levels remains throughout. As the barrier to entry in hotel positions is low, and employee functions have changed across many positions, the need to successfully staff up and hire in the future could include a revised approach to hiring that focuses on cross-functional skillsets and multitasking abilities. Nair et al. (2021) note that training improvements will also garner further efficiency gains through optimizing the number of multi-skilled staff members or by intentionally making all employees as flexible as possible in their prospective deployment.

Technology

Technological advances were an essential strategy component in mitigating the worst challenges of the COVID-19 period and shall remain important for employees and hospitality stakeholders throughout any recovery. Chen and Chen (2021) pointed out a variety of approaches being employed to address COVID-19 concerns, such as launching new services for beverage and food delivery, negotiating rent reductions, taking a portion of guest rooms off-line to increase separation distances, initiating numerous promotions as well as enhanced hygiene practices. With the successful implementation of technological solutions, managers could mitigate the more negative effects of the rollout of contactless hospitality and by applying intelligent devices may have ultimately increased customer satisfaction by targeting consumers more directly via self-service and robot service provision.

Furthermore, understanding how clientele acts and distributes information regarding 'smart' hotel service delivery should have provided a bespoke avenue for addressing service failures and customer complaints. This offered the prospect of established protocols for escalating complaints to human resolution, having first followed a critical path via socially distanced modes, including chatbots or virtual online meetings to try to remotely address such service encounter issues more promptly. Technology was also deployed in conjunction with a revised protocol by which guests could be welcomed whilst implementing techniques to combat the spread of COVID-19. Bonfanti et al. (2021) pointed out that several operators had already adopted contactless methods harnessing existing customer devices via apps to facilitate DIY check-in and check-out. Technological advances and digital innovations had also assisted in maintaining social distancing with digital interventions minimizing customer dwell times and queuing such as smartphones empowered to directly access rooms and order room service. Such innovations helped propel the hospitality industry forward despite constraints of lockdown, enfranchising clientele to make use of more seamless service on demand and thereby enhancing overall hospitality despite formidable social distance restrictions.

The new customer/guest experience and customer service (CX) design

Some hospitality firms innovated using design protocols, in hotel industry parlance known as 'CX' design (where CX is derived from the industry abbreviation for customer) which introduced enhanced levels of hygiene and cleanliness to ensure clientele an even healthier and safer stay. These included incorporating best practices as derived from a range of qualified in-house and external health professionals across hygiene, food safety, and infection prevention. The main areas addressed included investments in digital innovation and technology, protection measures and hygiene, reorganizing internal work practices (including service and escape), reducing customer dwell-time, updated communication and staff training. In combination, these inputs revised hotel operations and assimilated strict standards for cleanliness and health protection measures. Bonfanti et al. (2021) note that successful implementation also required hotel managers to reorganize the workplace environment and modify employee behavior to fully embrace these standards.

Cutting-edge CX design initiatives comprised safety-conscious reassurance, rapid deployment, proximity and intimacy but similarly required investments in both digital and physical operator-controlled touchpoints. Holistically, the guest experience redesign was not only beneficial to patrons but also essential to provide a safer working environment with the added potential to lead to longer-term cost efficiencies. Bergs et al. (2020) identified CX design as a strategic choice, providing long-term competitive advantage in the sector and a means of hospitality brand differentiation through more targeted health and safety consciousness means to navigate clientele safely though the pandemic. Thus, CX design gained mainstream acceptance as a means of placing customers' safety first whilst acting as regulating mechanism preventing frontline personnel, outsource providers, and more broadly the wider community from risks of infection. Bonfanti et al. (2021) highlighted the positive effects on the intended CX over time as lessons learned were inculcated to help hospitality operators to redefine a new normal and mitigate some of the risks of future outbreaks.

Additional results of the facemask, especially female employees

Face masking has become an essential part of the hospitality experience. Mandating employees to wear facemasks in the workplace appears to enhance customer perceptions of employee expertise, employee and hotel trustworthiness, as well as service quality according to Cobanoglu et al. (2020). Liang and Wu (2022) further corroborate that hospitality businesses are net beneficiaries of requiring front of house staff to wear facemasks whenever interacting with clientele. De rigor as part of the new customer experience, sending pre-purchase signals to inform consumers of their service quality and communicate desirable service attributes especially for those with no prior experience with a particular hotel product or service. Face coverings are also the most obvious apparel to directly affect clientele evaluations of service quality, employees, and hotels.

Unexpectedly, face masking perceptions appear to consistently vary between male and female wearers. In the absence of a facemask, customers perceive a higher quality of service as well as a greater level of trust towards hotels and employees based on female versus male employees. An unintended finding from Liang and Wu (2020) extensive literature review was that female staff engaged in reception and tourism services seem to amplify perceptions of enthusiasm, care, and social orientation. Despite women's characteristics matching men in respect of actual service work, such perception benefits typically skew customers towards providing higher evaluations of their overall service performance than men. This may well be related to occupational gender stereotypes that suggest women are perceived as more suitable to the provision of service work than men. According to the multivariate analysis of Liang and Wu (2022), to aid hospitality managers with recommendations to elevate customer service evaluations during the pandemic, proffered three distinct observations. 1) Customer service quality perception is improved though employee facemask mandates. 2) Customers' perceived female employees wearing face coverings as providing greater service quality than equivalent male employees, although the degree of improvement for male colleagues wearing facemasks remained greater than the difference between face-masked versus face-maskless female employees. 3) Customer perceptions of hotel and employee trustworthiness and employee expertise appeared to imply serial mediating roles.

RevPAR and COVID-19, what are customers willing to pay for?

Revenue per available room (RevPAR) within the hospitality industry was badly affected following the World Health Organization declaring COVID-19 a global health emergency. According to AHLA (2020), virtually all hospitality operators laid off a significant number of staff, suffered a massive number of reservation cancellations, with a concomitant collapse in average revenue per available room compared to virtually any pre-pandemic period. It became essential to understand the primary safety measures that were influencing consumers' hospitality choices and how much more, if anything, consumers were willing to pay for hotel safety measures during the pandemic. Park and Lehto (2021) examined these questions directly and created a table that placed monetary values on guests' willingness to pay more, reproduced directly from the original as Table 1 to assist the discussion.

Table 1: Guest willingness to pay more

Safety Measure Aspects	**Safety Measure Attributes**		**Willingness to Pay More Value in USD**
Cleanliness and Hygiene	1.	Adopting advanced cleaning technology	10.607
	2.	Providing a sanitation kit	9.236
	3.	Improving ventilation and air quality	8.936
	4.	For all guest rooms, 48-hour settling period	7.230
Physical Distancing	1.	Offering contactless check-in/check-out options	2.765
	2.	Limiting number of guests in hotel communal areas	4.827
	3.	Installing plexiglass partitions at front desks	4.564
	4.	Offering boxed or plated breakfast service instead of buffets	4.671
Staff and Guest Requirement	1.	Staff receiving comprehensive training for infection controls	8.071
	2.	Staff mandatory health check prior to their shifts	7.827
	3.	All guests are required pre-check-in health screening	4.206

It should be noted that Park and Lehto (2021) is not post-COVID-19 and does not extend into what is defined as the post-COVID-19 period in our data analysis below. The expectations of the post-COVID-19 era in their study were based upon customers decisions regarding safety practices and protocols rather than price sensitivity at the time. Given the timing issues related to knowledge about COVID-19 and sanitation in particular, the time frame of the database becomes critical. Whilst expectations emphasized in Table 1 might have been true in the immediate travel period surrounding the pandemic, more recent data has tended to emphasize other traditional attributes. Specifically, adopting advanced cleaning technology for example displayed the strongest influence on customers' choice behavior initially, with consumers increasing price sensitivity regarding practices that compromised guest experiences.

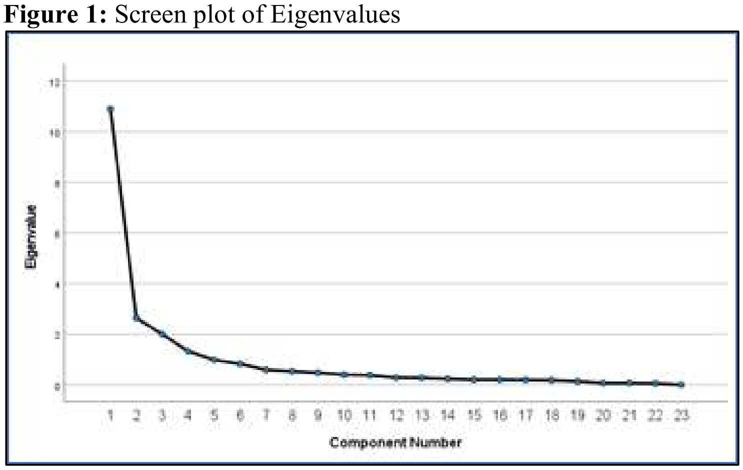
As contactless check-in/check-out and hygiene protocols became mainstream, the willingness to pay values observed in Table 1 began to reflect clientele complacency and or becoming numbed to the consequences of the "new normal" in the industry. As such, transitional data in Table 1 could not be expected to remain stable though time. Whilst it might be different in any number of ways, given there is now an inflationary period and greater strains on budgets, travelers could not remain less price sensitive versus cleanliness sensitive. This is particularly likely given that most of the advanced hygiene processes proffered proved to be mostly for show, given COVID-19 transmission proved extremely limited in terms of surface contact. In essence, whilst it appeared important during the initial phases where Table 1 data validated a 'perception' over science rationale, inevitably scientific facts have reasserted themselves in the minds of the public in the post COVID-19 period.

Data Analysis

The data set analyzed, which is based on a proprietary industry survey across multiple hotel groups, includes 26 variables of hotel performance regarding areas that are of most concern for hoteliers. Note some of these contain acronyms not obvious to those not operating within the hospitality sector; for example, EIWO is the acronym for 'everything in working order'. These variables may have both positive and negative connotations. Those variables with positive connotations are: 'Would Return', 'Inside Safe', 'Inside Clean', 'Inside EIWO', 'Inside Fresh Smelling', 'Inside Comfortable', 'Inside As Described', 'Inside Very Good Condition', 'Outside Safe', 'Outside Clean', 'Outside EIWO', 'Amenities Available', 'Outside Amenities Added', 'Staff Experienced', 'Staff Friendly', 'Staff Listened Well', 'Staff Helpful', 'Staff Responsive', and 'Staff Resolved Concern'. Overall Vacation Experience Scores for these variables ascend as the customer believes the hotel did a respectively better job. On the other side, the following variables had increasingly negative scores: 'Inside Wanted Amenities', 'Below Expectations', and 'Notify Staff?' These variables are mostly ordinal variables, so higher scores are better scores and lower scores are worse scores. The negative variables have the opposite effect. There are over 35,000 observations in the dataset, distilled down to monthly summaries. An 18-month period prior to COVID-19 was considered, an 18-month COVID-19 period (defined in this study as being between March 2020 and September 2021), and then the subsequent or post COVID-19 period of 13 months running from October 2021- November 2022 inclusive.

One problem with data of this type is there may be collinearity and the collinearity may confound the results of most types of analysis An initial Wald test for joint significance of the insignificant variables, alongside simple regressions were used as a robust initial step as part of this preliminary analysis. For that reason, a Principal Components factor analysis was subsequently conducted using the varimax rotation for the method of creating variables. The advantages of conducting a principal component analysis being that it is useful to restructure the data and create indexes (the components) that capture a sufficient amount of the variation in the hotel performance variables using fewer dimensions, because it is more likely that a combination of factors (indicating hotel performance) rather than any single given factor influence the outcomes of interest. The factor loadings for the data suggest that there are at best three factors that are relevant. Changes in the factor composition during the three relevant sub-periods were also examined. These composite factors have low loadings with most of the variables, but higher loadings with each specific variable. The screen plot below shows the critical number of factors appears to be three, that this remains the same for all three sub-periods and that there are at most three factors. However, the factor loadings themselves change and the coefficients change in each sub-period pre-COVID-19, during COVID-19, and post COVID-19.

Figure 1: Screen plot of Eigenvalues



Characterizing the most significant loadings for the purpose of better understanding the relationship between the loadings and the factors was set out. As such, Factor 1 has high positive loadings on "Selection of the Food & Beverage", "Service provided by the Food & Beverage staff", "Resort grounds were well maintained", "Quality of the Food & Beverage", "Everything at resort was in working order" ,"Overall Exterior", "Unit was comfortable", "Unit was in working order", "Resort was clean", "Unit amenities met my expectations", "Unit smelled fresh", "Unit looked great", "Overall Interior Unit", "Unit was clean", "Safety Security", "Likelihood to Return", "Resort staff made you feel special", "Resort staff was friendly", "Resort staff made you feel welcome", "Resort staff followed up on your requests", "Resort staff was helpful", "Resort check in experience", "Resort staff was responsive", and "Overall resort staff service". This Factor 1 variable is designated **"Overall Quality of Experience"**.

The second variable (Factor 2) had high loadings on "Resort was clean", "Overall Exterior", "Resort grounds were well maintained", "Everything at resort was in working order", "Pools & Spas met my expectations", "Quality of the Food & Beverage", "Selection of the Food & Beverage", "Service provided by the Food & Beverage staff", "Atmosphere of the Food & Beverage outlet", "Value for the money", and "Overall satisfaction with Food & Beverage". This Factor 2 variable was designated **"Overall Value of Experience"**. The third variable (Factor 3) had high factor loadings on "Activities Programs met my expectations" and "Exercise Rooms met my expectations". This Factor 3 variable was designated **"Activities and Exercise"**. From the Varimax rotation, composite factor scores were developed for each of the new variables, allowing for regression analysis modeling the best scores for overall vacation experience.

Table 2: Regression Coefficients for the best fit regression model 1 for pre-COVID-19 factors and Overall Experience

Model		B	Standard Error	Standardized Coefficients Beta	t-statistic	Significance	95% Confidence Interval for B Lower Bound	95% Confidence Interval for B Upper Bound
1	Constant	65.417	0.123	n/a	530.74	0.000	65.143	65.692
	Overall Quality of Experience	2.077	0.128	0.826	16.24	0.000	1.792	2.362
	Overall Value of Experience	1.2122	0.128	0.482	9.48	0.000	0.927	1.497
	Activities and Exercise	0.6157	0.128	0.245	4.81	0.001	0.331	0.901

Model	*R*	*R Square*	*Adjusted R Square*	*Standard Error of the Estimate*
1	.987a	0.974	0.966	0.46118

a. Predictors: (Constant), REGR factor score 3 for analysis 1, REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1.
b. Dependent Variable: Overall Experience

This suggests that in the pre-COVID-19 period the relationship between overall experience score and the three factors has a constant score of 65.417 out of 100. If there is no effort made other than a standard effort, the score would be 65.4. The "Overall Quality of Experience" score is 2.077. This suggests that every point increase on the quality of experience (or all those variable scores) will increase the Overall Experience by 2 points. An increase of "Overall Value of Experience" by one point will increase the Overall Experience by 1.21 points and increase of one point in "Activities and Exercise" will lead to a .6157 increase in the Overall Experience. However, it should be noted that many of the values are scaled to the factor. So, the scores which are on a scale of 1-10 for many of the variables are scaled to a factor score that ranges between 0-100. In addition, the factor rotation creates variables that explain 97.4% of the variation with an adjusted R-square of 96.6%.

Table 3: Regression Coefficients for the best fit regression model 2 for the COVID-19 period factors and Overall Experience

Model		B	Standard Error	Standardized Coefficients Beta	t-statistic	Significance	95% Confidence Interval for B Lower Bound	95% Confidence Interval for B Upper Bound
2	Constant	62.569	0.142	n/a	439.39	0.000	62.265	62.872
	Overall Quality of Experience	3.319	0.146	0.938	22.69	0.000	3.007	3.631
	Overall Value of Experience	1.092	0.146	0.308	7.47	0.000	0.780	1.404
	Activities and Exercise	-0.054	0.146	-0.015	-0.371	0.716	-0.366	0.258

Model	*R*	*R Square*	*Adjusted R Square*	*Standard Error of the Estimate*
2	.987a	0.974	0.969	0.62071

a. Predictors: (Constant), REGR factor score 3 for analysis 1, REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1.
b. Dependent Variable: Overall Experience

When the COVID-19 period and the varimax rotation were considered, in the pre-COVID-19 period since most variables were in Factor 1, what was not in the factor and was not included were: "Atmosphere of the Food & Beverage outlet", "Overall satisfaction with Food & Beverage", "Activities Programs met my expectations", "Pool's & Spas met my expectations", and "Exercise Rooms met my expectations". However, the COVID-19 period included some new variables, "Unit amenities met my expectations", "Overall Exterior", and "Everything at resort was in working order". These were proxies for the issues that guests were perhaps more exposed to facilities that were not maintained and it was understood that there was little ability for the hotel to provide the staff they had previously had in abundance to upkeep some of these basic amenities. Interestingly, the coefficient for "Overall Quality of Experience" had actually risen to 3.319 from 2.077, even though a few more factors were dropped. Thus, a one unit increase in quality led to a 3% increase in Overall Experience. This suggests that overall quality became more important to customers during COVID-19 hotel stays and that they were willing to sacrifice some elements of quality in place of others.

The second factor, “Overall Value of Experience” dropped to 1.092 from 1.21. Here, items that were included rather than dropped were examined. During COVID-19 Factor 2 (Overall Value of experience) added the following variables, "Activities Programs met my expectations", "Unit amenities met my expectations", "Exercise Rooms met my expectations". Once again, the factors, "Everything at resort was in working order", "Overall Exterior", and "Value for the money" were included in both periods. It seems people wanted value of amenities and exercise facilities where they could be more self-contained within the hotel. Perhaps this became more important during the COVID-19 period as there were fewer hotels providing amenities or maintaining these types of amenities.

The third factor (Activities and Exercise) also added the variable “Pools & Spas met my expectations” during the COVID-19 period. This might suggest that hotels had perhaps let their spas or pools fall into disrepair. The exercise room and activities were no longer part of the original factor. The factor coefficient dropped from 0.615 to -0.015 which was not significant but would have implied that the pool and spa were not as important during COVID-19. In the post COVID-19 period, many of the factor loadings returned towards the original factor loadings as customers began to adjust their ideas of what they expected from hotels in the post COVID-19 period.

Table 4: Regression Coefficients for best fit regression model 3 for post-COVID-19 period factors and Overall Experience

	Model	B	Standardized Coefficients Standard Error	Beta	t-statistic	Significance	95% Confidence Interval for B Lower Bound	Upper Bound
3	Constant	64.171	0.380	n/a	168.84	0.000	63.325	65.018
	Overall Quality of Experience	1.320	0.394	0.502	3.35	0.007	0.442	2.199
	Overall Value of Experience	1.436	0.394	0.546	3.64	0.005	0.557	2.315
	Activities and Exercise	1.250	0.394	0.475	3.17	0.010	0.371	2.129

Model	*R*	*R Square*	*Adjusted R Square*	*Standard Error of the Estimate*
3	.881a	0.775	0.708	1.42209

a. Predictors: (Constant), REGR factor score
3 for analysis 1, REGR factor score 2 for analysis 1, REGR factor score 1 for analysis 1.
b. Dependent Variable: Overall Experience

In the post COVID-19 period, many of the factor loadings returned to the original factor weights as customers began to adjust their ideas of what they expected from hotels in the post COVID-19 period. When considering this period and the varimax rotation, in the pre-COVID-19 period since most variables were in Factor 1 (Overall Quality of Experience) what was ***not*** in the factor and not included were observed to be "Likelihood to Return", "Activities Programs met my expectations", "Selection of the Food & Beverage", and "Service provided by the Food & Beverage staff". Other considerations previously out of factor 1 also dropped out, "Atmosphere of the Food & Beverage outlet", "Overall satisfaction with Food & Beverage", and "Pools & Spas met my expectations". The coefficient dropped from 3.319 to 1.320 suggesting the impact of factor 1 is a 1.32 increase in Overall Experience for each one unit increase in Overall Quality of Experience. Many of these variables may have dropped out as people relied less on the hotel for their food and other amenities or became accustomed to a lower service level post COVID-19. This further reinforced the view that overall quality became less important to customers during COVID-19 hotel stays and they were willing to sacrifice some elements of quality in place of others.

The second factor, “Overall Value of Experience” rose to 1.436 from 1.092. Here, items that were ***included*** rather than dropped were observed. During post COVID-19, Factor 2 (Overall Value of Experience) added the following variables: “Likelihood to Return”, “Overall resort staff service”, “Quality of the Food & Beverage”, “Resort staff made you feel special”, “Selection of the Food & Beverage”, “Resort staff made you feel welcome”, “Resort staff followed up on your requests”, “Overall satisfaction with Food & Beverage”, “Service provided by the Food & Beverage staff”, “Resort check in experience”, “Resort staff was friendly”, “Resort staff was helpful”, and “Resort staff was responsive”. In addition, “Atmosphere of the Food & Beverage outlet” returned to the list of loadings in Factor 2. It seems people wanted to be valued customers and for hotels to treat them better post COVID-19 when they are no longer self-contained in the hotel. Perhaps this became more important post COVID-19 as hotels providing amenities or maintaining these amenities became a more competitive advantage.

The third factor (Activities and Exercise) also added “Unit smelled fresh”, “Everything at resort was in working order”, and “Resort grounds were well maintained” in the post COVID-19 period. This might suggest that hotels had perhaps let their spas, pools, and grounds fall into disrepair. The exercise room and activities were no longer part of the original factor. The factor coefficient rose from -0.015 to 1.250, which was also significant suggesting that customers wanted the hotel to be better maintained and service levels needed to return on amenities. Thus, a one-point increase in activities and exercise will lead to a

1.25-point increase in “Overall Experience”. In addition, the loading included “Exercise Rooms met my expectations”. This suggests customers were using these amenities and thus expected that they were being maintained.

This analysis suggests that negative experiences have had an outsized negative impact on the overall satisfaction of resort guests. Staff can also have a strong impact on the experience of guests and perhaps incentive systems should be set up to reward behavior that leads to positive staff interactions. Next come the indoor experience of the guest in the resort. If the resorts allocate resources into the indoor appearance there is a more positive impact on their overall scores. Of the last score, the resort falling short of guests’ expectations had a clear negative effect on the overall score. However, a mitigating factor could be that if the staff responds to the guest concern in a timely manner, the impact may considerably mitigate the negative effect on expectations.

Conclusions

COVID-19 has significantly changed the essential factors of customer experience. Indeed, customer experience is being redefined to be less dependent on face-to-face service and more on delivering customer expectations via technology and streamlined processes. Given that the model shows Overall Experience is a function of Overall Quality of Experience, Overall Value of Experience, and Activities and Exercise, this has forced operators to shift much of the physical delivery of goods and services towards digitized ordering and remote fulfilment of goods and services, avoiding human contact and socialization. Review of the future of travel and resiliency demonstrates that nearly all data variables were significantly associated with changes in travel behavior (see Jiao and Azimian, 2021), including age, anxiousness, difficulty with expenses, educational status, gender, health status, household size, income, marital status, work loss, and work type. When the most disadvantaged communities were considered, such as impacts on the informal hospitality sectors epitomized by the global southern hemisphere, an amazing degree of resilience to disasters are in evidence, with an ability to recover fast being reminiscent of recovery after previous crises such as the 2004 Asian tsunami. Given the informal economy has its foundation in largely family-based employment, this appears to be a key factor in its natural resilience to such events. Minimal change in the nature of work in the informal sector during any post-COVID-19 period is therefore likely to be witnessed. However, overall resiliency gain is expected in the formal hospitality industry, which is witnessing many permanent procedural changes as a result of COVID-19. That is correspondingly, there is not a likely return to any previous ‘normal” in the formal sector, but an anticipated and steadfast progression via better incorporation of technology and data management within the customer experience.

As such, a further consideration in future research remains the online reservation system, including maid service options (daily, every other day, only before checking in, etc.) on the hotel website, so that guests can make preferences known in advance when they make their reservations. This would let guests choose (rather like the airline model) what level of service expectations for which they were willing to pay and allow hotels to have automated and simplified scheduling for housekeeping on any given day. Examples to enhance customer satisfaction this way may include giving a drink voucher for each day that customers agreed not to have the room cleaned for which the stated purpose being one of environmental rather than economic concerns.

Thus, the new world order of “No Hospitality Service for You” in the formal sector may not be so much about hospitality per se (see Shapoval et al. 2021) but a permanent reduction in service excellence and expectations that existed before COVID-19 that decreases the value of the in-person customer experience towards the preferred meta world of digitized service excellence. Digitized service excellence reduces human error (i.e., no humans directly involved), increases customer control (i.e., self-service and self-selection), and increases the importance and use of technology-dependent hospitality modes. Thus, the traditional approach at The Ritz-Carlton of ‘We are Ladies and Gentleman, serving Ladies and Gentlemen’, may likely become ‘We are Apps and Avatars, serving Ladies and Gentlemen.’

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