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Financial Crisis, Inclusion and Economic Development in the US and OIC Countries

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Dedication

To my parents, who instilled in me the value of education, a good work ethic and going above and beyond to give me the best life possible. To my brother and his wife, for supporting me and giving me the most precious gifts possible, Musa and Saba, the loves of my life. And to my best friend, Hina, for always being there for me. Lastly to Kabir Uncle, I am eternally grateful, I would never have been able to accomplish what I have without you. Thank you all for your selfless and loving support of me over the years as I have pursued my goals. I hope I made you all proud.

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Abstract

The following dissertation contains two distinct empirical essays which contribute to the overall field of Financial Economics. Chapter 1, entitled "Financial Inclusion and Economic Development in OIC Member Countries," examines whether the presence of Islamic finance promotes development and alleviates poverty. To do so, we estimate the influence of financial inclusion variables on development and poverty variables for OIC countries. Using data from the World Bank, we use dynamic panel analysis using methodology similar to Beck et al (2000) to study the effects of financial inclusion on economic development and use simple cross-sectional analysis similar to Beck et al (2004) to study the effects on poverty alleviation. We find that the countries with Islamic finance tend to outperform the rest of the world. We believe that the ability of financial institutions offering Shari'a compliant services to bring otherwise excluded people under the financial system plays a major role in increased development and reduced poverty in those countries. The results support our view that financial inclusion is causing development. Chapter 2 entitled, "Asymmetric Market Reactions to the 2007-08 Financial Crisis: From Wall Street to Main Street," examines the impact of significant news events during the 2007 – 2008 financial crisis on the abnormal stock returns for portfolios of financial and real sector firms. We recognize 17 significant news events from 2007 and 2008 and create equity portfolios using daily CRSP data from January 1, 2006 to December 31, 2009. We estimate event announcement interval abnormal returns in the context of an asset pricing model similar to Fama and French (1993) and Carhart (1997). We document significant negative abnormal returns for the portfolio of non-financial firms, and the smallest firms exhibit the largest negative abnormal returns, an indication of a significant spillover of financial market news to real sector stock returns. Smaller financial firms also exhibit negative abnormal event returns, and these results are driven by broker-dealer, depository, holding-investment, and real estate firms. The results provide new evidence regarding the incorporation of news events into asset prices during financial crises.

Keywords: Islamic banking, Financial inclusion, Economic development, Poverty, Financial crisis, Abnormal returns, Financial institutions

Chapter 1: Financial Inclusion and Economic Development in OIC Member Countries

1. Introduction

The financial system offers savings, credit, and risk management to individuals in a country. Inclusive financial services are more beneficial for poorer individuals increasing their ability to borrow and save money for education, investing in a business, making a large purchase, or health emergencies. An account provides a reliable place to save or to receive payments from family members, employers or the government. Without an account individuals have to rely on their own limited earnings and savings, which may contribute to persistent income inequality and slower economic growth. This topic has become a growing interest for researchers and policy makers. Involuntary financial exclusion can be problematic and needs policy action to remedy when there are individuals whose marginal benefit from using financial services are greater than the marginal costs, but are excluded by barriers. Evidence from international research efforts has revealed that there is a relationship between levels of financial exclusion and economic growth or poverty. Having an account increases savings, female empowerment, consumption, and investment of entrepreneurs. However, people in countries with low levels of financial inclusion struggle with financial problems due to the unavailability of financial services. Researchers and policymakers use financial inclusion strategies to increase the number of individuals, households and small and medium size enterprises that are now either fully or partially excluded from financial industry into the financial system. As people become more financially included, they gain power to use financial services to improve their life and that of their families.

There are almost 1.6 billion Muslims in the world, making up about 24% of the world's population. Many of whom are voluntarily excluded from the financial system, since the current financial system goes against the system of Islamic religious rules known as the Shari'a. In recent years, there has been an increase in Shari'a compliant financial products and insurances, which

plays a significant role in increasing the level of financial inclusion of Islamic countries. Increasing access to formal financial services in these countries will give the adults more ways to save and invest, which may help with economic growth in that country. According to Naceur, Bajaras and Massara (2015) only 27 percent of OIC households have an account at a formal institution, which compared to the rest of the world at 55 percent, is very low. Voluntary exclusion due to religious reason may in large part explain this disparity and increasing Islamic finance in this region may lead to increased economic growth and help alleviate poverty.

The results of this research into the financial inclusion in the members of the Organization of Islamic Cooperation (OIC) have importance for multiple reasons. First, researching Islamic countries will provide useful information about the relationship between financial inclusion and economic growth as well as poverty reduction. The demand for Shari'a compliant financial services is expected to increase and this information will be useful to provide desired financial products. Secondly, Shari'a compliant financial products have relatively low speculative characteristics compared to conventional financial services, and therefore has attracted a lot of attention in recent years, and these products have sufficient development potential. Poverty is an ongoing problem across many countries that are members of the OIC and studying variables that affect financial inclusion may help policymakers include more people in the financial system that are being excluded which may help reduce poverty.

Researchers have argued that the presence of Islamic finance promotes higher financial inclusion by attracting voluntarily excluded people to the financial system, thereby promoting growth in the country and reducing poverty (Beck, Demirgüç-Kunt, and Levine, 2004). We empirically study whether the presence of Islamic finance in a country promotes higher growth and lowers poverty. Positive impact of financial inclusion on growth is already established in the

literature (see among other Beck, Levine and Loayza (2000)). We contribute to the literature by presenting proof that Islamic finance leaves positive impact on an economy. We also use a few superior econometric techniques, which have not been used in this field of study so far.

Our major questions for the OIC countries are: does financial inclusion by Shari'a-complaint financial systems have a stronger impact on economic growth and does it also reduce poverty more effectively? This study examines the influence of financial inclusion upon the diffusion of Shari'a-complaint financial systems on economic development by estimating the dynamic relationship between financial inclusion and economic growth as well as poverty. We compare the effects of financial inclusion on development between countries with Islamic finance and countries without Islamic finance examining the dynamic relationship between financial inclusion and economic development and poverty variables using the panel data. For that purpose we divide our sample in four categories: the whole world, OIC countries, OIC countries with Islamic finance, and OIC countries without Islamic finance (following Naceur, Barajas, and Massara (2015)).

The procedure of this study is organized as follows: following Beck, Levine and Loayza (2000) we begin by selecting proxy variables for financial inclusion, economic development and poverty in OIC countries, and implement dynamic panel data analysis for separate classifications. We expect that we can take a closer look at the influence of financial inclusion on economic development and poverty in OIC countries. Second, in order to explore the dynamic relationship of proxy variables, we examine impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) of panel vector autoregressive (VAR) methodologies. By using this approach, it is expected that we can examine the overall relationships of variables and can draw information that is more meaningful by comparing the results from the dynamic panel data

analysis. We find that one of our proxy variables for financial inclusion, private credit growth, has a positive and significant relationship with economic growth. The effect is higher for OIC countries and in some cases for OIC countries offering Islamic finance. Usually, small businesses are able to generate more value per unit of investment. So, we interpret the higher numbers for OIC countries as inclusion of small investors and households who were able to get small amounts of credit. This implies that Islamic banks are extending private credit to otherwise excluded (voluntary, or involuntary) people in OIC countries helping the economy grow. However, our other financial inclusion proxies do not produce significant results. Third, we analyze panel Granger causality tests in order to examine the direction of the variables, thus we can observe whether there is a causal relationship between financial inclusion, economic development and poverty in OIC countries. The panel Granger causality tests help us see that there are several variables that cause each other, for example we find that financial development influences all the inclusion variables. However, the relationship is not one-way. We also see that financial deposits cause development. The positive impact is more pronounced for the countries with Islamic finance than the whole sample. Researching how different factors affect financial inclusion in OIC countries we can expand the financial system to include those left out. Policy makers can see what reasons people give as to why they do not have accounts, or how they can change some policies to reduce costs to individuals, so that they can save more and in turn reduce poverty and stimulate economic growth.

The rest of the paper is organized as follow: Section 2 is Literature Review, Section 3 goes over the data we used, Section 4 goes over the methodology and results of our economic growth analysis, Section 5 talks about the methodology and results of our poverty analysis, Section 6 concludes.

2. Literature Review

Study	Sample	Major Objectives	Findings
Standing Committee for Economic and Commercial Cooperation of the Organization of Islamic Cooperation (COMEC, 2014)		Explaining demand side and supply side factors to financial exclusion.	Demand side reasons include the lack of financial literacy and inadequate client protection regulations. Religious constraints and cultural characteristics are other reasons of voluntary financial exclusion. Supply side reasons include the suppliers' service quality, price and accessibility.
Demirguc-Kunt and Klapper (2012, 2013)	World Financial Index Database (Findex), they survey entire population in 2011.	Looking for variables that affect financial inclusion around the world.	They find that 50 percent of the world's adults have an account, and that account penetration differs largely between high-income and developing countries. Their results indicate that national-level financial development, measured by domestic credit to private sector as a percentage of GDP, is also significantly associated with account penetration.
Allen et al. (2012)		They look at the individual and country characteristics associated with the use of formal accounts and what policies are effective among those most likely to be excluded: the poor and rural residents.	They found that lowering account costs and smaller distance to financial intermediaries increases ownership and use of accounts. Policies targeted to promote inclusion, such as requiring banks to offer basic or low-fee accounts, exempting some depositors from tedious documentation requirements, allowing correspondent banking, and using bank accounts to make government payments, may be especially effective among those most likely to be excluded. Policies to reduce barriers to financial inclusion may expand the number of account users and encourage existing account holders to use their accounts more frequently and increase saving.

Demirguc-Kunt and Levine (2009)		This paper criticizes financial and economic theories of financial inequality.	Finance plays a crucial role in most theories of persistent inequality. Therefore, economic theory provides a rich set of predictions concerning both the impact of finance on inequality and about the relevant mechanisms. Most of the previous empirical research suggests that improvements in financial contracts, markets, and intermediaries expand economic opportunities and reduce inequality. Yet, there is a shortage of theoretical and empirical research on the impact of formal financial sector policies, such as bank regulations and securities law, on persistent inequality.
Demirguc-Kunt et al (2013a	The authors restrict their data to include 65,000 adults in 64 countries.	This study looks at Islamic finance and its influence on financial inclusion.	They find that Muslims are significantly less likely than non-Muslims to own a formal account or save at a formal financial institution. However they do not find any evidence that Muslims are less likely than non-Muslims to report formal or informal borrowing. They then look more closely at North African and Middle Eastern countries and find that there is little use of Shari'a-compliant banking products even though they find evidence of a hypothetical preference for Shari'a-compliant products among the respondents despite higher costs.
Demirguc-Kunt et al (2013b)	World Financial Index Database (2011)	This study looks at the gender differences in the use of financial services in developing countries.	They find that there are significant gender gaps in account ownership and usage of savings and credit services. The authors find that legal discrimination against women and gender norms explains some of the variation in account ownership. In countries where women do not have equal rights in their ability to work, head a household, choose where to live, or receive inheritance women are less likely to own an account, save and borrow. Violence against women and early marriage also contribute to the difference in use of financial services.

Anson et al (2013)	Global Findex includes data from 60 countries where postal accounts are offered.	They study the role of the post office in financial inclusion.	The paper finds that post offices are relatively more likely than traditional financial institutions to provide accounts to individuals who are most likely to be from financially vulnerable groups, such as the poor, less educated, and those out of the labor force. They also find that post offices can boost account ownership by acting as cash-merchants for transactional financial services, such as electronic government and remittance payments, and that partnerships between the post office and other financial institutions coincide with a higher bank account penetration.
Hannig and Jansen (2010)		They suggest that greater financial inclusion may enhance financial stability.	The recent financial crisis has shown that financial innovation can have devastating systemic impacts. They state that low-income savers and borrowers tend to maintain solid financial behavior throughout financial crises, keeping deposits in a safe place and paying back their loans. The potential costs of financial inclusion are compensated for by important dynamic benefits that enhance financial stability over time through a deeper and more diversified financial system.
Naceur, Bajaras and Massara (2015)		This paper looks at the relationship between the development of Islamic banking and financial inclusion.	In OIC countries, many financial inclusion indicators tend to be lower, and the percentage of citing religious reasons for not using bank accounts is far greater than in other countries; Islamic banking would therefore seem to be an effective opportunity for financial inclusion. Their results show that although physical access to financial services has grown more rapidly in the OIC countries, the use of these services has not increased as quickly. They find a positive but weak relationship between credit to households and to firms for financing investment.

We expand on previous literature to include how financial inclusion by Shari'a compliant financial systems have a greater impact on economic growth in OIC countries, and how it may help alleviate poverty. Many individuals in these areas choose not to use conventional banking in these areas due to religious reason and this study intends to show that there is a need to expand Islamic banking in these areas.

3. Data

This study will explore the relationship between the financial inclusion, economic growth and poverty of OIC countries since they have higher levels of voluntary financial exclusion relative to other countries. We will examine the relationship between economic growth and financial inclusion, which is growing proportionally with the development of Islamic financial systems. We will also examine the relationship between poverty and financial inclusion. The OIC consists of 57 countries. We use similar methodology to Hassan et al (2014) and Beck et al (2000) to explore this relationship.

Since OIC countries are located in a variety of geographical regions, such as Europe, the Middle East, Asia, and Africa, there must be many regional differences so we will divide the data by geographical regions. We will use the World Bank regional classifications to do so which will allow us to consider both the heterogeneity across regions and the homogeneity of similar geographic regions.

We used three different databases available via the World Bank; Global Financial Index (Findex) database, Global Financial Development database (GFDD), and the World Development Indicators (WDI) database. Our sample period covers the years 1990 through 2014.

4. Methodology and Empirical Findings for Economic Development Analysis

4.1 Proxy measures for financial inclusion and economic development

Financial inclusion by definition is the measure of how many individuals and firms use financial services, the key factors to measure financial inclusion are financial service usage statistics such as accounts penetration, savings, credit, insurance, etc. (Demirguc-Kunt and Klapper, 2012). Previous studies of financial inclusion have used the number of accounts at formal financial institutions, the number of loans from a formal institution, the use of ATMs, credit and debit card usage, etc. as proxy variables for financial inclusion. We will use Gross Domestic Product (GDP) growth rate, which is transformed with the log differencing of GDP (currently in USD)[1] as a proxy variable for economic growth. We will use the level of income as a proxy for poverty. We also utilize the following variables in Table A to measure key factors of financial inclusion:

Table A

Economic Variables that Affect Financial Inclusion	*Definition*
Private credit by deposit money banks to GDP (%)	Private credit by deposit money banks and other financial institutions to GDP, calculated using the following deflation method: $\{(0.5)*[F_t/P_{et} + F_{t-1}/P_{et-1}]\}/[GDP_t/P_{at}]$ where F is credit to the private sector, P_e is end-of period CPI, and P_a is average annual CPI.
Financial system deposits to GDP (%)	Demand, time and saving deposits in deposit money banks and other financial institutions as a share of GDP, calculated using the following deflation method: $\{(0.5: \{(0.5)*[F_t/P_{et} + F_{t-1}/P_{et-1}]\}/[GDP_t/P_{at}]$ where F is demand and time and saving deposits, P_e is end-of period CPI, and P_a is average annual CPI.

[1] $GDPG_t = \ln(GDP_t) - \ln(GDP_{t-1})$

Life insurance premium volume to GDP (%) +Nonlife insurance premium volume to GDP (%)	Ratio of life insurance premium volume to GDP (*Premium volume is the insurer's direct premiums earned (if Property/Casualty) or received (if Life/Health) during the previous calendar year)* + ratio of non-life insurance premium volume to GDP *(Premium volume is the insurer's direct premiums earned (if Property/Casualty) or received (if Life/Health) during the previous calendar year).*

In this study we are trying to evaluate the impact of financial intermediaries (inclusion) on growth and the sources of growth. In order to evaluate the impact we look for an indicator of the ability of financial intermediaries to research and identify profitable projects, monitor and control managers, ease risk management, and enable capital mobilization. We do not have a direct measure of these financial services. Therefore, we must use proxies for financial inclusion. Following Beck et al (2000) the primary measure of financial inclusion we use is a variable called Private Credit, which equals the value of credits by financial intermediaries to the private sector divided by GDP. This variable excludes credits issued by central banks and development banks, and only includes private credits issued deposit money banks and other financial intermediaries. We also use financial system deposits, and we add the life and non-life insurance premiums for a total insurance premium as a last measure of financial inclusion. This data is already deflated in the World Bank database as stated in the variable description and therefore should not produce misleading measures of financial inclusion, especially in highly inflationary environments.

4.2 Descriptive statistics

We divide our sample similar to how Naceur, Bajaras and Massara (2015) did in their paper to see the differences between the groups. The data is divided in to four groups, the whole world, OIC countries, OIC countries that use Islamic banking and OIC countries that do not use Islamic banking. The OIC countries we included in our sample are listed in Table 1.1 and divided in to the

subgroups depending on their use of Islamic finance. At first we look at the summary statistics. We only have 45 observations from OIC countries and the sample gets smaller as we subdivide. We construct a panel dataset with data averaged over each of the six 3-year periods between 1990 and 2013.

Table 1.1: Country Groups

OIC Countries with Islamic Banking (ISB)		OIC Countries without ISB
Afghanistan	Mauritania	Benin
Albania	Nigeria	Chad
Algeria	Oman	Comoros
Azerbaijan	Pakistan	Gabon
Bahrain	Qatar	Guinea
Bangladesh	Kingdom of Saudi Arabia	Guinea-Bissau
Brunei	Senegal	Guyana
Burkina Faso	Sudan	Kazakhstan
Cameroon	Syrian Arab Republic	Kyrgyz Republic
Cote d'Ivoire	Tunisia	Libya
Djibouti	Turkey	Mali
Arab Republic of Egypt	Uganda	Morocco
Gambia	United Arab Emirates	Mozambique
Indonesia	West Bank & Gaza	Niger
Islamic Republic of Iran	Republic of Yemen	Sierra Leone
Iraq		Somalia
Jordan		Suriname
Kuwait		Tajikistan
Lebanon		Togo
Malaysia		Turkmenistan
Maldives		Uzbekistan

Table 1.2 presents summary statistics of the means and medians of the various dependent and independent variables we are studying. From this table we can see that for most variables the variance between the mean and median decreases between OIC countries, and then OIC countries with Islamic banking and without. We also see that when comparing the OIC countries with Islamic banking to OIC countries without Islamic banking, the ones with Islamic countries fare better.

Table 1.2: Summary Statistics

This table shows the summary statistics

	World		*OIC*		*OIC with ISB*		*OIC no ISB*	
	Mean	*Med*	*Mean*	*Med*	*Mean*	*Med*	*Mean*	*Med*
GDP per capita	11554.83	4349.115	5342.226	1182.52	7333.945	1810.31	1981.199	604.015
Private credit	5644.347	964.3932	2233.721	261.4743	3300.525	315.4304	300.1392	68.04745
Financial Deposits	6108.904	1134.39	2929.483	339.5616	4305.01	631.2542	436.3394	83.5733
Insurance Premium	458.2061	52.27769	64.56178	12.43786	90.0759	15.19793	18.31743	3.089838
Growth of GDP per capita	0.0161675	0.0197618	0.0186435	0.0266313	0.0182658	0.0246127	0.0192808	0.0279138
Growth of Private Credit	0.0567007	0.0466234	0.042967	0.0379467	0.0459025	0.0432501	0.0376464	0.0364992
Growth of Financial Deposits	0.0531059	0.0472275	0.0494763	0.0439184	0.042777	0.0439184	0.0616187	0.0382181
Growth of Insurance Premium	0.0335451	0.0320496	0.0145349	0.0190314	0.0247138	0.0190314	-0.0039144	0.0174735
Number of obs	158		45		29		16	

We see that there are great discrepancies between the different categories, for example, the GDP per capita mean differs greatly from the world which is 11,554 USD to the OIC member countries mean of 5,342 USD. When we divide the OIC countries in to subcategories, the OIC with Islamic banking has a mean of 7,333 USD whereas without Islamic banking has a mean of 1,981 USD. These large discrepancies may be due to any number of socio-economic, or political reasons but it is still interesting to see these differences and are prevalent in almost all the variables labeled in Table 1.2. We continue our investigation further to see how many of these differences may be able to be overcome.

4.3 Cross Country Regression with Instrumental Variables

In the pure cross-sectional analysis we use data averaged for the countries in each group over 1990-2013. Such that, there is one observation per country. The basic regression takes the form

$$Y_t = \alpha + \beta\ Inclusion_i + \gamma' X_i + \varepsilon_i \quad (1)$$

Where Y is growth (GDP), Inclusion includes private credit and financial deposit, X represents a vector of conditioning information that controls for other factors associated with economic growth (insurance premium), and e is the error term. These variables are normalized using logarithm. Panel B of Table 1.3, uses the same basic regression but instead of the natural log of the averaged values we look at the growth of each variable.

Table 1.3: GMM regression on GDP per capita and the growth of GDP per capita

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a GMM regression of each financial access or depth variable on the different country subgroups. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated as an average for every three year period over 1990-2013.

Panel A: GDP per Capita

Variable	*World*	*OIC*	*OIC with ISB*	*OIC no ISB*
Private credit	1.448067***	2.533751***	2.532039***	5.398959***
	(12.5)	(20.02)	(19.94)	(5.75)
Financial Deposits	1.531709***	2.033711***	2.00129***	3.773944***
	(11.48)	(8.28)	(7.96)	(7.85)

Panel B: Growth of GDP per Capita

Variable	*World*	*OIC*	*OIC with ISB*	*OIC no ISB*
Growth of Private credit	0.3981974***	0.2739034***	0.3219448***	0.1662368
	(15.56)	(5.21)	(4.41)	(2.29)
Growth of financial deposit	0.3786112***	0.2351243***	0.3396295***	0.1024002**
	(13.13)	(5.14)	(6.27)	(1.96)

Looking at the results of Table 1.3 Panel A, the proxies we used for financial inclusion for economic growth are all correlation significantly with economic growth across all categories. We see that private credit and GDP per capita are positively and significantly correlated across all subgroups, therefore, increasing private credit will increase GDP per capita. The same inference can be made for the relationship between financial deposits and GDP per capita. In Panel B of the same table, we look at the relationship of GDP growth with the growth of our proxy variables for financial inclusion and find that growth of private credit is positively and significantly correlated with GDP growth for OIC countries and OIC countries with Islamic banking, this implies that increasing private credit in OIC countries with Islamic banking will increase economic growth even more. The growth of financial deposits is positively and significantly correlated to GDP

growth for OIC countries, OIC countries with Islamic countries and OIC countries without Islamic banking, this implies that increase financial deposits in the OIC region will increase GDP growth. The results of Panel B shows that Islamic banking can help economic development.

4.4 Dynamic Panel Estimation of Transformed data

In our dataset some of the observations are extreme and therefore transformation smoothens the dataset. Beck et al (2000) follows a similar technique in their study. They smooth their data for five-year periods. However, our main focus in this study are developing or underdeveloped countries which have many missing variables before 1990. Considering the much smaller timespan of our data we smooth our data over three-year periods. Given that we are using 3-year periods, the forecasting horizon for the growth innovation, that is, its unanticipated component, extends about three years into the future.

The cross-country estimations help us determine whether the cross-country variable in economic growth can be explained by variance in the exogenous component of financial inclusion. There are some limitations with pure cross-sectional instrumental variable estimator. Therefore using panel techniques may help with these issues. First, besides the cross-country variance, we also would like to know whether changes in financial development over time within a country have an effect on economic growth through its various channels. By using a panel data set, we gain degrees of freedom by adding the variability of the time-series dimension. It also allows us to exploit substantial additional variability.

Our panels were divided into the different subgroups over the period 1990-2013. Many countries were dropped due to the lack of data. We average the data over 6 non-overlapping 3-year periods. The regression equation can be specified as follows:

$$y_{i,t} = \alpha'^{X^1{}_{i,t}} + \beta' X^2{}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \qquad (2)$$

where y represents our dependent variable, X^1 represents a set of lagged explanatory variables, and X^2 represents a set of contemporaneous explanatory variables, μ is an unobserved country-specific effect, λ is a time-specific effect, ε is the time-varying error term, and i and t represent country and 3-year time period, respectively.

For estimating panel data, if the dependence variable has a serial auto-correlation, the regression with the lagged dependent variables as independent variables can reduce the serial auto-correlation of an error term. When dealing with panel data, a similar approach can be adopted that considers the auto correlation of the dependent variable, however, the estimation will be biased because of the correlation between the lagged dependent variables and the error term. To handle this issue, Arellano and Bond (1991) suggested a generalized method of moments (GMM) method that estimated a dynamic panel model, which can remove the auto correlation of the error term and reduce the correlation between endogenous variables and the error term.

Arellano and Bond (1991) suggests to first-difference the regression equation to eliminate the country-specific effect, as follows:

$$y_{i,t} - y_{i,t-1} = \alpha'\left({X^1}_{i,t-1} - {X^1}_{i,t-2}\right) + \beta'\left({X^2}_{i,t} - {X^2}_{i,t-1}\right) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}) \quad (3)$$

This procedure solves the first econometric problem, but introduces a correlation between the new error term, $\varepsilon_{i,t} - \varepsilon_{i,t-1}$, and the lagged dependent variable, $y_{i,t-1} - y_{i,t-2}$, when it is included in ${X^1}_{i,t-1} - {X^1}_{i,t-2}$. To address this correlation and endogeneity problem, Arellano and Bond (1991) propose using the lagged values of the explanatory variables in levels as instruments. Under the assumptions that there is no serial in the error term, ε, and that the explanatory variables X, where $X=[X^1X^2]$, are weakly exogenous, we can use the following moment conditions:

$$E\left[\left(X_{i,t-s}(\varepsilon_{i,t} - \varepsilon_{i,t-1})\right)\right] = 0 \; for \; s \geq 2; t = 3, \ldots., T. \quad (4)$$

Table 1.4: One-step estimator of Arellano and Bond (1991)

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a one-step estimator of Arellano and Bond (1991) regression of each financial access or depth variable on the different country subgroups. We are not assuming homoskedastic error term. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated as an average for every three year period over 1990-2013.

Panel A: Logarithmic Normal GDP per Capita

Variable	*World*	*OIC*	*OIC w ISB*	*OIC no ISB*
GDP $_{(t-1)}$	0.4833413***	0.342608**	0.3864354**	0.281021
	(7.56)	(2.11)	(2.16)	(1.44)
Private credit	0.0738162**	0.067773	0.0733849	0.0077065
	(3.01)	(1.62)	(1.59)	(0.09)
Financial deposit	0.0174615	0.1537017	0.0765998	0.2297937
	(0.68)	(1.35)	(0.54)	(1.23)
Insurance premium	0.1306594***	0.0788955	0.1696078**	0.035003
	(6.70)	(1.44)	(2.41)	(0.88)
Constant	3.119995***	3.347337***	3.264903***	3.658337***
	(8.13)	(5.37)	(5.76)	(4.25)
Number of Obs	454	110	78	32

Panel B: GDP per capita Growth

Variable	*World*	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP growth $_{(t-1)}$	0.0380665	0.3190367**	0.1355443	0.1060055
	(0.52)	(2.43)	(0.75)	(0.86)
Private Credit growth	0.1149442***	0.1629874***	0.1583385**	0.1382548**
	(6.7)	(2.56)	(1.96)	(2.02)
Financial Deposit deposits	0.0079107	-0.1799248	-0.1601209	-0.0667024
	(1.29)	(-1.27)	(-0.77)	(-0.92)
Insurance premium growth	0.0668688**	0.1510212**	0.1132784	0.085385***
	(2.31)	(2.01)	(0.83)	(2.94)
Constant	0.0144444***	0.0131772	0.0185722***	0.0122033*
	(4.91)	(1.61)	(2.96)	(1.70)
Number of Obs	454	110	78	32

We first test for autocorrelation and reject our null of no autocorrelation in the first differenced errors at 10% level. In Table 1.4 Panel A, we see that previous period GDP (GDP_{t-1}) is positively and significantly correlated with GDP per capita, this implies that last periods GDP

is correlated with this period's GDP. The sample for OIC countries with no Islamic banking is so small that most tests do not yield significant results. In this panel we also see that *Insurance premium* has a positive and significant correlation with GDP per capita for both the world and for OIC countries with Islamic banking. In Panel B of the same table, we can see that *private credit growth* is positively and significantly correlated with GDP growth for all categories. And *insurance premium growth* is positively and significantly correlated to GDP growth for all categories except OIC countries with Islamic banking. We cannot make any inferences about Islamic banking from this Panel B but Panel A shows promising results for Islamic banking.

There are some issues by first-differencing. We lose the pure cross-country dimension of the data. Second, differencing may decrease the signal-to-noise ratio, thereby exacerbating measurement error biases. Also, Alonso-Borrego and Arellano (1999) and Blundell and Bond (1997) show that if the lagged dependent and the explanatory variables are persistent over time, lagged levels of these variables are weak instruments for the regressions in differences. Simulation studies show that the difference estimator has a large finite-sample bias and poor precision. Therefore, to deal with these issues we use an alternative method that estimates the regression in differences jointly with the regression in levels, as proposed by Arellano and Bover (1995). Using Monte Carlo experiments, Blundell and Bond (1997) show that this system estimator reduces the potential biases in finite samples and asymptotic imprecision associated with the difference estimator.

According to Beck et al (2000) the key reason for this improvement is the inclusion of the regression in levels, which does not eliminate cross-country variation or intensify the strength of measurement error. Furthermore, the variables in levels maintain a stronger correlation with their instruments, as explained below, than the variables in differences, particularly as variables in levels

are more serially correlated than in differences. However, being able to use the regression in levels comes at the cost of requiring an additional assumption. This requirement occurs because the regression in levels does not directly eliminate the country-specific effect. Instead, appropriate instruments must be used to control for country-specific effects. The estimator uses lagged differences of the explanatory variables as instruments. They are valid instruments under the assumption that the correlation between l and the levels of the explanatory variables is constant over time, such that

$$E\left[X_{i,t+p}\mu_i\right] = E\left[X_{i,t+q}\mu_i\right] \text{ for all p and q. (5)}$$

Under this assumption, there is no correlation between the differences of the explanatory variables and the country-specific effect. For example, this assumption implies that financial inclusion may be correlated with the country-specific effect, but this correlation does not change through time. Thus, under this assumption, lagged differences are valid instruments for the regression in levels, and the moment conditions for the regressions in levels are as follows:

$$E\left[\left(X_{i,t-s} - X_{i,t-s-1}\right)\left(\varepsilon_{i,t} + \mu_i\right)\right)\right] = 0 \; for \; s = 1; t = 3, \ldots., T. \text{ (6)}$$

When we conduct the two-step estimator with Windmeijer bias-corrected robust VCE we get similar results. In Table 1.5 Panel A, the variables are normalized using logarithm. The results in this panel show that GDP_{t-1} is positively and significantly correlated to *GDP* across all categories except OIC countries with no Islamic banking. The coefficient for OIC countries with Islamic banking (.4526937) is the highest amongst the categories showing that Islamic banking has a stronger correlation with GDP growth. We also see that *insurance premium* has a positive and significant correlation with *GDP* for the world and OIC countries with Islamic banking. The coefficient for OIC countries with Islamic banking (.1795919) is greater than the coefficient for

the world (.1285623), this indicates that Islamic finance may increase the amount of insurance premium greater than conventional banking.

In Panel B, we find that *private credit growth* is positively and significantly correlated to *GDP growth* across all categories. The coefficient for OIC countries with Islamic banking is the highest (.1755136) indicating that it has the highest correlation with GDP growth. The other variables are insignificant, this indicates that increasing private credit growth helps with economic development, however, Islamic banking may not necessarily make a difference.

Table 1.5: A two-step estimator with Windmeijer bias-corrected robust VCE

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a two-step estimator of Arellano and Bond (1991) regression with Windmeijer bias corrected robust VCE of each financial access or depth variable on the different country subgroups. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated as an average for every three year period over 1990-2013.

Panel A: GDP per Capita

	World	OIC	OIC with ISB	OIC no ISB
GDP$_{(t-1)}$	0.3701538***	0.4189563***	0.4526937***	0.3416179
	(3.97)	(2.71)	(3.69)	(0.07)
Private credit	0.0933789***	0.0657183	0.0745181	0.0664196
	(2.56)	(1.42)	(1.22)	(0.04)
Financial deposit	0.0228976	0.0893011	0.0147499	0.120207
	(0.41)	(0.63)	(0.13)	(0.05)
Insurance premium	0.1285623***	0.1048327	0.1795919***	0.0263911
	(4.64)	(1.58)	(3.63)	(0.01)
Constant	3.834359***	3.012194***	3.053495***	3.349737
	(6.79)	(5.44)	(6.94)	(0.13)
Number of Obs	454	110	78	32

Panel B: GDP per Capita Growth

	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP growth$_{(t-1)}$	0.0379681	0.283067	0.0642162	0.091998
	(0.39)	(1.57)	(0.28)	(0.44)
Private credit growth	0.1045932***	0.13559**	0.1755136**	0.1490604***
	(6.07)	(2.05)	(2.51)	(2.76)
Financial deposit growth	0.0014505	-0.1066476	-0.1360692	-0.0474504
	(0.15)	(-0.49)	(-0.68)	(-0.80)
Insurance premium growth	0.0890107	0.1364984	0.0800184	0.0895022
	(1.50)	(1.40)	(0.59)	(1.54)
Constant	0.0122836***	0.0098502	0.0195817**	0.0023855
	(2.80)	(1.11)	(2.43)	(0.27)
Number of Obs	453	110	78	32

The results of the one-step estimator of Arellano and Bover (1995) regression are presented in Table 1.6. The results in Panel A are similar to the previous results, where *GDP$_{t-1}$* is correlated to *GDP* for all categories except OIC countries without Islamic banking. We also find that *private*

credit is positively and significantly correlated to GDP for the world and OIC countries. We cannot conclude whether these correlations are stronger due to Islamic banking or not. In Panel B, we see better and more significant results. *Private credit growth* is positively and significantly correlated to *GDP growth* across all groups. The coefficient for OIC countries with Islamic banking (.1608909) is greater than the other coefficients, signifying that it is more strongly correlated to GDP growth, and therefore Islamic finance can be beneficial in increasing GDP growth even further. *Insurance premium growth* is also positively and significantly correlated to *GDP growth* across all groups except OIC countries with Islamic banking.

Table 1.6: One-step estimator of Arellano and Bover (1995) not assuming homoskedastic error term

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a one-step estimator of Arellano and Bover (1995) regression of each financial access or depth variable on the different country subgroups. We are not assuming homoskedastic error term Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated as an average for every three year period over 1990-2013.

Panel A: GDP per Capita				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP$_{(t-1)}$	0.5506868***	0.7490871***	0.6248235***	0.8553244
	(6.22)	(7.00)	(3.56)	(10.91)
Private credit	0.0790888*	0.1744954*	0.1485452	0.1945388
	(1.94)	(1.79)	(1.25)	(1.60)
Financial deposit	0.0037956	-0.0927124	-0.1077349	-0.0925915
	(0.22)	(-0.82)	(-0.84)	(-0.98)
Insurance premium	0.1357285***	-0.0045981	0.1433709	-0.0564309
	(4.91)	(-0.05)	(1.23)	(-1.01)
Constant	2.602588***	1.474334***	2.277986***	0.6788371
	(6.03)	(3.21)	(3.32)	(1.74)
Number of Obs	574	139	99	40
Panel B: GDP per Capita Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP growth$_{(t-1)}$	0.0921583	0.3462706***	0.2512558	0.2594781***
	(1.62)	(2.87)	(1.06)	(3.50)
Private credit growth	0.1255999***	0.1656607**	0.1608909*	0.1366351**
	(6.75)	(2.51)	(1.87)	(2.16)
Financial deposit growth	0.0097476	-0.1756344	-0.1604298	-0.0846551
	(1.28)	(-1.11)	(-0.68)	(-1.40)
Insurance premium growth	0.0689376**	0.1535817*	0.1386411	0.1266342***
	(2.33)	(1.72)	(0.90)	(4.50)
Constant	0.0122348***	0.0120093**	0.0144873**	0.0096149**
	(5.15)	(2.01)	(2.52)	(1.77)
Number of Obs	573	139	99	40

We then do a two-step estimator with Windmeijer bias-corrected robust VCE. The results of this regression are presented in Table 1.7. Panel A, shows that *GDP$_{(t-1)}$* for the world, OIC countries and OIC countries with Islamic banking are all positive and significant. Private credit and insurance premium is also positive and significant for the world but not for the other

subgroups. From Panel A we cannot make any conclusion about Islamic banking being better. Looking at the growth of the same variables in Panel B, *GDP growth*$_{(t-1)}$ is positive and significant for OIC countries and OIC countries without Islamic banking. We also find that *private credit growth* for OIC countries is also positive and significantly correlated to *GDP growth* as well as for OIC countries with Islamic banking. This results may indicate some preference for Islamic banking, however the other variables are inconclusive. *Insurance premium growth* is positive and significantly correlated to *GDP growth* for the world, OIC countries and OIC countries without Islamic banking.

Table 1.7: A two-step estimator with Windmeijer bias-corrected robust VCE

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a two-step estimator of Arellano and Bover (1995) regression with Windmeijer bias corrected robust VCE of each financial access or depth variable on the different country subgroups. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated as an average for every three year period over 1990-2013.

Panel A: GDP per capita				
	World	*OIC whole*	*OIC Islamic*	*OIC non-Islamic*
GDP$_{(t-1)}$	0.5114023***	0.7637287***	0.6380059***	0.796915
	(4.82)	(6.76)	(4.24)	(0.63)
Private credit	0.0870991**	0.1388783	0.1320848	0.154713
	(2.08)	(1.37)	(1.1)	(0.24)
Financial deposit	0.0058688	-0.0570806	-0.0906835	-0.0712696
	(0.17)	(-0.46)	(-0.85)	(-0.06)
Insurance premium	0.1325068***	-0.0169092	0.1184969	-0.0371378
	(3.83)	(-0.17)	(1.54)	(-0.02)
Constant	2.842381***	1.377937***	2.223892***	1.078095
	(5.04)	(3.07)	(3.19)	(0.14)
Number of Obs	574	139	99	40
Panel B: GDP per Capita Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP growth$_{(t-1)}$	0.1499212	0.3414409***	0.235832	0.3815464**
	(1.96)	(2.88)	(0.98)	(2.34)
Private credit growth	0.1117029	0.1212988**	0.1670115**	0.0896763
	(5.44)	(2.07)	(2.2)	(0.89)
Financial deposit growth	0.0033135	-0.1200763	-0.1579043	-0.0598815
	(0.26)	(-0.8)	(-0.72)	(-0.66)
Ins. premium growth	0.1177448**	0.1523254**	0.132466	0.1515774***
	(2.42)	(1.96)	(0.93)	(5.57)
Constant	0.0077825***	0.0110387*	0.0148895***	0.004765
	(2.82)	(1.71)	(2.57)	(0.75)
Number of Obs	573	139	99	40

4.5 Dynamic Panel Estimation of non-Transformed Data

In our next set of regressions we use non-transformed data and repeat the tests we conducted before. First we conduct the Arellano Bover (1995) and Blundell and Bond (1999) test. We reject our null of no autocorrelation in the first differenced errors at the 10% level. In table 1.8

Panel A we regress *GDP per capita* against our proxy variables and also a one period lag of those variables, and a three period lag of *GDP* and in Panel B we regress the growth of the same variables. Our results, in Table 1.8 Panel A, indicate that $GDP_{(t-1)}$ for all subgroups is positive and significant, indicating that the current period GDP is related to last period's GDP. $GDP_{(t-2)}$ is positive and significant for OIC countries and for OIC countries without Islamic banking. It is interesting to see that $GDP_{(t-3)}$ for the world is positive and significant for the world, however it is negative and significant for OIC countries and OIC countries without Islamic banking. Private credit for the current period, t, is positive and significant for the world, OIC countries and for OIC countries without Islamic banking. *Private Credit* $_{(t-1)}$ on the other had is negative and significant for the world, OIC countries, and for OIC countries without Islamic banking. Panel B, shows us that *GDP growth* $_{(t-1)}$ is significant for OIC countries with and without Islamic countries, however it is positive for OIC countries with Islamic countries and negative for OIC countries without Islamic banking. Panel B shows that *GDPgrowth* $_{(t-1)}$ is negative and significant for OIC countries and OIC countries without Islamic banking. *Private Credit growth* $_t$ is positive and significant for the world, OIC countries and OIC countries with Islamic banking. This may indicate a positive facet of using Islamic banking.

Table 1.8: One-step estimator of Arellano and Bond (1991) for non-transformed data

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a One-step estimator of Arellano and Bond (1991) of each financial access or depth variable on the different country subgroups. We are not assuming homoskedastic error term. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated over 1990-2013.

Panel A: GDP per Capita	World	OIC	OIC with ISB	OIC no ISB
GDP $_{(t-1)}$	0.6118871***	0.4643959**	1.021504***	0.3561427**
	(2.96)	(2.4)	(9.94)	(2.31)
GDP $_{(t-2)}$	0.0824758	0.388776*	-0.1031914	0.6945054***
	(0.59)	(1.9)	(-0.96)	(2.88)
GDP $_{(t-3)}$	0.0618273**	-0.1329119*	-0.067272	-0.25479**
	(2.2)	(-1.91)	(-1.44)	(-2.24)
Private Credit$_t$	0.0657614***	0.0818454***	0.0491252	0.0766525**
	(3.25)	(2.84)	(1.46)	(2.12)
Private Credit $_{(t-1)}$	-0.07138***	-0.0410152	-0.0608905**	-0.0154008
	(-6.45)	(-1.45)	(-2.04)	(-.31)
Financial Deposits$_t$	0.0061666	-0.058164	-0.0012461	-0.0749061
	(0.51)	(-1.17)	(-0.03)	(-1.17)
Financial Deposits $_{(t-1)}$	0.0445986***	0.0583999	0.0481144	0.027319
	(2.56)	(1.41)	(1.18)	(.34)
Insurance premium$_t$	0.0675809**	0.1229508	0.0372441	0.1684373
	(2.3)	(1.54)	(1.17)	(1.58)
Insurance premium $_{(t-1)}$	-0.0039443	-0.0626745	0.0007884	-0.1025805*
	(-0.4)	(-1.61)	(0.03)	(-1.67)
Number of Obs	2239	580	396	184

Panel B: GDP per Capita Growth	World	OIC	OIC with ISB	OIC no ISB
GDP growth $_{(t-1)}$	0.0481295	-0.3209801	0.1934359*	-0.5751084***
	(.35)	(-1.36)	(1.66)	(-4.52)
GDP growth $_{(t-2)}$	-0.0068168	0.1467375	0.0003266	0.2667124*
	(-.21)	(1.4)	(.01)	(1.66)
GDP growth $_{(t-3)}$	0.0204754	-0.0102016	-0.0771245	-0.0246647
	(.61)	(-.18)	(-1.41)	(-.19)
Private Credit growth$_t$	0.0399737***	0.1124262***	0.0852201*	0.0741902
	(2.68)	(3.42)	(1.85)	(1.57)
Private Credit growth $_{(t-1)}$	-0.041564	-0.0185661	-0.0131792	-0.1072467
	(-3.48)	(-.79)	(-.49)	(-1.29)
Financial Deposits$_t$	-0.009993	-0.1233693**	-0.0479041	-0.0935055

	(-.93)	(-2.12)	(-.79)	(-1.43)
Financial Deposits $_{(t-1)}$	0.0493786***	0.0447284	0.0369477	0.0935303
	(2.97)	(1.47)	(.99)	(1.22)
Ins. Premium growth$_t$	0.0563684**	0.1155644*	0.0239276	0.1472185
	(2.02)	(1.68)	(.71)	(1.63)
Ins. Premium growth $_{(t-1)}$	0.015319*	0.0151406	-0.0095902	0.0399444*
	(1.74)	(.67)	(-.48)	(1.77)
Number of Obs	2015	536	368	168

For Table 1.9, we repeat the Arellano and Bover (1995) and Blundell and Bond (1999) estimators. We regress *GDP per capita* against 3 period lags of itself as well as against our proxy variables of financial inclusion. In Panel A we find that for the non-transformed data, *GDP* $_{(t-1)}$ is positive and significantly correlated to *GDP per ca*pita across all categories. *GDP*$_{(t-3)}$ is negatively and significantly correlated to *GDP per cap*ita for the world, OIC countries and OIC countries with Islamic banking. This shows that if GDP per capita increases this year, three years from now the GDP will decrease. *Private credit* is also negative and significantly correlated to *GDP per capita* for the world and for OIC countries with Islamic banking. This result is different from our previous results which found a positive correlation between the two variables. In Panel B, *GDP Growth* $_{(t-1)}$ is negative and significant for OIC countries and for OIC countries without Islamic banking. Private credit growth is positive and significant for the world, OIC countries and OIC countries with Islamic banking. We cannot draw any inferences about Islamic banking from this table.

Table 1.9: Arellano and Bover/Blundell and Bond system estimator

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to an Arellano and Bover (1995)/Blundell and Bond system estimator of each financial access or depth variable on the different country subgroups. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated over 1990-2013.

Panel A: GDP per Capita

	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP $_{(t-1)}$	0.943474***	0.621765**	1.224554***	0.4445286*
	3.62	2.22	10.79	1.89
GDP $_{(t-2)}$	0.0981844	0.5899437*	-0.1852345	0.7675793**
	.34	1.69	-1.55	2.08
GDP $_{(t-3)}$	-0.141766*	-0.3148939**	-0.0975485**	-0.2653401
	-1.81	-2.27	-2.03	-1.57
Private Credit	-0.0152611*	-0.0304785	-0.0224611***	0.0245371
	-1.88	-1.56	-2.64	.79
Financial Deposit	0.0212423*	0.0440662	0.0423566***	-0.0225753
	1.86	1.39	2.82	-.40
Insurance Premium	0.0488989**	0.0334519	0.0182875	0.0215659
	2.33	.94	1.19	.63
Constant	0.5933507*	0.6068301**	0.2699222***	0.3476399*
	1.94	2.20	4.01	1.87
Number of Obs	2544	671	452	219

Panel B: GDP per Capita Growth

	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP Growth $_{(t-1)}$	-0.1450318	-0.3717239*	0.1363742	-0.5556563***
	-0.75	-1.92	1.23	-5.37
GDP Growth $_{(t-2)}$	-0.1083693***	0.0085858	-0.0013577	0.0711521
	-2.59	0.17	-0.03	1.26
GDP Growth $_{(t-3)}$	-0.0577341	0.0101441	-0.0478679	0.0272925
	-1.18	0.27	-1.00	0.54
Private Credit growth	0.0611857***	0.098901***	0.0618412*	0.0619089
	2.68	2.80	1.87	1.21
Financial Deposit growth	-0.0013343	-0.1070429**	-0.0298627	-0.0535929
	-0.11	-2.02	-0.58	-1.29
Ins. Premium growth	0.0455243*	0.1112617*	0.0272016	0.1271037
	1.92	1.72	0.81	1.54
Constant	0.0268915***	0.0267851***	0.0179177***	0.0267405***
	5.36	7.35	6.27	4.19
Number of Obs	2411	629	427	202

When we do the two-step estimator with Windmeijer bias-corrected robust VCE, the results are shown below in Table 1.10. In Panel A, we find that $GDP_{(t-1)}$ is positive and significantly correlated to *GDP per capita* for all groups. The coefficient for OIC countries with Islamic finance (0.8380702) is greater than the other categories, indicating a stronger correlation between current and previous period GDP. *Insurance premium* is also positively and significantly correlated to *GDP per capita* for the world, OIC countries and OIC countries with Islamic banking. We see that again *insurance premium* seems to be an indication of Islamic banking having a positive effect on GDP growth. In Panel B, *private credit growth* and *insurance premium growth* are both positively and significantly related to GDP per growth for the world and OIC countries, however not for the other subgroups. We cannot make any conclusion about Islamic banking from Panel B, since the results are insignificant.

Table 1.10: A two-step estimator with Windmeijer bias-corrected robust VCE

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a two-step estimator of Arellano and Bover (1995) with Windmeijer bias-corrected robust VCE of each financial access or depth variable on the different country subgroups. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated over 1990-2013.

Panel A: GDP per capita				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP $_{(t-1)}$	0.7284787***	0.6461802***	0.8380702***	0.5795497**
	7.01	5.07	26.1	2.44
Private credit	0.020472	0.0357064	0.0030546	0.0529797
	0.99	1.37	0.21	0.57
Financial deposit	0.0306508**	0.0325457	0.0201298	0.0428391
	1.9	1.49	0.80	0.54
Insurance premium	0.0699674***	0.0731393*	0.0619324***	0.0306873
	3.37	1.72	3.03	0.83
Number of Obs	2455	637	433	204
Panel B: GDP per Capita Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP growth $_{(t-1)}$	0.0438323	-0.2714901	0.2119906	-0.6303148
	0.37	-1.06	1.50	-1.13
Private credit growth	0.0391214***	0.0824208*	0.0518425	0.0685774
	2.95	1.67	1.46	1.05
Financial deposit growth	0.0000566	-0.0883838	-0.0295082	-0.0295053
	0.01	-1.49	-0.71	-0.47
Insurance premium growth	0.0462002*	0.1029017*	0.0265016	0.0795776
	1.91	1.74	0.97	1.48
Number of Obs	2305	591	404	187

In Table 1.11, we repeat the two-step estimator with Windmeijer bias-corrected robust VCE, this time we assume the variables are endogenous. In Panel A, *GDP $_{(t-1)}$* again is positively and significantly correlated to *GDP per capita* across all groups. *GDP $_{(t-3)}$* is negatively and significantly correlated to GDP per capita for OIC countries and OIC countries with Islamic banking. *Financial deposits* are positively and significantly correlated to GDP per capita for the world and OIC countries with Islamic banking. *Insurance premium* is also positively and

significantly correlated to GDP per capita for the world, OIC countries and OIC countries with Islamic banking. In Panel B, we find that *GDP growth*$_{t-1}$ is positive and significantly correlated to OIC countries with Islamic banking but negative and significantly correlated for OIC countries with no Islamic countries. *Private credit growth* is positively and significantly correlated to *GDP growth* for all categories except OIC countries without Islamic banking.

Table 1.11: Two-step estimator with Windmeijer bias-corrected robust VCE with endogenous variables

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to of each financial access or depth variable on the different country subgroups. We assume the variables are endogenous. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated over 1990-2013.

Panel A: GDP per Capita				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP $_{(t-1)}$	0.7424142***	0.5929716**	1.097554***	0.3618759**
	3.66	2.46	12.75	1.96
GDP $_{(t-2)}$	0.0406162	0.3801694	-0.1584083*	0.5532129**
	0.24	1.43	-1.69	2.27
GDP $_{(t-3)}$	-0.0216312	-0.1717721**	-0.0821811*	-0.1282949
	-0.68	-2.18	-1.69	-1.19
Private Credit	0.0204716	0.0137677	-0.0016698	0.034361
	1.62	1.01	-0.31	1.07
Financial Deposit	0.0263046**	0.0132857	0.033581***	-0.0210583
	2.33	0.47	2.80	-0.33
Insurance Premium	0.0649705***	0.068041*	0.0438016***	0.0736055
	2.78	1.89	3.04	1.26
Number of Obs.	2361	618	418	200
Panel B: GDP per Capita Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP Growth$_{(t-1)}$	-0.1380385	-0.3269644	0.1778858*	-0.5453351***
	-0.65	-1.60	1.80	-4.65
GDP Growth $_{(t-2)}$	-0.0154404	0.1535279**	0.0454022	0.1761807**
	-0.38	1.99	1.04	2.11
GDP Growth $_{(t-3)}$	-0.0189271	-0.0192294	-0.0738474	0.0213701
	-0.51	-0.57	-1.34	0.31
Private Credit growth	0.0673272***	0.0764501***	0.0548166**	0.0483215
	3.32	4.07	3.00	0.97
Financial Deposit growth	0.0107387	-0.0645309**	-0.0128664	-0.0494419
	0.83	-2.00	-0.40	-0.94
Ins. Premium growth	0.0450164*	0.1001777*	0.0361923	0.1304655
	1.76	1.79	1.24	1.54
Number of Obs.	2235	579	395	184

4.6 Panel VAR methodology

While the dynamic panel estimation can present the dynamic effect of financial inclusion key factors for economic growth, the examination for dynamic causality, direction, and timing will show more sufficient information about the relationship of variables. The most well-known method for exploring the dynamic relationship of variables is the vector autoregressive (VAR) methodology, but it is only applicable for time series data, not for panel data. To use the VAR method for panel data, we need to use a panel data vector autoregressive methodology, which is a transformed VAR methodology for panel data. This approach combines the VAR approach of treating all variables as endogenous variables and controls heterogeneity of the panels (Love and Zicchino, 2006). The panel VAR model for this study is as follows:

$$Y_{it} = C + \sum_{s=1}^{m} A_s Y_{i,t-s} + \eta_i + d_{c,t} + e_t (2)$$

Where Y_{it} is a variable vector including all financial inclusion variables, $d_{c,t}$ are country-specific time dummies, and s will be determined based on Arellano-Bond test for the serial correlation of GDP growth and POV for all OIC countries. It should be assumed that all panel individuals have the same structure if the VAR approach using panel data is applicable. For this, we included η_i in equation (2) to consider fixed effects, due to the lagged dependence variable, however fixed effects will correlate with repressors and create biased estimation coefficients. To correct this bias, we used forward mean-differencing, also referred to as the “Helmert procedure” (see Arellano and Bover, 1995), which is known to be a method that preserves the orthogonality between transformed variables and regressors (Love and Zicchino, 2006). Therefore, this study estimates the dynamic VAR model with the GMM system using lagged regressors.

To estimate the impulse-response functions (IRFs), we can calculate confidence intervals using the matrix of IRFs from the coefficients of the panel VAR. For this, we will calculate the standard error of IRFs and create confidence intervals using Monte Carlo simulations approach.

On the other hand, forecast error variance decompositions (FEVDs) are a method that can show the percentage of variation in one variable that is affected by the shock of another variable over time. That is, since FEVD can show the response of one variable over time to a single innovation in itself or another variable, FEVDs can represent the strength of the whole effect. Therefore, we can report FEVDs over two, five, and ten years to examine the cumulative total effects over time.

We first conduct a unit root test for our four variables, GDP growth, private credit, financial deposit and insurance. We reject the null hypothesis of unit root test for our four variables. We look for cointegration between the variables and we find that we reject H_0 for all variables except GDP growth and private credit. Which implies that all the other variables are cointegrated of order (1, 1). However, Phillip-Perron rejects all the variables. However it shows that GDP growth is not cointegrated with the other variables. Economically these variables should be cointegrated therefore we are assuming that they are and moving on to estimating Panel VAR and Granger causality.

Table 1.12: Panel VAR

This table shows the estimated coefficient, z-statistic (in parentheses), and number of observations corresponding to a panel VAR regression of each financial access or depth variable on the different country subgroups. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated over 1990-2013.

Panel A: GDP Growth

	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP Growth$_{(t-1)}$	0.3208333***	0.2831538***	0.4031887***	0.1399427
	7.43	2.76	3.17	0.81
GDP Growth$_{(t-2)}$	0.0717159*	0.2155516**	0.093669	0.3045929*
	1.83	2.41	1.49	1.65
Private Credit growth$_{(t-1)}$	-0.0010166	-0.0004113	-0.0070202	0.0084326
	-0.1	-0.02	-0.27	0.17
Private Credit growth$_{(t-2)}$	-0.0054866	-0.0145711	-0.0057198	-0.041223
	-0.5	-1.06	-0.43	-1.01
Financial Deposit growth$_{(t-1)}$	0.0543897***	0.0638664**	0.0603798*	0.106369
	4.16	2.30	1.84	1.62
Financial Deposit growth$_{(t-2)}$	-0.0245731	-0.0760608	-0.0110612	-0.1849432
	-0.87	-0.96	-0.39	-0.94
Insurance premium growth$_{(t-1)}$	-0.0006252	0.0020391	-0.0186759	0.0054959
	-0.11	0.12	-1.03	0.23
Insurance premium growth$_{(t-2)}$	-0.00000773	-0.0256678	0.0260844	-0.0624258*
	0	-1.11	1.37	-1.82

Panel B: Private Credit Growth

	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP Growth$_{(t-1)}$	0.9027304***	0.8607781***	0.9289518***	0.7829477***
	9.63	4.32	3.54	2.75
GDP Growth$_{(t-2)}$	0.055749	0.0104022	0.1272772	-0.2341829
	0.65	0.06	0.63	-0.91
Private Credit growth$_{(t-1)}$	0.6213705***	0.6126877***	0.5825644***	0.6551784***
	14.03	6.28	4.24	4.94
Private Credit growth$_{(t-2)}$	-0.1252048***	-0.0894335	-0.0250844	-0.2805829**
	-3.12	-1.18	-0.36	-2.36
Financial Deposit growth$_{(t-1)}$	-0.1328897***	-0.200418*	-0.1940266	-0.1903437
	-2.62	-1.69	-1.36	-0.95
Financial Deposit growth$_{(t-2)}$	0.0310482	-0.0587696	-0.0776796	0.0656653
	0.75	-0.58	-0.85	0.35
Insurance premium growth$_{(t-1)}$	-0.0970508***	-0.0793074	-0.1418272**	-0.0298357
	-4.44	-1.64	-2.49	-0.44

	World	OIC	OIC with ISB	OIC no ISB
Insurance premium growth$_{(t-2)}$	-0.0343707	0.0234696	0.0152154	0.015574
	-1.19	0.51	0.29	0.22
		Panel C: Financial Deposit Growth		
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP Growth$_{(t-1)}$	0.5737774***	0.4684178***	0.4067512**	0.6200728**
	5.41	3.19	2.28	2.51
GDP Growth$_{(t-2)}$	0.1186029	0.2461392*	0.2876968**	0.1775296
	1.30	1.91	2.03	0.72
Private Credit growth$_{(t-1)}$	-0.2214927	-0.0605166	-0.052211	-0.0469387
	-1.58	-0.91	-0.66	-0.42
Private Credit growth$_{(t-2)}$	0.1682343**	0.0740805	0.0968169**	0.002459
	2.07	1.56	2.21	0.02
Financial Deposit growth$_{(t-1)}$	0.7699885***	0.3834329***	0.3830782***	0.3876418**
	2.65	4.43	3.93	2.42
Financial Deposit growth$_{(t-2)}$	-0.281466	-0.209389***	-0.2155383***	-0.1625487
	-2.04**	-2.87	-2.74	-1.08
Insurance premium growth$_{(t-1)}$	-0.1089369***	-0.0913037**	-0.1586385***	-0.0351291
	-3.18	-2.14	-2.88	-0.65
Insurance premium growth$_{(t-2)}$	0.0199515	0.0364254	0.0375319	0.0243204
	0.82	0.95	0.74	0.47
		Panel D: Insurance Premium Growth		
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
GDP Growth$_{(t-1)}$	0.4629607***	0.2940479	0.2834881	0.355314
	3.53	1.11	0.95	0.81
GDP Growth$_{(t-2)}$	0.1294539	-0.0282616	0.093018	-0.319607
	0.96	-0.12	0.32	-0.98
Private Credit growth$_{(t-1)}$	0.0897362	0.0602435	0.0821924	-0.0038391
	1.61	0.50	0.83	-0.02
Private Credit growth$_{(t-2)}$	-0.0610528	-0.0888598	-0.1124901*	-0.0751436
	-1.44	-1.3	-1.74	-0.39
Financial Deposit growth$_{(t-1)}$	0.0641689	0.1702459	0.1165349	0.3795216*
	1.23	1.54	1.03	1.73
Financial Deposit growth$_{(t-2)}$	0.0032914	-0.0244879	-0.0545491	0.0004079
	0.07	-0.22	-0.53	0.00
Insurance premium growth$_{(t-1)}$	0.0163518	-0.0050237	-0.073545	0.0448622
	0.37	-0.05	-1.04	0.24
Insurance premium growth$_{(t-2)}$	0.056554	-0.0666765	0.0515245	-0.1742345*
	1.38	-0.99	0.74	-1.81

For our panel VAR regression, each variable is regressed on 2 lags of each of the variables including itself. And the same regression is done for each of the other variables. The results are presented in Table 1.12 above. Panel A looks at the GDP growth, we see that *GDP Growth*$_{(t-1)}$ it is positively and significantly correlated to *GDP growth* for all groups except OIC with no Islamic banking, for which the results are insignificant. Looking at the coeffecients we find that OIC countries with Islamic banking has the highest coefficient with 0.4031887 with a 1 percent significance, the coefficients for the other categories are lower, indicating that countries with Islamic banking is doing better on average. *Financial Deposit growth*$_{(t-1)}$ is positive and significantly correlated to GDP and OIC countries with Islamic banking are higher than the coefficient for the world, indicating that Islamic banking may be beneficial in this region. *Insurance premium growth*$_{(t-2)}$ is negative and significant for OIC countries with not Islamic banking.

Panel B looks at Private credit growth, we see that the results show that the first and third lags of GDP growth positively affects the current GDP, *GDP Growth*$_{(t-1)}$ is positively and significantly correlated to private credit growth. Again the coefficient for OIC countries with Islamic banking (.9289518) is higher than the other coefficients, indicating that it has a stronger correlation with private credit growth. The one period lag of private credit is positively and significantly correlated to current period private credit growth for all groups. The two period lag of private credit is negatively and significantly correlated to the current period private credit growth for the world and for OIC countries with no Islamic banking. *Financial Deposit growth*$_{(t-1)}$ is negatively and significantly correlated to private credit growth for the world and OIC countries. *Insurance premium growth*$_{(t-1)}$ is negatively and *Insurance premium growth*$_{(t-1)}$ correlated to private credit growth for the world and OIC countries with Islamic banking.

Panel C looks at financial deposit growth, we find that it is positively and significantly correlated to *GDP Growth*$_{(t-1)}$ across all groups, the coefficient for OIC countries without Islamic banking (.6200728) is the highest, therefore we cannot draw any conclusions about Islamic finance being beneficial. The two period lag of GDP is also positively and significantly correlated for OIC countries and OIC countries with Islamic banking. The one period lag of private credit growth does not produce significant results but the *Private Credit growth*$_{(t-2)}$ positively and significantly correlated to financial deposit growth for the world and OIC countries with Islamic banking. The one period lag of financial deposit growth is positively and significantly correlated to the current period for all groups and the two period lag is negatively and significantly correlated for OIC countries and OIC countries with Islamic banking. *Insurance premium growth*$_{(t-1)}$ is negatively and significantly correlated to financial deposit growth across all groups. All the coefficients for OIC countries with Islamic banking are lower than the other categories in this Panel and therefore we cannot arrive at any conclusions about Islamic banking for this panel.

Panel D looks at insurance premium growth. The results for this part of the table are mostly insignificant.

4.7 Panel Granger causality test

In order to examine the directions of causality between variables, we estimate the panel Granger causality test. A Granger causality test that uses panel data can be separated in two ways. The first method is to treat the panel as one large stacked set of data, in which all coefficients are assumed to be common over whole cross-sections. The Granger causality test (Granger, 1969) is then estimated in a standard method in which all coefficients are assumed to be the same across the panels without concerning cross-sectional differences and the panel data is treated the same as ordinary time series data.

The second method is to examine the Granger causality test with the assumption that all the coefficients are different across all cross-sections, which is adopted by Dumitrescu-Hurlin (2012). This method calculates the standard Granger causality tests for each panel and calculates a Zbar statistic from the average of the test statistics.

We need to examine the Granger causality test with the first method, because although our panel data has cross-sectional differences between countries, there are a lot of missing data in the GFDD for the OIC countries to calculate appropriate Granger causality statistics. Accordingly, we use the Granger causality test approach that assumes all cross-sections have the same coefficients and treats the panel as one large stacked set of data. It is expected that the Granger causality test can show the overall direction of causality for all variables.

Table 1.13: Panel VAR-Granger causality Wald test

This table shows the estimated χ^2 corresponding to a Panel VAR-Granger causality Wald test of each financial access or depth variable on the different country subgroups. The variables in Panel A are normalized using logarithm. In the cross-country regressions in the left-hand portion of the table, each dependent variable is evaluated over 1990-2013. The hypothesis is that excluded variable does not Granger-cause Equation variable and the alternative hypothesis is that the excluded variable Granger-causes the equation variable

Panel A: GDP Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
	χ^2	χ^2	χ^2	χ^2
Private credit growth	0.399	1.446	0.345	1.238
	0.819	0.485	0.841	0.538
Financial Deposit Growth	17.621	6.836	3.458	3.143
	0	0.033	0.177	0.208
Ins. Premium Growth	0.012	1.47	3.661	3.312
	0.994	0.479	0.16	0.191
ALL	23.679	10.887	6.313	6.546
	0.001	0.092	0.389	0.365
Panel B: Private Credit Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
	χ^2	χ^2	χ^2	χ^2
GDP Growth	92.787	19.107	15.455	9.332
	0	0	0	0.009
Financial Deposit Growth	6.881	3.44	2.798	0.95
	0.032	0.179	0.247	0.622
Ins. Premium Growth	21.741	2.717	6.236	0.198
	0	0.257	0.044	0.906
ALL	114.586	31.278	32.169	11.411
	0	0	0	0.076
Panel C: Financial Deposits Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
	χ^2	χ^2	χ^2	χ^2
GDP Growth	31.115	13.503	9.868	6.305
	0	0.001	0.007	0.043
Private credit growth	4.954	2.492	4.957	0.216
	0.084	0.288	0.084	0.898
Ins. Premium Growth	10.336	4.91	9.065	0.472
	0.006	0.086	0.011	0.79
ALL	77.963	23.67	28.926	6.724
	0	0.001	0	0.347
Panel D: Insurance Premium Growth				
	World	*OIC*	*OIC with ISB*	*OIC no ISB*
	χ^2	χ^2	χ^2	χ^2

GDP Growth	13.141	1.241	1.19	1.674
	0.001	0.538	0.552	0.433
Private credit growth	3.224	1.692	3.053	0.188
	0.199	0.429	0.217	0.91
Financial Deposit Growth	1.656	2.411	1.365	3.18
	0.437	0.3	0.505	0.204
ALL	29.014	9.298	11.577	8.621
	0	0.158	0.072	0.196

Table 1.13 shows our results for the Granger Causality test. We set our null hypothesis, H_0, as excluded variable does not Granger-cause Equation variable and the alternative hypothesis, H_a, as excluded variable Granger-causes Equation variable. Here, we find that financial deposit is granger causing GDP growth. However, the relationship is not one way. GDP growth in turn granger causes growth in financial deposit. Each of the variables has significant causation effect on financial deposit and private credit. Insurance premium seems to be affected by only GDP growth. These results along with panel VAR indicate that improvement in financial deposits has had a positive impact on growth. The effects are stronger for OIC countries.

5. Methodology and Empirical Findings for Poverty Analysis

5.1 Proxy measures for financial inclusion and poverty

Another aspect of this study is looking at poverty alleviation. Can increased Islamic banking help with poverty alleviation? To answer this question we have to use proxies for financial inclusion. Beck, Demurgic-Kunt and Levine (2004) study whether financial development disproportionately raises the incomes of the poor and alleviates poverty. They find that financial development reduces income inequality by disproportionately boosting the incomes of the poor. They use proxy measures for poverty alleviation which we will also be looking at. The variables are described in the Table B below.

Table B

Poverty Variables That affect Financial Inclusion	*Definition*
GDP per capita	GDP per capita in constant 1995 US$
Income share held by lowest 20%	Percentage share of income or consumption held by the poorest 20% of the population
Growth of GINI	The Gini coefficient is the ratio of the area between the Lorenz Curve, which plots share of population against income share received, to the area below the diagonal. It lies between 0 and 1, where 0 is perfect equality and 1 is perfect inequality. The growth rate is calculated as the log difference between the last and the first available observations, divided by the number of years.
Growth of Headcount	Headcount is the percentage of the population living below the national poverty line, as defined as living on $1 a day. The growth rate is calculated as the log difference between the last and the first available observations, divided by the number of years.
Growth of poverty gap	The poverty gap is defined as the mean shortfall from the poverty line, expressed as a percentage of the poverty line. The growth rate is calculated as the log difference between the last and the first available observations, divided by the number of years.

In this part of our study we are trying to evaluate the impact of financial intermediaries (inclusion) on poverty and poverty alleviation. As we do not have a direct measure of financial inclusion, we must use proxies for financial inclusion. Following Beck et al (2004) to study the impact of financial development on the poor, we use the proxy variables listed in Table B. These variables include, the growth of the income of the poorest 20 percent in each subcategory, using this variable we should be able to see how financial development will affect the poorest portion of the economy. Next we use the growth of the Gini coefficient, this variable measure income inequality in each country, the Gini coefficient ranges between zero – perfect equality -and one, where larger values imply greater income inequality. We look at the growth rate of the Gini

coefficient to see whether income inequality is growing or shrinking in the economy. Our third variable is the growth of headcount, equals the growth rate in the percentage of the population living below $1 dollar per day. And our last proxy for poverty is the growth rate of the Poverty Gap, the mean shortfall from the poverty line, expressed as a percentage of the poverty line.

5.2 Methodology for Poverty Alleviation

To study the relationship between financial inclusion growth and poverty alleviation we use a basic ordinary lease squares equation (OLS). We follow methodology similar to Beck et al (2004) and use cross-country regressions, calculating growth rates of income, inequality and poverty over two different periods, one with data starting in 1990 and the other with the longest available time period and averaging financial inclusion development and other explanatory variables over the corresponding time period. The reason for using cross-country regressions is the lack of poverty data, this data is only available for a few years in a very unbalanced time series form.

First we calculate the income growth of the poor. To do so we use data over the period 1990-2015 and use the following equation:

$$(y_{i,p,t} - y_{i,p,t-n})/n = \alpha FD_i + \beta X_i + \varepsilon_i \quad (7)$$

In this regression, $y_{i,p,t}$ represents the logarithm of average per capita income of the poorest income quintile, GINI index, *poverty gap, and poverty headcount ratio* in country *i* in year *t*, FD_i is the matrix of average growth in measures of financial inclusion in country i, and X_i is a dummy for countries with Islamic finance.

Table 1.14: Cross-sectional Poverty Alleviation

The coefficients in this table are the results of simple OLS regressions. All the variables reflect average growth (per year) over the whole available sample period. Significance levels of 10 percent (*), 5 percent (**), and 1 percent (***) are also indicated.

	GINI Index	*Income share by lowest 20%*	*Poverty Gap*	*Poverty Headcount Ratio*
Panel A: Data starting 1990				
Private Credit	-0.03609	0.078673	0.253217	-0.10169
	(0.127)	(0.129)	(0.103)	(0.365)
Private Deposit	-0.01018	0.121741**	-0.79264***	-0.22729
	(0.692)	(0.021)	(0)	(0.125)
Insurance Premium	0.028258*	0.024842	-0.2373***	-0.17402***
	(0.085)	(0.517)	(0)	(0.002)
Islamic Finance Dummy	-0.00398	0.010769*	0.012024	-0.01838*
	(0.146)	(0.063)	(0.324)	(0.086)
Constant	0.000157	0.008278**	-0.00132	0.002792
	(0.925)	(0.022)	(0.891)	(0.727)
Number of Obs	135	121	75	102
Panel B: For all the available years				
Private Credit	-0.01895	0.073018	0.293591*	-0.07256
	(0.512)	(0.242)	(0.09)	(0.538)
Private Deposit	0.026543	0.138782*	-0.85546***	-0.21201
	(0.476)	(0.066)	(0)	(0.194)
Insurance Premium	0.008388	0.019984	-0.22627***	-0.17177***
	(0.617)	(0.607)	(0)	(0.002)
Islamic Finance Dummy	-0.00511**	0.009699*	0.013051	-0.01597
	(0.069)	(0.098)	(0.295)	(0.142)
Constant	-0.00014	0.006644*	5.37E-05	-0.00122
	(0.94)	(0.092)	(0.996)	(0.883)
Number of Obs	135	121	75	102

The results in Table 1.14, are rather interesting. Looking at the Islamic finance dummy, we see that there is a positive and significant relationship with the income share held by the lowest 20 percent, this implies that Islamic finance has a positive impact on the income of the poorest individuals in the OIC countries. We also see that Islamic finance has a negative and significant correlation with poverty, this implies that the poverty rate is decreasing with Islamic finance. These results are very motivating, they show that Islamic finance is beneficial to this region. We also see

in Panel B of Table 1.14 that Islamic finance also has a negative and significant relationship with the Gini index, this shows that the growth the Gini coefficient is negative, which implies that the income inequality between the rich and the poor is decreasing, which is also an indication of poverty reduction. Looking at the other variables we see that private deposit growth has a positive and significant correlation with income share of the lowest 20 percent of the population and also a negative and significant correlation with poverty gap. These results imply that private deposit had a significant influence in increasing the income of the poor as well as decreasing the poverty gap. Insurance premium growth has a negative and significant correlation with poverty gap as well as poverty headcount ratio, implying that insurance premium can help reduce both of these variables. We cannot draw any useful conclusions from the private credit growth variable. The growth in financial intermediaries, especially Islamic banking, seems to have a positive effect on poverty alleviation. Therefore, it is worthwhile to increase Islamic banking in this region.

6. Conclusion

In this paper we aim to find the connection between financial inclusion variables and its effect on the poverty levels in OIC countries. Having access to financial services is important. It offers savings, credit, and risk management to individuals who have accounts. Inclusive financial services is beneficial for all individuals. It helps increase their ability to borrow and save money for large or emergency situations. Involuntary financial exclusion can be problematic and needs policy action to remedy this issue. Studies have found that there is a relationship between levels of financial exclusion and economic growth or poverty. Researchers and policymakers use financial inclusion policies to increase the number of individuals, households and small and medium size enterprises that are now either fully or partially excluded from financial industry. As

people become more financially included, they gain power to use financial services to improve their life and that of their families.

About a quarter of the world's population is Muslim and a significant proportion of these individuals voluntarily exclude themselves from the financial system, since commercial financial services go against Shari'a law. There has been an increase in Shari'a compliant financial products and insurances, which plays a significant role in increasing the level of financial inclusion of Islamic countries. Increasing access to formal financial services in these countries will give the adults more ways to save and invest, which may help with economic growth in that country.

There are many different reasons that studying financial inclusion and economic growth in OIC countries is important. Researching Islamic countries will provide useful information about the relationship between financial inclusion and economic growth. The demand for Shari'a compliant financial services is expected to increase and this information will be useful to provide desired financial products. Shari'a compliant financial products have relatively low speculative characteristics compared to western financial services, and therefore has attracted a lot of attention in recent years, and these products have sufficient development potential. Poverty is an ongoing problem across many countries that are members of the OIC and studying variables that affect financial inclusion may help policymakers include more people in the financial system that are being excluded which may help reduce poverty.

Our results for the effect of financial inclusion on GDP growth, has some positive and significant results in regards to private credit growth. These two variables are positively and significantly correlated for most of the tests we conducted. Therefore we can say that Islamic finance is a positive initiative in OIC countries. However financial deposits do not have significant results for most of the tests we conducted and therefore we cannot draw any conclusions for that

variable. We were unable to divide our sample, due to lack of data, into Islamic banks and commercial banks and therefore, even though we attribute the economic growth to Islamic finance it may also be due to an increase in commercial banking. Our answer to the first part of our question, does financial inclusion have an impact on economic growth, is answered by our results, yes it does but not as much as we had hoped for. Increasing Islamic finance and commercial banking will be beneficial in these areas, giving businesses and individuals more access to funds to increase their investment and savings opportunities.

The results for the effect of financial inclusion on poverty alleviation has even more noteworthy implications. Since we were able to include a dummy variable for Islamic banking we can see the affects that variable has on our poverty proxy variables. We see that Islamic finance has a positive and significant impact on income share of held by the lowest 20 percent of the population implying that Islamic finance has a positive impact on the income of poor people in OIC member countries. We also see that Islamic finance has negative and significant correlation with poverty headcount ratio, implying that it helps alleviate the percentage of individuals living below $1 per day. Islamic finance also has a negative and significant correlation with the growth of Gini coefficient, implying that there is less variation in the income of the rich and the poor which indicates that individuals are increasing their income.

We conclude by saying that Islamic finance can help increase economic growth and decrease poverty. However, the countries covered in this study are mostly developing nations who may be experiencing large amount of growth, and the data was hard to come by since developing countries lack data. There is no Islamic financial development index, which would have been useful to truly study the effects of Islamic finance in this region, and may be an idea for future research.

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Chapter 2: Asymmetric Market Reactions to the 2007-08 Financial Crisis: From Wall Street to Main Street

1. Introduction

The 2007 – 2008 U.S. economic recession was one of the worst in recent history, second only to the Great Depression. The financial crisis that caused the recession resulted in the failure of many financial institutions and had important real sector implications, including the near-collapse of the U.S. auto industry. As a consequence, government agencies and policymakers strived to enact policies and design programs in order to help curtail the financial crisis and restore faith in the financial system.

The financial crisis unfolded over a period of roughly two years in 2007 and 2008, whereby information regarding the scope and severity of the crisis were made known to the financial markets and regulators and policymakers began to respond to the crisis. The 2013 *USA Today* article "A Repeat of 2008? Not Impossible" outlines many of the events that were significant in the evolution of the financial crisis and provides a timeline of the major events associated with the financial crisis and the dates on which those events where announced to the public and financial markets. The financial crisis began with an increase in defaults in subprime mortgages in February 2007. Banks and hedge funds were left with assets that were of questionable value and, thus, were highly illiquid. There were several events that took place shortly, thereafter. Such as, Freddie Mac announced that it would no longer buy risky subprime loans and New Century Financial filed for bankruptcy protection. A few months later Bear Stearns liquidated two hedge funds that invested in risky subprime mortgage-backed securities, among other events. As the crisis got worse, the Federal Reserve (Fed) realized that normal monetary policy changes were not enough to address the situation, and policymakers began a series of unconventional policies in an attempt to control the spread of the crisis.

By 2008, as a result of the financial crisis, the U.S. economy was in recession. The crisis in subprime mortgages had infected the credit markets, so the Federal Reserve began to create new facilities, changed its lending rules, and even injected large amounts of capital into financial institutions. On January 11, 2008, Bank of America agreed to purchase the failing Countrywide Financial. Then Fed stepped in and guaranteed $30 billion of the troubled financial institution Bear Stearns' assets in order to facilitate its purchase by J.P. Morgan Chase. In July, the Fed seized IndyMac Federal Bank, as it was about to fail. In September, Fannie Mae and Freddie Mac were taken over by the government, Bank of America agreed to purchase Merrill Lynch, and Lehman Brothers filed for bankruptcy court protection as well as, American International Group (AIG) accepted an $85 billion federal bailout, giving the government almost an 80% stake in the company. The government gained control of other investment banks and incited more buyouts of smaller banks.

As a further response to the continuing financial crisis, Congress proposed a $700 billion relief package known as the Troubled Asset Relief Program (TARP) on September 29, but it was initially rejected. This sent the Down Jones industrial average down 778 points, the single worst point drop in history. Less than a week later, on October 3, 2008, Congress passed a version of TARP and President Bush signed it.

There are several important events during the U.S. financial crisis of 2007 and 2008 that made the entire financial system vulnerable. The series of failures or near failures of so many financial institutions during the crisis motivates our analysis of how the financial markets react to these types of financial crisis events. Financial markets can be volatile and react to events in the economy when information becomes available. In perfectly efficient markets, this information can be incorporated into asset prices instantaneously, risk can be priced efficiently, and we

should observe no unexpected returns in the market, as defined in the context of an asset pricing model. However, when markets are less efficient at producing information, perhaps during a time of great uncertainty like a financial crisis, events may be unanticipated, and stock prices may move suddenly in unpredictable ways. Therefore, studying the abnormal returns surrounding the announcement of crisis events can help investors, regulators, and policymakers understand how markets react to financial sector news and lead to a better understanding of the function and efficiency of the financial markets. There is some existing literature pertaining to the impact of specific events in the financial crisis, but there are currently no studies that look at the cumulative and individual effects of crisis announcements on stockholder wealth. Additionally, there is limited research on the degree to which crisis events impact other financial firms, as well as the degree to which financial market event announcements spillover to the stock returns of real sector firm. Therefore, we conduct empirical analyses that increases the understanding of the how financial crisis information is incorporated into asset prices.

For our empirical analysis, we create portfolios of financial, real sector, and event firms and test for the existence of abnormal stock returns surrounding event days when significant financial crisis news was released to the financial markets. We use daily stock return data from the CRSP database from January 1, 2006 to December 31, 2009 and use event day and interval dummy variables to estimate financial crisis event-related abnormal returns in the context of an asset pricing model robust to the factors of Fama and French (1993) and Carhart (1997). We examine estimated crisis event abnormal returns for portfolios of different size financial, real sector, and event firms, formed using industry SIC Codes and stock ticker symbols. Our results show that portfolio abnormal returns for non-financial, financial, and event-related firms are significant for daily intervals surrounding the announcement of financial crisis news. In

particular, we find that estimated abnormal returns are negative for non-financial firms of all sizes, as well as small and mid-sized financial firms; however, the abnormal returns are positive for larger financial institutions.

In an extension of our results, we further examine the financial services industry by forming portfolios of two-digit SIC industry financial firms. The results show that the negative abnormal returns in response to financial crisis events seen by smaller financial firms are mainly driven by the negative and significant abnormal returns for portfolios of broker-dealer, depository, holding-investment, and real estate firms. In addition, the positive abnormal returns experienced by larger financial firms are mainly driven by positive and significant abnormal returns for the portfolio of large depository institutions. Finally, we analyze the impact of individual financial crisis event announcements on stock market abnormal returns. The results show that, while not all events are associated with abnormal returns, there are several events during the recent financial crisis that consistently correspond to abnormal returns for portfolios having different characteristics. For example, the credit rating downgrade of Countrywide financial, the government backing of Bear Sterns' assets, the collapse of mortgage companies Freddie Mac and Fannie Mae, the government rescue of AIG, and U.S. automakers' requesting access to TARP funds are all associated with consistent negative abnormal announcement returns for small and mid-sized portfolios of both financial and real sector firms. On the other hand, the conversion of Morgan Stanley and Goldman Sachs into holding companies, the government rescue of Citigroup, and the extension of TARP funds to major U.S. automakers are associated with positive abnormal event day returns, particularly for real sector and larger financial firms.

The results provided in this study present new empirical evidence regarding the impact of financial crises on both financial sector and real firms and sheds light on how financial crisis risk

is priced in the financial markets. For example, the estimation of negative abnormal returns for non-financial portfolios of all sizes illustrates that there is significant spillover of the impact of financial crisis events to the abnormal stock returns of non-financial firms. In fact, the estimated negative abnormal returns for smaller real sector firms are larger than those estimated for small financial firms. In addition, we can interpret positive and significant abnormal returns for large depository institutions in response to financial crisis news as a perception of depository institutions having relatively lower risk, potentially due to possible Federal government intervention. Finally, despite mixed results in the direction and magnitude of abnormal returns in response to individual crisis events, some events, such as the conversion of Morgan Stanley and Goldman Sachs into holding companies and the government bailout of Citigroup are met with positive abnormal returns, as large financial firms and policymakers attempted to dampen the crisis.

The paper proceeds as follows. Section 2 describes previous literature on the subject. Section 3 describes the data and methodology used in the empirical analyses. Section 4 presents the specific financial crisis events and reports event interval summary statistics. Section 5 estimates event interval abnormal returns for portfolios of financial, real sector, and financial sub-industry firms. In section 6, we analyze the event interval abnormal returns for portfolios of firms directly impacted by the crisis events. Our results are extended in Section 7 with an analysis of the specific impact of each crisis event on the estimated abnormal returns of portfolios of financial, real sector, and event firms. Section 8 concludes.

2. Previous Literature

Study	Sample	Major Objectives	Findings
Kabir and Hassan (2005)	Their sample consists of commercial banks, S&L Institutions, investment banks and insurance companies and their sample period is June 6, 1996 to October 14, 1998.	Analyze the announcements pertaining to the Long Term Capital Management (LTCM) hedge fund in 1998.	The day following LTCM publically announced its losses the returns of all portfolios reacted adversely. The involvement of the Fed with LTCM resulted in a positive impact on the industry and the day on which the market came to know about the bailout, the returns of all portfolios declined. However, once the bailout was announced by the media the following day, the market reacted favorably.
Safa, Hasan & Maroney (2012)	They look at the returns of firms from four financial industries - banking, insurance, brokerage firms, and S&Ls for the period September 5, 2007 to December 31, 2008	Study AIG announcements in 2007 and 2008	They find that the dates pertaining to AIG's announcements of heavy losses result in no significant impact on the market. They find no significant evidence that supports the Federal Reserve's perception of AIG as too-big-to-fail, but the near failure of AIG spread a serious contagion effect and caused an increased systemic risk in the financial industry.
Mamun, Hassan & Johnson (2010)	Their sample consists of banks, brokerage firms, insurance companies and S&Ls for the period January 2006 to December 2008.	Investigate whether the market responds to government intervention.	They find that adjustments to the TAF had negative effects on the market, whereas the creation of and announcements related to TSLF and PDCF had positive wealth effects for bank portfolios, savings and loans portfolios, and primary dealer portfolios

Li, Madura & Richie (2013)	Their sample consists of new bonds issues, they screen the newly issued bonds to eliminate all preferred securities, but retain equity-linked and pay-in-kind (PIK) bonds. Their sample period is from September 15, 2007 through March 15, 2009.	Examine the reaction of the bond market after the collapse of prominent investment banks.	After the Fed's first bailout of Bear Stearns, bonds recovered with a positive abnormal return. Once Lehman Brothers Merrill Lynch and AIG filed for bankruptcy, there was a negative and significant corporate bond market response, which was more pronounced for financial firms, larger firms, and firms that had higher financial leverage.
Ivashina and Scharfstein (2010)	Their sample consists of syndicated loans issued between 2000 and 2008.	They examine the period after the failure of Lehman Brothers in September 2008, when there was a run by short-term bank creditors, making it hard for banks to roll over their short term debt.	Their results show that banks were less likely to cut their lending if they had better access to deposit financing, thereby making them less dependent on short-term debt. Banks that co-syndicated more of their credit lines with Lehman Brothers were more vulnerable and reduced their lending to a greater extent.
Sorokina and Thornton (2013)		Conduct an event study on the equity market reaction to the Dodd-Frank Wall Street Reform Act.	Dodd-Frank may have lowered the risk for financial firms, but it may have increased the risk for the overall economy.
Berger, Black, Bouwman & Dlugosz (2014)	They used data on discount window and TAF usage during the crisis over the period of August 20, 2007 to December 31, 2009.	Examine the impact of the discount window and Term Auction Facility, which banks used these facilities and whether they affected bank lending.	They find that small banks that borrowed funds had less capital and higher portfolio risk, consistent with a greater need for the funds. Large banks receiving funds were generally healthier. They do not find any evidence that small and large banks that utilized the programs increased their lending, relative to banks that did not.

Berger and Roman (2013)	Their sample consists of 572 BHCs, 87 commercial banks, 48 thrifts and 2 S&L, and their sample period is 2006:Q1 to 2010:Q4.	Look at a program enacted by the government by examining the Troubled Assets Relief Program (TARP) and whether or not it gave banks that participated a competitive advantage.	They find that TARP recipients did have a competitive advantage, as it increased their market shares and market power.
Hoffman (2012)	Uses two survey datasets from the Pew Research Center.	Examine public opinion surrounding the TARP program	They found that it was "one of the most hated, misunderstood, and effective policies in modern economic history".
Cornett, Li & Tehranian (2013)	This study examines quarterly operating performance of TARP Capital Purchase Program recipient banks and TARP non-recipient banks from the first quarter of 2007 through the first quarter of 2011.	Examine how the pre-crisis health of banks is related to the probability of receiving and repaying TARP funds.	They examine the healthiest (over-achiever) versus the least healthy (under-achiever) banks and Find that TARP under-achievers have weaker income production, and they also have liquidity issues. TARP over-achievers, on the other hand, perform well, but still have some liquidity issues that hurt their lending.
Hipper and Hassan (2015)		Analyzes the impact of macroeconomic and financial stress on the profitability of financial firms by utilizing data from 1980 to 2010 and modelling firm profitability and stock returns using a panel regression, fixed-effect methodology.	They show that that the profitability of all firms is negatively affected by increases in macroeconomic and financial stress. Their results coincide with the risks associated with recent trends in the financial services industry, such as deregulation, global market integration, financial product innovation, and the increasing predominance of non-depository intermediation.

We extend previous studies in this area by testing for abnormal returns surrounding significant event announcements during the recent financial crisis of 2007 and 2008 in order to examine their impact on the equity markets. We include crisis events that contain relevant information regarding the severity of the crisis, including credit downgrades and financial firm failures, as well as policy response news, such as the creation of government-sponsored assistance programs. We extend the literature in this area by providing empirical results regarding the impact of these events on the financial markets and portfolios of stocks from different industries and of different sizes.

3. Data and Methodology

3.1 The Data

In this study, we generate equity portfolios having different characteristics and calculate abnormal returns for the designated event intervals surrounding financial crisis news announcements. Specially, we analyze estimated abnormal portfolio returns achieved over four intervals surrounding the event announcements: a.) the event announcement day (t=0); b.) the interval including the day prior to the announcement through the announcement day (t=–1, 0); c.) the interval from the day prior to the announcement through the day following the event announcement (t=–1, +1); and d.) the interval from two days prior to the announcement through the day following the event announcement (t=–2, +1). We assume that announcement information is incorporated into prices efficiently; however, including intervals surrounding the event days adds robustness to the analysis by allowing for the anticipation of announcements as well as short delays in announcement reactions due to the timing of the announcements and other factors.

In order to achieve a representative sample of returns adequate to apply an asset pricing model, we sample daily stock return data from the CRSP database from January 1, 2006 to December 31, 2009, which spans the time frame of the identified financial crisis events. For the purpose of estimating abnormal event returns, we gather equity portfolio risk factors, including the risk-free rate and the risk factors of Fama and French (1993) and Carhart (1997) from the website of Kenneth French in order to apply an asset pricing model and calculate event-day abnormal returns. We test for the presence of event announcement abnormal returns for portfolios of firms in different industries and sub-industries using SIC codes reported by CRSP, and we examine the event announcement abnormal returns of portfolios composed of firms of different sizes by sorting firms based on market capitalization. In section 5, we analyze the portfolio of financial firms defined by firms with reported SIC codes between 6000 and 6999. Later in section 5, we further analyze the event abnormal returns of seven financial firm subsector portfolios, defined by reported two-digit SIC codes. We also examine the abnormal event announcement returns of portfolios of different sizes by sorting firms into market capitalization terciles. For each day t, we define the market capitalization as the opening price of the stock on day t (or closing price of day $t-1$) multiplied by the number of shares outstanding for day $t-1$. We then form small, mid, and large capitalization portfolios by sorting firms into terciles by market capitalization for each day. In addition, we also utilize the calculated market capitalizations to weight the portfolios when constructing value-weighted portfolios.

3.2 Event abnormal return estimation methodology

In testing for abnormal returns, an event study methodology is often employed, whereby normal returns are estimated over an interval leading up to the event, and abnormal returns can be seen as the excess return over the normal return. However, when analyzing the abnormal

returns surrounding financial crisis event announcements, the relatively short time period under which the financial crisis evolved and the relative proximity of the events make this type of event study impractical. Therefore, in this paper, we use a methodology similar to Hippler and Hassan (2015), Kabir and Hassan (2005) and Safa, Hasan and Maroney (2012) by using observed market returns and priced risk factors to examine how important announcements during the financial crisis affect the financial markets, the real sector, and the financial services industry. For example, Hassan and Kabir (2005) use a similar methodology to analyze the effect of the Long-Term Capital Management (LTCM) crisis on financial institutions and the effect of the Fed's intervention measures. We use a similar model to analyze the impact of crisis event announcements on equity portfolios using the asset pricing risk factors of Fama and French (1993) and Carhart (1997) and an ordinary least squares (OLS) estimation methodology.

In our first empirical specification, we estimate the model:

$$R_{p,t} = \alpha_p + \beta_1 RF_t + \beta_2 MRP_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \gamma Event_t + \varepsilon_{p,t}, \qquad (1)$$

where $R_{p,t}$ is either the equal or valued-weighted return on a portfolio, *p*, for day *t*. The explanatory variables *RF*, *MRP*, *SMB*, *HML*, and *UMD* represent the returns of the risk-free Treasury bill, the excess market portfolio, the small-minus-big portfolio, the high-minus-low portfolio, and the momentum portfolio of Fama and French (1993) and Carhart (1997) on day *t*, respectively. Finally, $Event_t$ is a dummy variable equal to unity if day *t* falls within one of the four crisis event announcement intervals, as previously defined. Accordingly, $\beta_1 - \beta_5$ represent the portfolio returns explained by the asset pricing model, α represents the average abnormal return for portfolio *p*, which we expect to equal zero, and γ represents the abnormal return for portfolio *p* over the reported crisis event announcement interval.

In addition, in section 7, we modify Eq. 1 to observe the specific impact of individual crisis event announcements on portfolio abnormal returns. Similar to Hassan and Kabir (2005), we calculate the abnormal return of portfolio *p* in response to event *i*, by estimating the parameters of Eq. 2:

$$R_{p,t} = \alpha_p + \beta_1 RF_t + \beta_2 MRP_t + \beta_3 SMB_t + \beta_4 HML_t + \beta_5 UMD_t + \sum_{i=1}^{17} \gamma_i Event_i + \varepsilon_{p,t} \quad (2)$$

In Eq. 2, $R_{p,t}$ represents the return of portfolio *p* on day *t*, and the explanatory factors include those specified in Eq. 1; however, the abnormal returns for the 17 crisis events are measured using a set of 17 dummy variables, each having a value of one corresponding to each crisis event day. In Eq. 2, α_p represents the portfolio *p*'s average abnormal return, which we expect to equal zero, and each coefficient for the event dummy variables, γ_i, represents the estimate of portfolio *p*'s abnormal return for event day *i*.

We estimate the parameters in Eqs. 1 and 2 utilizing an ordinary least squares (OLS) econometric estimation procedure. In Section 5, we present the results for estimates of abnormal returns for portfolios of financial and non-financial firms, in Section 6, we present the estimates for portfolios of firms directly related to the event announcements, and in Section 7, we provide estimates of event day abnormal returns for each specific event.

4. Crisis events and returns

We identify 17 event announcements surrounding the financial crisis of 2007 and 2008, which are reported in the September 15, 2013 *USA Today* article "A Repeat of 2008? Not Impossible". Table 2.1 summarizes the crisis announcements and their associated dates.

Table 2.1: Significant Event Dates in the 2007 – 2008 Financial Crisis

Significant dates and announcements made pertaining to the financial crisis of 2007 and 2008 used in this study. These dates are identified in the article "A Repeat of 2008? Not Impossible." from *USA Today*.

Event	Event Date	Event
Event 1	Feb. 27, 2007	Mortgage giant Freddie Mac says it will no longer buy the most risky subprime loans
Event 2	Apr. 02, 2007	Subprime mortgage lender New Century Financial files for bankruptcy court protection
Event 3	Jul. 31, 2007	Investment bank Bear Stearns liquidates two hedge funds that invested in risky securities backed by subprime mortgage loans
Event 4	Aug. 16, 2007	Fitch Ratings cuts the credit rating of mortgage lender Countrywide Financial to its third lowest investment-grade rating
Event 5	Jan. 11, 2008	Bank of America, the largest U.S. bank by market value, agrees to buy Countrywide Financial for about $4 billion.
Event 6	Mar. 16, 2008	The Federal Reserve agrees to guarantee $30 billion of Bear Stearns' assets in connection with the government sponsored sale of the investment bank to JPMorgan Chase
Event 7	Jul. 11, 2008	Federal regulators seize IndyMac Federal Bank after it becomes the largest regulated thrift to fail
Event 8	Sep. 07, 2008	Mortgage giants Fannie Mae and Freddie Mac are taken over by the government.
Event 9	Sep. 15, 2008	Bank of America agrees to purchase Merrill Lynch for $50 billion.
		Lehman Brothers files for bankruptcy court protection.
Event 10	Sep. 16, 2008	American International Group, the world's largest insurer, accepts an $85 billion federal bailout that gives the government a 79.9% stake in the company.
Event 11	Sep. 21, 2008	Goldman Sachs and Morgan Stanley, the last two independent investment banks, become bank holding companies, subject to greater regulation by the Federal Reserve.
Event 12	Sep. 25, 2008	Federal regulators close Washington Mutual Bank and its branches and its assets are sold to JPMorgan Chase in the biggest U.S. bank failure history.
Event 13	Sep. 29, 2008	Congress rejects a $700 billion Wall Street financial rescue package, known as the Troubled Asses Relief Program or TARP, sending the Dow Jones Industrial average down 778 points, its single worst point drop ever.
Event 14	Oct. 03, 2008	Congress passes a revised version of TARP, and President Bush signs it.
Event 15	Nov. 18, 2008	Ford, General Motors, and Chrysler executives testify before Congress, requesting federal loans from TARP.
Event 16	Nov. 23, 2008	The Treasure Department, Federal Reserve and Federal Deposit Insurance Corp. agree to rescue Citigroup with a package of guarantees, funding access, and capital. Citigroup will issue preferred shares to the Treasury and FDIC in exchange for protection against losses on a $306 billion pool of commercial and residential securities it holds
Event 17	Dec. 19, 2008	The US Treasury authorizes loans of up to $13.4 billion for GM and $4.0 billion for Chrysler from TARP. Ford ultimately takes no money.

Table 2.2 presents summary statistics of the market portfolio returns on the event day intervals under study, as well as those over the entire sample period, January 1, 2006 to December 31, 2009. We report market return statistics on the event days as well as the intervals surrounding event days. The summary statistics reported in Table 2.2 are reported for both the equal and value-weighted market portfolios, as reported by CRSP.

Table 2.2: Event Day Market Returns

Equal and value-weighted CRSP market returns for event days surrounding the financial crisis. Daily CRSP returns are sample from Jan. 1 2006 to Dec. 31, 2009. Event returns are based on 17 events identified as being influential to the financial crisis of 2007 to 2008. See Table 2.1 for event day definitions. Event returns are calculated over four event intervals: the event day [t=0], the interval beginning the day prior to the event day and continuing through the event day [t=–1, 0], the interval beginning the day prior to the event and continuing through the day following the event day [t=–1. +1], and the interval beginning two days prior to the event and continuing through the day following the event day [t=–2, +1]. Event interval average daily returns are compared with those of non-event interval returns.

	CRSP Equal-weight Market Return					CRSP Value-weight Market Return			
	Mean	Std. Dev.	Min.	Max.		Mean	Std. Dev.	Min.	Max.
Non-Event Return	0.06	1.52	-8.03	10.74	Non-Event Return	0.03	1.63	-9.00	11.52
Event Return [t=0]	-0.82	2.64	-6.09	6.43	Event Return [t=0]	-0.78	3.21	-8.28	6.68
Diff.	0.89	1.54			Diff.	0.81	1.67		
Non-Event Return	0.07	1.51	-8.03	10.74	Non-Event Return	0.03	1.61	-9.00	11.52
Event Return [t=-1,0]	-0.49	2.38	-6.09	6.43	Event Return [t=-1,0]	-0.38	2.90	-8.28	6.68
Diff.	0.55	1.55			Diff.	0.40	1.67		
Non-Event Return	0.08	1.47	-8.03	10.74	Non-Event Return	0.04	1.57	-9.00	11.52
Event Return [t=-1,+1]	-0.60	2.55	-6.68	6.43	Event Return [t=-1,+1]	-0.43	2.96	-8.28	6.68
Diff.	0.68	1.54			Diff.	0.47	1.67		
Non-Event Return	0.09	1.45	-8.03	10.74	Non-Event Return	0.05	1.55	-9.00	11.52
Event Return [t=–2,+1]	-0.66	2.54	-6.88	6.43	Event Return [t=-2,+1]	-0.55	2.90	-8.28	6.68
Diff.	0.75	1.54			Diff.	0.60	1.66		

Table 2.2 shows that the average non-event daily market return over the sample under study, January 1, 2006 to December 31, 2009, is 0.06 percent per day for the CRSP equal weight portfolio and 0.03 percent for the CRSP value weighted portfolio. The standard deviations of the daily market returns of the CRSP equal and value weighted portfolios are similar at 1.52 and 1.63 percent, respectively. In contrast, the average crisis event day market return (t=0) is negative. The CRSP equal weight market portfolio fell by an average of 0.82 percent on event days, while the CRSP value weighted index fell by 0.78 percent per day. In addition, the standard deviation of market returns is significantly higher on event days. Returns for the CRSP equal weight portfolio have an event day standard deviation of 2.64 percent, while those of the CRSP value weighted portfolio have a standard deviation of 3.21 percent. Statistical tests of equal return variances across non-event and event days are rejected at the one percent level.

Table 2.2 also reports the average crisis event announcement returns for three intervals surrounding the event announcements. The results in Table 2.2 for the event announcement intervals are similar to those of the event days; however, the average market returns are lowest on the actual event announcement days (t=0). Statistical tests for equality of variances among the event and non-event days are rejected for all announcement intervals presented in Table 2.2.

The results presented in Table 2.2 motivate our further analysis of the event interval abnormal returns surrounding significant events during the financial crisis. We show that average market portfolio returns are lower on days surrounding significant financial crisis events. For example, from 2006 to 2009, the CRSP value weighted portfolio yields an average return of 0.03 percent per day; however, on financial crisis event announcement days, the average reported return is -0.78 percent. We continue our analysis of the impact financial crisis event

announcements by analyzing whether the lower reported event day returns are explained by traditional asset pricing models, or whether the financial crisis appears to signify unpriced risk.

5. Real sector and financial portfolio event interval abnormal returns

Despite the fact that many news events during the onset of the financial crisis pertained to financial service institutions, the crisis had significant repercussions for both the real and financial sectors of the U.S. and global economies. The crisis spurred unprecedented policy actions, including monetary policy activity, a real sector stimulus package, government loans and bailouts, and an overhaul of U.S. financial regulations. Accordingly, it is important to acknowledge the impact that significant crisis events have on both the financial and real sectors of the economy. In this section, we examine the abnormal returns surrounding significant events of the financial crisis for both financial and real sector firms. In addition, we examine the role that firm size plays in the pricing of risk surrounding the financial crisis. Finally, we conduct a further analysis of the finance industry to examine how financial crisis events impact different financial sub-industries.

5.1 Event interval abnormal returns for financial and real sector portfolios

In this section, we examine the abnormal returns surrounding significant events of the financial crisis for both financial and real sector firms. We divide the sample of CRSP firms into financial and non-financial firms based on reported industry SIC codes. Financial firms are firms with an SIC code between 6000 and 6999, and we create equal and value-weighted portfolios of financial and non-financial firms using daily CRSP return data. To determine whether real sector and financial firms experience abnormal returns during the financial crisis, we employ an ordinary least squares (OLS) estimation methodology to the specification provided in Equation 1

and estimate the abnormal returns surrounding announcements during the financial crisis for equal and value weighted portfolios of real and financial sector firms. Results are presented for four specifications, each reporting abnormal returns over different event announcement day intervals.

Panel A of Table 2.3 shows the abnormal return estimations for the portfolio of non-financial, or real sector, firms. The results exhibit a significant spillover of financial crisis event news to the real economy. Many of the events surrounding the financial crisis pertain only to firms in the financial services industry and the government's response to their distress. However, Table 2.3 shows that the impact of these events significantly affects the abnormal stock returns of real sector firms as well. Panel A of Table 2.3 shows that all event interval dummy variable coefficients are negative, and all but one are significant at the ten percent level or better. Negative event dummy coefficients imply that, when applying a traditional asset pricing model, the portfolios of non-financial, real sector firms experience negative and significant abnormal returns in response to financial sector crisis event announcements in the days leading up to and immediately after their announcement.

Table 2.3: Non-financial and financial portfolio event interval abnormal returns

OLS estimations of the abnormal returns for real sector and financial portfolios for event intervals surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal and value weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event interval dummy variables estimate event interval abnormal returns. Financial firms are defined by SIC codes between 6000 and 6999.

Panel A: Non-Financial Portfolios

Variable	VWRET	EWRET	VWRET	EWRET	VWRET	EWRET	VWRET	EWRET
Intercept	0.03861***	0.10535***	0.04087***	0.1095***	0.04389***	0.11696***	0.04438***	0.12177***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
RF	-0.0306	-4.45132***	-0.0837	-4.56905***	-0.1503	-4.73207***	-0.1582	-4.8273***
	0.970	*0.008*	*0.917*	*0.006*	*0.852*	*0.004*	*0.844*	*0.004*
MRP	1.02***	0.889***	1.02***	0.89***	1.02***	0.89***	1.02***	0.888***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	-0.0164*	0.4917***	-0.0169*	0.4883***	-0.018*	0.4849***	-0.0174*	0.4863***
	0.099	*0.000*	*0.089*	*0.000*	*0.070*	*0.000*	*0.078*	*0.000*
HML	-0.176***	-0.0465*	-0.1754***	-0.044*	-0.1754***	-0.0445*	-0.1746***	-0.0409*
	0.000	*0.059*	*0.000*	*0.074*	*0.000*	*0.069*	*0.000*	*0.094*
UMD	0.0693***	-0.102***	0.0696***	-0.0997***	0.0699***	-0.0987***	0.0699***	-0.0984***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Event [t=0]	-0.0265	-0.37311***						
	0.599	*0.000*						
Event [t=-1,0]			-0.06478**	-0.27774***				
			0.076	*0.000*				
Event [t=-1,+1]			.	.	-0.09227***	-0.30919***	.	.
			.	.	*0.002*	*0.000*	.	.
Event [t=-2,+1]			.	.	.	.	-0.07824***	-0.30106***
			.	.	.	.	*0.004*	*0.000*

Table 2.3 (continued): Non-financial and financial portfolio event interval abnormal returns

	Panel B: Financial Firm Portfolios							
Variable	VWRET	EWRET	VWRET	EWRET	VWRET	EWRET	VWRET	EWRET
Intercept	-0.0243	0.0242	-0.0300	0.0232	-0.0340	0.0278	-0.0337	0.0283
	0.319	*0.169*	*0.222*	*0.190*	*0.167*	*0.117*	*0.173*	*0.112*
RF	1.4632	-0.8761	1.6038	-0.8605	1.6907	-0.9640	1.6770	-0.9726
	0.417	*0.499*	*0.373*	*0.507*	*0.347*	*0.457*	*0.352*	*0.453*
MRP	1.01***	0.687***	1.01***	0.688***	1.01***	0.688***	1.011***	0.687***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	0.0240	0.195***	0.0263	0.1942***	0.0285	0.1929***	0.0270	0.1935***
	0.279	*0.000*	*0.235*	*0.000*	*0.197*	*0.000*	*0.222*	*0.000*
HML	0.6679***	0.1821***	0.6659***	0.1824***	0.6665***	0.1827***	0.6647***	0.1836***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
UMD	-0.2156***	-0.1429***	-0.2171***	-0.1424***	-0.2177***	-0.1419***	-0.2176***	-0.1419***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Event [t=0]	0.19957**	-0.1134	.	.	.	.	.	.
	0.077	*0.162*	.	.	.	.	.	.
Event [t=-1,0]			0.22672***	-0.0327	.	.	.	.
			0.005	*0.577*	.	.	.	.
Event [t=-1,+1]	.	.	.	.	0.21986***	-0.09576***	.	.
	.	.	.	.	*0.001*	*0.051*	.	.
Event [t=-2,+1]	.	.	.	.	.	.	0.16819***	-0.08149**
	.	.	.	.	.	.	*0.005*	*0.061*

Table 2.3, Panel A also reports slight differences in the estimated event announcement interval abnormal returns between the equal and value weighted portfolios. The equal weighted portfolio returns exhibit larger negative abnormal returns and they have lower reported p-values than those of the value weighted portfolios. For example, the equal weighted non-financial portfolio exhibits negative abnormal returns that are significant at the one percent level across all event intervals. In contrast, the event day abnormal returns are negative, but insignificant for the event day (t=0) and only significant at the ten percent level for the [–1, 0] interval. In addition, while the coefficients for each interval vary within similar ranges, their ranges vary between the portfolio construction methods, with the equal-weighted non-financial portfolio exhibiting larger negative returns. The differences in the coefficient estimates and their significance level across equal and value-weighted portfolios imply that firm size may play role in the abnormal returns yielded in response to financial crisis events.

Panel B of Table 2.3 reports the estimated event interval abnormal returns for the portfolio of financial firms, and some key differences in the estimated abnormal returns are reported across non-financial and financial firms. Similar to the results reported for real sectors firms, the event interval coefficients for the equal-weighted financial portfolio are all negative, and those of the two longest intervals leading up to the event day are positive at the ten percent levels, with p-values of 0.051 and 0.061, respectively. The negative coefficients reported for the event dummy variables for the equal-weighted financial portfolios are consistent with those reported for the real sector firms and imply negative financial sector abnormal returns in response to important financial crisis announcements. However, the results reported for the value-weighted portfolio of financial firms differ from those of the real sector firms reported in Panel A. The event interval dummy variable coefficients are positive and significant at the ten

percent level or better for all event intervals when value-weighted returns are used as the measure of financial portfolio return. The positive and significant event interval coefficients of the value-weighted financial portfolio imply positive abnormal returns to financial firms in response to the financial crisis event announcements.

In Table 2.3, we show that the estimated abnormal returns differ slightly across value and equal weighted portfolios for real sector firms; however, the difference is pronounced for the financial firm portfolios. In fact, the estimated event abnormal returns change signs across equal and value weighted portfolios for financial firms. Since firm size, measured by market capitalization, explains the difference between the average returns of the value and equal weighted portfolios, both sets of results imply that estimated abnormal returns are dependent upon firm size. For both real sector and financial firms, the estimated abnormal returns are higher (less negative) for value-weighted portfolios, which implies that larger firms yield higher (or zero) abnormal returns in response to financial crisis events. In the case of real sector firms, Panel A of Table 2.3 implies that abnormal returns are less negative (or zero) for larger firms, while Panel B of Table 2.3 implies that larger financial firms actually experience positive abnormal returns, while smaller financial firms exhibit negative (or zero) abnormal returns. We include the impact of firm size on estimated abnormal returns in the following sections.

5.2 Firm size and event interval abnormal returns

The recent financial crisis brought the term “Too big to fail” to the American lexicon, because of the belief that the U.S. government would not allow its largest and most important institutions to fail. During the financial crisis, large firms such as Lehman Brothers and Bear Stearns collapsed; however, to prevent the further spread of the financial crisis and the associated recession, U.S. policymakers enacted a series of programs to support important institutions such

as AIG, Citigroup, and the auto industry. However, at first, only large institutions deemed important for the stability of the national economic and financial infrastructure were able to participate in such programs. Therefore, announcements pertaining to such programs may have a different impact on firms of different sizes.

In the previous section, we show that estimated event interval abnormal returns differ across equal and value weighted portfolios, and we suggest that estimated abnormal returns differ across firm size, measured by market capitalization. In this section, we examine the effect that firm size has on estimated event interval portfolio abnormal returns for the portfolios of non-financial and financial firms. We analyze the impact of firm size on our previous results by creating three equal-weighted, size tercile portfolios sorted daily by market capitalization: small, mid, and large. We then apply the same estimation procedure as in the previous section, and the results are presented in Table 2.4.

Table 2.4: Non-financial and financial size portfolio event interval abnormal returns

OLS estimations of the abnormal returns for non-financial and financial portfolios for event intervals surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event interval dummy variables estimate event interval abnormal returns. Financial firms are defined by SIC codes between 6000 and 6999. Portfolios are divided into small, medium, and large size portfolios based on market capitalization.

Panel A: Non-financial firm portfolios

	Small Non-financial Firms				*Mid-cap Non-financial Firms*				*Large Non-Financial Firms*			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Intercept	0.23983***	0.24864***	0.26209***	0.26929***	0.03649*	0.03758*	0.04171**	0.04703**	0.03996**	0.04252**	0.04736***	0.0493***
	0.000	*0.000*	*0.000*	*0.000*	*0.058*	*0.052*	*0.032*	*0.016*	*0.018*	*0.012*	*0.005*	*0.004*
RF	-13.1202***	-13.3781***	-13.6699***	-13.8057***	-0.4260	-0.4551	-0.5467	-0.6598	0.1753	0.1089	0.0021	-0.0350
	0.000	*0.000*	*0.000*	*0.000*	*0.764*	*0.748*	*0.700*	*0.641*	*0.888*	*0.930*	*0.999*	*0.977*
MRP	0.499***	0.502***	0.502***	0.498***	1.091***	1.091***	1.091***	1.089***	1.076***	1.076***	1.076***	1.075***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	0.2512***	0.2428***	0.2359***	0.2393***	0.8924***	0.8918***	0.8904***	0.8904***	0.331***	0.3296***	0.3277***	0.3285***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
HML	-0.0003	0.0056	0.0041	0.0111	-0.0085	-0.0080	-0.0079	-0.0058	-0.1309***	-0.1298***	-0.1299***	-0.1281***
	0.996	*0.903*	*0.929*	*0.809*	*0.683*	*0.701*	*0.705*	*0.779*	*0.000*	*0.000*	*0.000*	*0.000*
UMD	-0.1756	-0.1698	-0.1679	-0.1676	-0.1095	-0.1091	-0.1086	-0.1082	-0.0213	-0.0204	-0.0198	-0.0197
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.044*	*0.054*	*0.060*	*0.061*
Event [t=0]	-0.92281***	.	.	.	-0.0660	.	.	.	-0.13121*	.	.	.
	0.000	.	.	.	*0.456*	.	.	.	*0.092*	.	.	.
Event [t=-1,0]	.	-0.65342***	.	.	.	-0.0575	.	.	.	-0.12278**	.	.
	.	*0.000*	.	.	.	*0.369*	.	.	.	*0.029*	.	.
Event [t=-1,+1]	.	.	-0.66278***	.	.	.	-0.10473**	.	.	.	-0.16115***	.
	.	.	*0.000*	.	.	.	*0.051*	.	.	.	*0.001*	.
Event [t=-2,+1]	.	.	.	-0.60686***	.	.	.	-0.14755***	.	.	.	-0.14988***
	.	.	.	*0.000*	.	.	.	*0.002*	.	.	.	*0.000*

Table 2.4 (continued): Non-financial and financial size portfolio event interval abnormal returns

	Panel B: Financial firm portfolios											
	Small Financial Firms				*Mid-cap Financial Firms*				*Large Financial Firms*			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Intercept	0.05382*	0.05564**	0.06607**	0.06745**	0.0192	0.0179	0.0236	0.0236	-0.0003	-0.0037	-0.0060	-0.0057
	0.040	*0.035*	*0.012*	*0.011*	*0.391*	*0.428*	*0.297*	*0.300*	*0.988*	*0.839*	*0.747*	*0.759*
RF	-2.4519	-2.5124	-2.7434	-2.7639	-0.6820	-0.6630	-0.7903	-0.7857	0.4938	0.5818	0.6292	0.6190
	0.203	*0.193*	*0.153*	*0.150*	*0.679*	*0.688*	*0.632*	*0.634*	*0.714*	*0.666*	*0.641*	*0.647*
MRP	0.412***	0.413***	0.412***	0.411***	0.697***	0.698***	0.697***	0.697***	0.953***	0.952***	0.953***	0.953***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	-0.0156	-0.0183	-0.0219	-0.0201	0.257***	0.2557***	0.254***	0.2549***	0.3433***	0.3448***	0.3462***	0.3453***
	0.510	*0.441*	*0.354*	*0.395*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
HML	0.0036	0.0053	0.0055	0.0082	0.1319***	0.1325***	0.1328***	0.1338***	0.4103***	0.409***	0.4094***	0.4084***
	0.899	*0.851*	*0.845*	*0.771*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
UMD	-0.1701***	-0.1683***	-0.1671***	-0.1671***	-0.1212***	-0.1204***	-0.1197***	-0.1198***	-0.1375***	-0.1386***	-0.1389***	-0.1388***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Event [t=0]	-0.30572***	.	.	.	-0.17852*	.	.	.	0.14537*	.	.	.
	0.011	.	.	.	*0.084*	.	.	.	*0.085*	.	.	.
Event [t=-1,0]	.	-0.19132**	.	.	.	-0.0570	.	.	.	0.15066***	.	.
	.	*0.028*	.	.	.	*0.445*	.	.	.	*0.013*	.	.
Event [t=-1,+1]	.	.	-0.29662***	.	.	.	-0.12959**	.	.	.	0.13878***	.
	.	.	*0.000*	.	.	.	*0.038*	.	.	.	*0.007*	.
Event [t=-2,+1]	.	.	.	-0.24886***	.	.	.	-0.1011*	.	.	.	0.10533**
	.	.	.	*0.000*	.	.	.	*0.068*	.	.	.	*0.020*

Table 2.4 shows the impact of firm size, measured by market capitalization, on the estimated abnormal event interval returns of real and financial sector portfolios. Table 2.4, Panel A shows the estimated event abnormal returns for the size-tercile portfolios of non-financial firms. The event interval dummy coefficients are all negative and significant at the one percent level for the small capital portfolio, which implies that small real sector firms experience negative abnormal returns in response to financial crisis event announcements, even after controlling for the small-minus-big portfolio returns of Fama and French (1993). However, as implied by previous results, the estimates for the mid and large capital firm portfolios show that the estimated abnormal returns for portfolios of larger firms are less pronounced than those of the small capital portfolio. All event interval dummy coefficients are negative, and all but two are significant at the ten percent level or better; however, the negative abnormal portfolio returns of mid and large capital real sector firms are smaller in economic significance than those of the small capital portfolios; the small capital real sector portfolio abnormal returns are on the order of six times the magnitude of those of the larger portfolios. The results presented in Panels A of Table 2.4 expand on previous results and show that non-financial, real sector firms experience negative abnormal returns in response to financial crisis event announcements; however, the negative abnormal returns are more pronounced from smaller firms.

Panel B of Table 2.4 examines the impact of firm size on the estimated event interval abnormal returns of the equal-weighted financial firm portfolio. We sort financial firms into size-tercile portfolios based on market capitalization for each day and estimate event interval abnormal returns using the estimation methodology described in previous sections. The first four specifications in Panel B of Table 2.4 show the estimated abnormal returns for the portfolio of the smallest 33 percent of financial institutions sorted by market capitalization. Consistent with

the sample of real sector firms, we report negative event interval dummy variable coefficients, and all coefficients are significant at the five percent level or better. In addition, the estimated interval coefficients for the mid cap portfolio are all negative, and all except the [-1, 0] event interval are significant at the ten percent level or better.

In contrast to the results presented for the non-financial portfolios and the small and mid-capital portfolios of financial firms, Table 2.4 reports that the event interval dummy variable coefficients are all positive and significant at the ten percent level or better for the portfolio of large capital financial institutions. Positive and significant event interval dummy variable coefficients imply that larger financial institutions experienced positive abnormal returns associated with financial crisis event announcements.

The results reported in Table 2.4 shed interesting insights into how financial crisis and intervention news is incorporate into real and financial sector assets prices. As expected, portfolios of small and medium sized financial firms exhibit significant negative abnormal returns in response to financial crisis event announcements. However, the portfolio of large financial institutions does not report significant negative abnormal returns. In fact, Panel B of Table 2.4 reports that the portfolio of large financial institutions experience positive and significant event interval abnormal return, which imply larger than expected stock returns for large financial institutions in response to crisis events. Positive estimated abnormal returns for large financial institutions are interesting in the context of the recent 2008 financial crisis. One explanation for positive abnormal returns is the financial market's expectation that larger financial institutions are better able to withstand the increased risks associated with the financial crisis. However, even large financial institutions, such as Citigroup and AIG, were under considerable stress during the financial crisis, to the point where they required Federal

government assistance. Therefore, an alternative explanation for large financial firm positive abnormal financial crisis event returns is the markets expectation that the largest financial institutions would not be allowed to fail. So, while non-financial and smaller financial institutions are left to absorb the impact of the financial crisis, the expectation that large financial firms would receive government assistance resulted in positive abnormal crisis event returns for these firms.

Moreover, Table 2.4 shows that real sector firms of all sizes report significant negative abnormal returns in response to financial crisis event announcements. In addition, the magnitudes of the negative estimated abnormal event returns for the portfolio of smaller non-financial firms are larger than those estimated for financial firms. These results illustrate the significant negative spillover effect that financial crisis event announcement have on real sector stock returns, and the impact appears to be largest for small firms.

5.3 Finance sub-industry portfolio abnormal event interval returns

In this section, we conduct a further examination of the finance industry by analyzing the estimated abnormal event announcement returns for portfolios composed of firms in finance industry sub-sectors. The financial crisis continues to have a lasting impact on the financial services industry; in the aftermath of the financial crisis, regulators, policymakers, and the like seek to understand the cause of the financial crisis and design new policies with the goal of preventing future financial crises of a similar nature. The financial crisis was precipitated by the collapse of the housing market, and was exacerbated by failures to absorb the risks posed by certain financial products and institutions, such as mortgage backed security derivatives and default insurers such as AIG. Accordingly, some financial institutions and sub-industries were more directly involved with the financial crisis than others. In addition, regulations differ across

different types of financial firms. For example, depository institutions face capitalization requirements and restrictions on asset purchases, while non-depository institutions are allowed more self-regulation. Therefore, understanding how financial crisis events impact the stock returns of different types of financial institutions can help stakeholders develop a better understanding of financial sector risk.

We examine the event abnormal returns across finance subindustries by forming portfolios of firms in the same two-digit SIC classification. The sample of financial firms is divided into seven financial sector sub-industries: broker-dealer, depository, holding-investment, insurance brokers, insurance carriers, non-depository credit, and real estate. In addition, in light of previous results showing the impact of firm size on abnormal event returns, we also divide the sub-industry portfolios into size portfolios and report the results for small and large size sub-industry portfolios. Table 2.5 reports the event interval abnormal returns for the portfolios of financial firm sub-industries and allows for a more detailed examination of the cumulative impact of the financial crisis on the financial services industry. The reported regression coefficients for the event intervals show that the financial crisis announcements appear to have a different impact on different sub-sectors within the financial services industry, as well as different size firms within financial sub-industries.

Table 2.5: Financial sub-industry size portfolio event interval abnormal returns

OLS estimations of the abnormal returns for financial sub-industry portfolios for event day intervals surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event interval dummy variables estimate event day abnormal returns. Financial firms are defined by SIC codes between 6000 and 6999. Portfolios are divided into small, medium, and large size portfolios based on market capitalization. Financial firms are divided into sub-industries, based on SIC code: broker-dealer; depository; holding-investment; insurance brokers; insurance carriers; non-depository credit; and real estate. Pricing model factor coefficients are excluded for space.

Panel A: Broker-Dealer

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	-0.73624***	.	.	.	-0.0460	.	.	.
	0.005	.	.	.	*0.839*	.	.	.
Event [t=-1,0]	.	-0.38775**	.	.	.	-0.0275	.	.
	.	*0.043*	.	.	.	*0.866*	.	.
Event [t=-1,+1]	.	.	-0.27488*	.	.	.	0.0057	.
	.	.	*0.087*	.	.	.	*0.967*	.
Event [t=-2,+1]	.	.	.	-0.25483*	.	.	.	-0.0435
	.	.	.	*0.074*	.	.	.	*0.720*

Panel B: Depository

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	-0.36058*	.	.	.	0.4551**	.	.	.
	0.067	.	.	.	*0.034*	.	.	.
Event [t=-1,0]	.	-0.1925	.	.	.	0.65893***	.	.
	.	*0.176*	.	.	.	*0.000*	.	.
Event [t=-1,+1]	.	.	-0.35226***	.	.	.	0.65826***	.
	.	.	*0.003*	.	.	.	*0.000*	.
Event [t=-2,+1]	.	.	.	-0.32606***	.	.	.	0.63808***
	.	.	.	*0.002*	.	.	.	*0.000*

Panel C: Holding-Investment

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	-0.22486**	.	.	.	-0.0018	.	.	.
	0.050	.	.	.	*0.985*	.	.	.
Event [t=-1,0]	.	-0.15405*	.	.	.	-0.0306	.	.
	.	*0.063*	.	.	.	*0.641*	.	.

Event [t=-1,+1]	.	.	-0.25064***	.	.	.	-0.0518	.
	.	.	*0.000*	.	.	.	*0.346*	.
Event [t=-2,+1]	.	.	.	-0.21055***	.	.	.	-0.0704
	.	.	.	*0.001*	.	.	.	*0.150*

Panel D: Ins Brokers

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	0.3772	.	.	.	0.49316*	.	.	.
	0.555	.	.	.	*0.051*	.	.	.
Event [t=-1,0]	.	0.0117	.	.	.	0.1954	.	.
	.	*0.980*	.	.	.	*0.284*	.	.
Event [t=-1,+1]	.	.	-0.5746	.	.	.	0.2388	.
	.	.	*0.137*	.	.	.	*0.118*	.
Event [t=-2,+1]	.	.	.	-0.1338	.	.	.	0.1296
	.	.	.	*0.697*	.	.	.	*0.340*

Panel E: Insurance Carriers

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	-0.1209	.	.	.	0.36063*	.	.	.
	0.552	.	.	.	*0.073*	.	.	.
Event [t=-1,0]	.	0.1437	.	.	.	0.1616	.	.
	.	*0.327*	.	.	.	*0.266*	.	.
Event [t=-1,+1]	.	.	0.0202	.	.	.	0.1533	.
	.	.	*0.870*	.	.	.	*0.208*	.
Event [t=-2,+1]	.	.	.	-0.0721	.	.	.	0.0562
	.	.	.	*0.509*	.	.	.	*0.603*

Panel F: Non-dep Credit

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	-0.7068	.	.	.	-0.3068	.	.	.
	0.110	.	.	.	*0.303*	.	.	.
Event [t=-1,0]	.	-0.4235	.	.	.	-0.0490	.	.
	.	*0.185*	.	.	.	*0.820*	.	.
Event [t=-1,+1]	.	.	-0.4178	.	.	.	0.2181	.
	.	.	*0.118*	.	.	.	*0.227*	.

Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=-2,+1]	.	.	.	-0.2558	.	.	.	0.1394
	.	.	.	*0.282*	.	.	.	*0.384*

Panel G: Real Estate

	Small				Large			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Event [t=0]	-1.48093***	.	.	.	0.0884	.	.	.
	0.001	.	.	.	*0.691*	.	.	.
Event [t=-1,0]	.	-1.37828***	.	.	.	0.2061	.	.
	.	*0.000*	.	.	.	*0.200*	.	.
Event [t=-1,+1]	.	.	-0.56479**	.	.	.	-0.1196	.
	.	.	*0.044*	.	.	.	*0.375*	.
Event [t=-2,+1]	.	.	.	-0.3071	.	.	.	-0.1936
	.	.	.	*0.218*	.	.	.	*0.105*

Panels A, B, C, and G of Table 2.5 show that smaller financial firms across four of the financial sub-industries are negatively impacted by financial crisis event announcements. The event interval announcement coefficients for broker-dealer, depository, holding-investment, and real estate firms are all negative, and a majority of the event intervals are statistically significant at the ten percent level or better, implying that these types of financial firms drive the small financial portfolio negative returns reported in Table 2.4. On the other hand, the estimated abnormal return coefficients are not negative and significant for the portfolios of larger financial firms. In fact, consistent with previous results, the estimated abnormal return coefficients are positive and significant for large depository institutions, and the coefficients are significant at the five percent level or better. To a lesser extent, insurance brokers and insurance carriers exhibit some positive abnormal returns as well, as the event day abnormal return coefficients (t=0) are positive and significant at the ten percent level. No other event intervals exhibit statistically significant abnormal returns for financial two-digit SIC industry portfolios.

The results presented in Table 2.5 expand on our results reporting negative crisis event interval abnormal returns for small financial firms, but positive abnormal returns for large financial institutions. By estimating abnormal returns for different size portfolios consisting of firms in different financial sub-industries, we show that small broker-dealer, depository, holding-investment, and real estate firms all experience significant negative abnormal returns in response to financial crisis events announcements, which corresponds to the fact that weaknesses in the real estate and financial markets likely to negatively affect these firms are revealed during crisis event announcements. However, results also show that large depository institutions and, to a lesser extent, large insurance companies, exhibited positive event interval abnormal returns in response to financial crisis announcements. Positive abnormal portfolio returns for large

depository and insurance firms are consistent with expectations these firms are relatively less risky, given the fact that the Federal government is unlikely to let large financial intuitions fail. Indeed, large banks, such as Citigroup, and large insurance carriers, such as AIG, were given substantial assistance during the financial crisis.

6. Event Portfolio Abnormal Returns

As an extension of our analysis, we examine the event interval abnormal returns of a portfolio of firms directly associated with the announcement events identified in our study. To construct the portfolio of event firms, we identify all the firms associated with the event announcements defined in Table 2.1 by their stock ticker symbol during the sample period. We then construct equal and value weighted portfolios consisting of these firms, which include the following 17 firms: Freddie Mac, New Century Financial, Bear Stearns, Countrywide, Bank of America, J.P. Morgan Chase, IndyMac, Fannie Mae, Merrill Lynch, Lehman Brothers, American International Group (AIG), Goldman Sachs, Morgan Stanley, Washington Mutual, Ford, General Motors, and Chrysler.

Table 2.6 reports the estimated event interval abnormal returns for the equal weighted, size-tercile portfolios of the firms directly impacted by the identified financial crisis announcements. The results reporting the abnormal returns for the portfolio of event firms and the role that firm size in the magnitude and direction of reported abnormal returns are similar to those reported for the portfolio of financial firms in Table 2.4, which is not surprising, considering a majority of the event firms are in the financial sector.

Table 2.6: Event firm size portfolio event interval abnormal returns

OLS estimations of the abnormal returns for event-related firm portfolios for event intervals surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event interval dummy variables estimate event interval abnormal returns. Event related firms include Freddie Mac, New Century Financial, Bear Stearns, Countrywide, Bank of America, J.P. Morgan Chase, IndyMac, Fannie Mae, Merrill Lynch, Lehman Brothers, American International Group (AIG), Goldman Sachs, Morgan Stanley, Washington Mutual, Ford, General Motors, and Chrysler.

	Small Event Firms				*Medium Event Firms*				*Large Event Firms*			
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Intercept	-0.0374	-0.0060	-0.0456	-0.0438	-0.1389	-0.1232	-0.1271	-0.1471	0.0036	-0.0177	-0.0292	-0.0287
	0.903	*0.984*	*0.883*	*0.888*	*0.273*	*0.333*	*0.320*	*0.252*	*0.966*	*0.834*	*0.730*	*0.736*
RF	-4.7717	-5.8285	-4.8896	-4.8723	2.8889	2.5318	2.6257	3.0704	0.0517	0.5479	0.7975	0.7670
	0.832	*0.796*	*0.829*	*0.830*	*0.757*	*0.786*	*0.779*	*0.743*	*0.993*	*0.929*	*0.897*	*0.901*
MRP	0.92***	0.941***	0.948***	0.94***	1.526***	1.525***	1.525***	1.528***	1.137***	1.139***	1.139***	1.142***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	0.0493	0.0015	-0.0076	0.0037	-0.4935***	-0.4954***	-0.4964***	-0.4923***	-0.4269***	-0.4228***	-0.4168***	-0.4208***
	0.859	*0.996*	*0.978*	*0.989*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
HML	0.9149***	0.946***	0.9274***	0.942***	0.6325***	0.6356***	0.6336***	0.6307***	1.7361***	1.7311***	1.7325***	1.7279***
	0.006	*0.005*	*0.006*	*0.005*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
UMD	-1.2959***	-1.2627***	-1.2637***	-1.2646***	-0.7519***	-0.7507***	-0.7508***	-0.7527***	-0.5845***	-0.5872***	-0.5889***	-0.5885***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Event [t=0]	-5.54449***	.	.	.	0.0014	.	.	.	0.1940	.	.	.
	0.000	.	.	.	*0.998*	.	.	.	*0.616*	.	.	.
Event [t=-1,0]	.	-3.42978***	.	.	.	-0.3590	.	.	.	0.58233**	.	.
	.	*0.001*	.	.	.	*0.394*	.	.	.	*0.037*	.	.
Event [t=-1,+1]	.	.	-1.73843**	.	.	.	-0.1851	.	.	.	0.58334***	.
	.	.	*0.043*	.	.	.	*0.600*	.	.	.	*0.013*	.
Event [t=-2,+1]	.	.	.	-1.38115*	.	.	.	0.1026	.	.	.	0.44953**
	.	.	.	*0.070*	.	.	.	*0.743*	.	.	.	*0.030*

Table 2.6 reports negative and significant event interval coefficients over all estimation intervals for the portfolio of small event firms, implying that the smallest of the firms directly impacted by the event announcements experienced negative abnormal returns in response to those announcements. In addition, the magnitude of the estimates abnormal returns are larger than those reported by the portfolios of small financial and non-financial firms reported in Table 2.4. So, although our previous results indicate that real sector small cap firms experience lower abnormal event interval returns than financial sector firms, an extension of the analysis shows that the portfolio of the smallest event firms experience the largest negative abnormal returns in response to financial crisis event announcements.

However, in contrast the results pertaining to the small cap portfolio of event firms, and consistent with results presented for financial firms, Table 2.6 reports that the portfolio of the largest firms directly linked to the event announcements exhibit positive and significant event interval coefficients for the three longest event intervals, which implies that positive abnormal returns were achieved by large firms that were directly associated with the financial crisis event announcements.

The results presented in Table 2.6 present interest insights into the abnormal event interval returns seen by firms directly related to the financial crisis in the context of the recent financial crisis and the actions taken to curtail the crisis. Estimated negative event interval abnormal returns for smaller event-related firms, but positive abnormal returns for larger event-related firms are consistent with many of the event that took place during the financial crisis. For example, many of the larger financial institutions, such as AIG were given substantial help by

the Federal government in order to prevent their failure, and, consequently, we report positive abnormal returns for the portfolio of large event firms. On the other hand, relatively smaller firms, such as Lehman Brothers and New Century Financial were allowed to fail, and consequently, we report negative abnormal returns for the portfolio of small firms. In addition, as part of the negotiations between troubled firms and regulators in an attempt to end the financial crisis, agreements were reached for some larger firms to acquire the smaller and weaker firms. For example, Bank of America agreed to purchase Countrywide and Merrill Lynch, while Washington Mutual and Bear Stearns were purchased by JP Morgan Chase. The purchase arrangements signaled weaknesses in the firms being purchased and allowed to acquiring firms to purchase distressed assets at lower costs. Consequently, we report abnormal returns consistent with these activities, with larger firms achieving positive abnormal event interval announcements and smaller firm achieving negative returns.

7. Event Day Portfolio Abnormal Returns

In previous results, we show that real sector, financial, and event firms all exhibit statistically significant event interval abnormal returns in response to financial crisis event announcements. In addition, we provide evidence with respect to which types of firms exhibit abnormal returns in response to announcements pertaining to the financial crisis. As an extension of the analysis of event interval returns, we now examine the impact of particular events on the abnormal returns of real, financial, and event firm stock portfolios. In an empirical analysis we apply the asset pricing model of Fama and French (1993) and test for the presence of event day abnormal returns by estimating the coefficients of Equation 2 using the methodology described in Section 4. The resulting dummy variable coefficients representing each event day estimate the abnormal return of a given portfolio in response to a particular financial crisis event announcement. In section

7.1, we estimate event day abnormal returns for portfolios of real sector, financial, and event firms, as defined in previous analyses. Then, in Section 7.2 we extend the analysis to the two-digit SIC code financial sector sub-industries, in a fashion similar to that presented in Section 5.2. The resulting analyses provide more robust evidence regarding the pricing of financial risk into the returns of portfolios having different characteristics. In addition, this analysis sheds lights on the types of crisis and intervention events that result in returns that are not priced by standard asset pricing models.

7.1 Real sector, financial and event firm abnormal event day returns

Table 2.7 reports the estimated event day abnormal returns for each financial crisis event announcement for financial and non-financial portfolios. Similar to previous results, both real sector and financial sector firms exhibit significant event day abnormal returns in response to financial crisis announcements; however, not all events report statistically significant abnormal returns.

Table 2.7: Non-financial and financial firm portfolio event day abnormal returns

OLS estimations of the abnormal returns for non-financial and financial portfolios for event days surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event day dummy variables estimate event day abnormal returns. Financial firms are defined by SIC codes between 6000 and 6999. Portfolios are divided into small, medium, and large size portfolios based on market capitalization.

	Non-Financial Firms			*Financial Firms*		
	Small	Mid	Large	Small	Mid	Large
Variable	EWRET	EWRET	EWRET	EWRET	EWRET	EWRET
Intercept	0.23998***	0.03645*	0.04071**	0.05597**	0.0212	0.0000
	0.000	*0.052*	*0.014*	*0.031*	*0.339*	*0.999*
RF	-13.1587***	-0.4110	0.1185	-2.6392	-0.8542	0.4837
	0.000	*0.767*	*0.923*	*0.168*	*0.602*	*0.719*
MRP	0.502***	1.091***	1.077***	0.415***	0.699***	0.955***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	0.2599***	0.8928***	0.3319***	-0.0129	0.2596***	0.3383***
	0.000	*0.000*	*0.000*	*0.591*	*0.000*	*0.000*
HML	0.0321	-0.0006	-0.1239***	0.0175	0.1449***	0.4186***
	0.489	*0.979*	*0.000*	*0.540*	*0.000*	*0.000*
UMD	-0.1734***	-0.1034***	-0.0150	-0.1615***	-0.114***	-0.1293***
	0.000	*0.000*	*0.151*	*0.000*	*0.000*	*0.000*
Event 1	-1.55226**	-0.4362	0.1939	0.0303	0.2199	0.1723
	0.049	*0.217*	*0.533*	*0.950*	*0.598*	*0.614*
Event 2	0.0517	-0.0064	0.3142	0.0419	-0.1370	-0.1780
	0.948	*0.986*	*0.311*	*0.931*	*0.741*	*0.601*
Event 3	0.7296	0.5660	0.3495	0.4586	0.3407	0.2514
	0.353	*0.108*	*0.259*	*0.344*	*0.412*	*0.461*
Event 4	-3.80594***	-0.8999**	-1.24428***	-1.58052***	-0.5755	0.73954**
	0.000	*0.011*	*0.000*	*0.001*	*0.167*	*0.031*
Event 5	0.2864	-0.3028	0.0005	0.4756	0.0458	0.4208
	0.716	*0.390*	*0.999*	*0.327*	*0.912*	*0.217*
Event 6	-1.53724*	-0.2403	-0.66307**	-1.15547**	-0.5004	-0.6473*
	0.051	*0.495*	*0.033*	*0.018*	*0.229*	*0.058*
Event 7	-0.4843	0.58426*	0.0013	-0.1118	0.2843	0.2659
	0.539	*0.097*	*0.997*	*0.818*	*0.494*	*0.436*
Event 8	-2.29253***	-0.2368	-0.8718***	-0.80887*	-0.4676	-0.2966
	0.004	*0.502*	*0.005*	*0.096*	*0.261*	*0.385*
Event 9	-1.1101	-0.3571	-0.3021	-0.4168	-0.4032	0.3225
	0.161	*0.313*	*0.333*	*0.393*	*0.335*	*0.347*
Event 10	-2.7172***	-0.75879**	-0.51523*	-1.59418***	-1.71718***	-0.57872*
	0.001	*0.032*	*0.098*	*0.001*	*0.000*	*0.091*
Event 11	1.47378*	1.48068***	0.68545**	0.4510	0.6803	-0.1244
	0.063	*0.000*	*0.028*	*0.356*	*0.104*	*0.717*
Event 12	-0.9368	0.0902	-0.1651	0.1277	0.1886	-0.2941
	0.234	*0.798*	*0.595*	*0.793*	*0.650*	*0.389*
Event 13	-0.0500	-0.0397	0.0147	-0.0010	-0.6773	0.2993
	0.951	*0.913*	*0.963*	*0.998*	*0.113*	*0.393*
Event 14	0.0819	-0.2871	-0.4588	0.3578	0.5377	0.7694**
	0.917	*0.415*	*0.140*	*0.461*	*0.196*	*0.024*
Event 15	-0.3189	-1.43963***	-0.91106***	-1.70558***	-1.60862***	-0.5012
	0.686	*0.000*	*0.003*	*0.000*	*0.000*	*0.143*
Event 16	-1.1580	1.45441***	1.25958***	0.7250	0.1166	1.02871***
	0.147	*0.000*	*0.000*	*0.141*	*0.782*	*0.003*
Event 17	-2.27427***	-0.2865	0.0939	-0.4500	0.6618	0.86036**
	0.004	*0.416*	*0.762*	*0.354*	*0.111*	*0.012*

Table 2.7 reports negative and significant coefficients corresponding to Event 4, the downgrading of Countrywide's credit rating, for real sector firms of all sizes, as well as for small financial institutions. The coefficients for Event 6, which corresponds to the government backing of Bear Stearns, are also all negative and are significant at the ten percent level or better for the smallest and largest-sized real sector and financial firms. The coefficients for Event 8, which corresponds to the government takeover of Freddie Mac and Fannie Mae, are negative and are significant at the ten percent level for small and large real sector firms, as well as small financial institutions. Similarly, the coefficients for Event 10, corresponding to the announcement of the government bailout of AIG, are negative and significant at the ten percent level or better for both real sector and financial firms of all sizes. Finally, the coefficients for Event 15, which corresponds to requests from the big three U.S. automakers for government financial assistance, are negative and significant at the ten percent level or better for larger real sector firms and smaller financial institutions.

There are, however, some financial crisis event announcements that correspond to significant positive abnormal portfolio returns, particularly for larger firms. For example, the Event 4 coefficient, which corresponds with the downgrade of Countrywide's credit rating and is negative for real sector firms of all sizes, is positive and significant for the largest 33 percent of financial institutions. In addition, the coefficients for Event 11, which correspond to the announcements of Goldman Sachs and Morgan Stanley becoming bank holding companies, are positive and significant at the ten percent level or better for real sector firms of all sizes. However, the coefficients are not statistically different from zero for the sample of financial institutions. Finally, the coefficients for Event 16, which corresponds to the announcement of the

Federal government’s rescue of Citigroup, are positive and significant at the ten percent level or better for larger non-financial sector firms and financial institutions.

In Table 2.8, we report the estimates of abnormal event day returns for firms directly associated with the event announcements, as defined in section 6, and results are similar to those reported in previous tables.

Table 2.8: Event firm size portfolio event day abnormal returns

OLS estimations of the abnormal returns for non-financial and financial portfolios for event days surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event day dummy variables estimate event day abnormal returns. Portfolios are divided into small, medium, and large size portfolios based on market capitalization. Event related firms include Freddie Mac, New Century Financial, Bear Stearns, Countrywide, Bank of America, J.P. Morgan Chase, IndyMac, Fannie Mae, Merrill Lynch, Lehman Brothers, American International Group (AIG), Goldman Sachs, Morgan Stanley, Washington Mutual, Ford, General Motors, and Chrysler.

	Small	Mid	Large
Variable	EWRET	EWRET	EWRET
Intercept	-0.0137	-0.1280	0.0015
	0.962	*0.302*	*0.986*
RF	-6.9927	1.9670	0.3200
	0.743	*0.830*	*0.959*
MRP	0.941***	1.54***	1.141***
	0.000	*0.000*	*0.000*
SMB	0.0011	-0.4749***	-0.4279***
	0.997	*0.000*	*0.000*
HML	1.2718***	0.709***	1.7554***
	0.000	*0.000*	*0.000*
UMD	-1.2187***	-0.7***	-0.5532***
	0.000	*0.000*	*0.000*
Event 1	-0.4007	1.7203	-0.5336
	0.941	*0.461*	*0.734*
Event 2	-0.1964	-0.2282	-0.0787
	0.971	*0.922*	*0.960*
Event 3	-0.6341	-0.7424	0.1854
	0.907	*0.750*	*0.906*
Event 4	-3.6372	3.5264	0.8576
	0.503	*0.131*	*0.584*
Event 5	-4.6852	4.4674*	0.0287
	0.387	*0.055*	*0.985*
Event 6	-22.6147***	-4.2371*	-0.1089
	0.000	*0.069*	*0.945*
Event 7	-0.0419	-3.5164	0.1453
	0.994	*0.132*	*0.926*
Event 8	-50.1223***	-5.9181**	-1.8478
	0.000	*0.011*	*0.238*
Event 9	-27.8057***	-7.8376***	-3.1374**
	0.000	*0.001*	*0.046*
Event 10	-2.5615	-0.7816	-2.4171
	0.637	*0.738*	*0.123*
Event 11	26.3259***	11.088***	2.3680
	0.000	*0.000*	*0.132*
Event 12	-8.0546	-4.7157**	-0.9069
	0.137	*0.043*	*0.562*
Event 13	3.4811	1.7124	3.1758**
	0.532	*0.474*	*0.048*
Event 14	-5.2586	1.6564	-0.7841
	0.332	*0.477*	*0.616*
Event 15	7.8629	0.6789	-0.3530
	0.148	*0.771*	*0.822*
Event 16	-5.6252	5.2772**	7.3358***

	0.306	*0.026*	*0.000*
Event 17	0.5446	-1.9613	-0.5850
	0.920	*0.400*	*0.708*

Table 2.8 reports negative coefficients for Event 6 for all event firm size portfolios, and the coefficients are significant for small and mid-sized event firm portfolios, which corresponds to negative abnormal returns in response to the government's rescue of Bear Stearns. Similarly, the coefficients for Event 8, which corresponds to the takeover of Freddie Mac and Fannie Mae, are negative for all event firm size portfolios and are significant at the ten percent level for the small and medium sized event firm portfolios. In addition, the coefficients for event 9, which corresponds with the announcement of the Lehman Brothers bankruptcy, are negative and significant for all event firm size portfolios.

Similar to the portfolios of non-financial firms, the coefficients for Event 11, which correspond to the announcements of Goldman Sachs and Morgan Stanley becoming bank holding companies, are positive and significant at the ten percent level or better for small and mid-sized event firm portfolios. In addition, the coefficients for Event 16, which corresponds to the announcement of the Federal government's bailout of Citigroup, are positive and significant at the ten percent level or better for the middle and large sized portfolios of event firms.

In addition, consistent with previous result presented in Table 2.6, the magnitude of the estimated event portfolio event day abnormal returns are much larger than those estimated for the financial and non-financial portfolios in Table 2.7. Larger estimated event returns imply that financial crisis announcement have the largest impact on portfolio of firms that are directly associated the announcements.

7.2 Financial sector sub-industry event day abnormal returns

In this section, we extend our analysis of the impact of individual event announcements to further examination of the finance industry. We create portfolios of different types of financial firms in order to test whether the impact of the event announcements under study have a homogeneous effect across all financial firms. Accordingly, abnormal event day returns are estimated for the two-digit SIC industry portfolios.

Table 2.9: Finance sub-industry size portfolio abnormal event day returns

OLS estimations of the abnormal returns for non-financial and financial portfolios for event days surrounding important announcements during the financial crisis of 2007 and 2008. See Table 2.1 for event definitions. Daily CRSP returns are sampled from Jan. 1 2006 to Dec. 31, 2009. Dependent variables include the equal weighted daily portfolio returns. Abnormal returns are calculated using the factors of Fama and French (1993) and Carhart (1997). Event day dummy variables estimate event day abnormal returns. Financial firms are defined by SIC codes between 6000 and 6999. Portfolios are divided into small, medium, and large size portfolios based on market capitalization.

Panel A: Small financial sub-industry portfolios

Variable	Broker-Dealer EWRET	Depository EWRET	Holding-Investment EWRET	Ins Brokers EWRET	Ins Carriers EWRET	Non-dep Credit EWRET	Real Estate EWRET
Intercept	0.19883***	0.07902*	0.04453*	0.0635	0.12996***	0.1865*	0.33283***
	0.000	*0.063*	*0.067*	*0.647*	*0.003*	*0.051*	*0.001*
RF	-8.7128**	-5.2835*	-1.5059	1.7382	-5.9112*	-12.8234*	-18.4247**
	0.037	*0.092*	*0.401*	*0.865*	*0.067*	*0.070*	*0.013*
MRP	0.8242***	0.1371***	0.5302***	0.8478***	0.7733***	0.5117***	0.3802***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	0.4726***	-0.0278	-0.0220	0.8738***	0.6359***	0.2049**	0.1318
	0.000	*0.479*	*0.327*	*0.000*	*0.000*	*0.021*	*0.154*
HML	0.2392***	0.0805*	-0.0452*	-0.1073	0.3822***	0.3645***	0.3067***
	0.000	*0.086*	*0.093*	*0.484*	*0.000*	*0.001*	*0.006*
UMD	-0.1868***	-0.266***	-0.1089***	-0.3945***	-0.1772***	-0.3477***	-0.2563***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Event 1	-0.1017	0.0604	0.0506	1.1329	0.5059	0.4789	-0.9764
	0.924	*0.940*	*0.912*	*0.664*	*0.538*	*0.790*	*0.603*
Event 2	-0.3721	0.0634	0.0918	-0.0841	-0.1090	-0.3891	-0.7998
	0.725	*0.936*	*0.840*	*0.974*	*0.894*	*0.828*	*0.669*
Event 3	-0.0973	1.0434	0.2951	3.4885	0.2456	-0.5146	-0.7483
	0.927	*0.190*	*0.517*	*0.180*	*0.764*	*0.774*	*0.689*
Event 4	-0.1326	-1.2190	-1.61802***	2.3991	-0.3507	-2.3448	-4.7728**
	0.901	*0.127*	*0.000*	*0.358*	*0.669*	*0.192*	*0.011*
Event 5	0.4939	0.9017	0.2852	-5.7272**	1.0544	1.2578	-0.1987
	0.641	*0.257*	*0.531*	*0.028*	*0.198*	*0.483*	*0.915*
Event 6	-3.18844***	-1.2932	-0.86436*	2.3332	-1.55798*	-0.6597	-5.17869***
	0.003	*0.105*	*0.058*	*0.370*	*0.057*	*0.713*	*0.006*
Event 7	0.3239	-0.5071	0.0237	0.1552	-1.90553**	2.8226	0.6721
	0.760	*0.525*	*0.959*	*0.952*	*0.020*	*0.116*	*0.720*

Event 8	-1.3103	-1.4691	-0.3634	-2.7278	-1.0438	-3.3599*	-0.3451
	0.217	*0.066*	*0.425*	*0.295*	*0.203*	*0.061*	*0.854*
Event 9	-4.70964***	-1.0392	-0.2402	-1.0550	0.3469	-4.38285**	1.1494
	0.000	*0.195*	*0.600*	*0.687*	*0.674*	*0.015*	*0.541*
Event 10	-3.22967***	-0.7835	-1.69685***	-2.3615	-1.1790	-2.1349	-1.9453
	0.002	*0.327*	*0.000*	*0.366*	*0.152*	*0.235*	*0.300*
Event 11	2.99648***	-0.1492	0.5309	1.7633	2.35482***	-3.63818**	0.6669
	0.005	*0.852*	*0.247*	*0.501*	*0.004*	*0.044*	*0.723*
Event 12	0.0537	0.6518	-0.0111	-1.6722	0.0483	2.5678	0.1502
	0.960	*0.413*	*0.981*	*0.521*	*0.953*	*0.152*	*0.936*
Event 13	-1.8135*	1.879**	-0.3354	5.6661**	0.9410	1.7140	-1.1851
	0.096	*0.022*	*0.473*	*0.034*	*0.264*	*0.352*	*0.538*
Event 14	1.5500	1.1684	-0.0906	-1.6423	2.03689**	1.6248	-1.7472
	0.144	*0.143*	*0.842*	*0.528*	*0.013*	*0.365*	*0.351*
Event 15	-1.6295	-0.6990	-2.28391***	1.8073	-2.06039**	-3.22643*	2.5433
	0.126	*0.381*	*0.000*	*0.488*	*0.012*	*0.073*	*0.175*
Event 16	0.5956	-2.2078***	1.8676***	-2.3558	0.5002	1.5897	-7.7796***
	0.580	*0.006*	*0.000*	*0.372*	*0.547*	*0.382*	*0.000*
Event 17	-2.0267*	-2.3802***	0.5510	5.7595**	-1.7356**	-3.4326*	-4.5448**
	0.056	*0.003*	*0.226*	*0.027*	*0.034*	*0.056*	*0.015*

Table 2.9 (continued): Finance sub-industry size portfolio abnormal event day returns

Panel B: Large financial sub-industry portfolios

Variable	Broker-Dealer EWRET	Depository EWRET	Holding-Investment EWRET	Ins Brokers EWRET	Insurance Carriers EWRET	Non-dep Credit EWRET	Real Estate EWRET
Intercept	-0.0319	-0.0820	0.0219	-0.0176	0.0201	-0.0136	0.0032
	0.507	*0.076*	*0.256*	*0.748*	*0.646*	*0.830*	*0.947*
RF	3.8779	4.1214	-0.2136	0.6795	-1.7359	-2.2433	-0.0242
	0.276	*0.227*	*0.881*	*0.867*	*0.591*	*0.632*	*0.995*
MRP	1.3348***	1.0482***	0.8391***	0.8369***	1.026***	1.1165***	1.1918***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
SMB	0.3249***	0.7717***	0.1774***	0.24***	-0.1022***	0.4177***	0.6918***
	0.000	*0.000*	*0.000*	*0.000*	*0.012*	*0.000*	*0.000*
HML	0.3995***	0.9411***	0.1901***	0.4574***	0.6482***	0.7262***	0.3194***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
UMD	-0.2793***	-0.2686***	-0.0611***	-0.0967***	-0.1133***	-0.4938***	-0.2156***
	0.000	*0.000*	*0.000*	*0.006*	*0.000*	*0.000*	*0.000*
Event 1	0.2391	0.2937	-0.0492	0.5259	1.0064	0.6871	1.66636*
	0.792	*0.735*	*0.892*	*0.611*	*0.221*	*0.564*	*0.066*
Event 2	-0.0441	-0.9745	0.1689	-0.6231	-0.0857	-0.2318	-0.2328
	0.961	*0.260*	*0.640*	*0.545*	*0.917*	*0.845*	*0.797*
Event 3	-0.4070	-0.2605	0.5887	0.9534	-0.0147	-1.1406	0.4727
	0.652	*0.763*	*0.103*	*0.354*	*0.986*	*0.336*	*0.601*
Event 4	0.0781	3.65987***	-0.3809	-0.6905	0.5654	0.8646	-0.4983
	0.931	*0.000*	*0.293*	*0.504*	*0.492*	*0.468*	*0.583*
Event 5	0.6269	-0.6788	0.5899	-0.2135	0.0328	1.6460	-0.8087
	0.487	*0.433*	*0.103*	*0.836*	*0.968*	*0.166*	*0.371*
Event 6	-4.95733***	0.4362	-0.5006	0.7111	-0.5228	-1.7130	-0.1530
	0.000	*0.614*	*0.166*	*0.490*	*0.524*	*0.150*	*0.866*
Event 7	-0.8175	1.0905	0.2726	-0.1366	-0.1186	0.5036	-0.0386
	0.366	*0.208*	*0.451*	*0.895*	*0.885*	*0.672*	*0.966*
Event 8	-0.2459	0.8967	-0.3487	-0.9301	-0.0610	-8.3223***	-0.6329
	0.786	*0.301*	*0.335*	*0.367*	*0.941*	*0.000*	*0.485*
Event 9	2.18336**	1.60288*	-0.4242	0.3623	1.9377**	-0.3557	-1.4494
	0.016	*0.066*	*0.243*	*0.727*	*0.019*	*0.766*	*0.112*

Event 10	2.06976**	2.08733**	-1.64632***	0.7786	-0.2031	-1.3621	-0.5720
	0.022	*0.016*	*0.000*	*0.451*	*0.805*	*0.253*	*0.529*
Event 11	-1.78948**	-1.2534	0.1757	1.6674	-0.2713	3.07516*	-0.9709
	0.049	*0.150*	*0.629*	*0.108*	*0.742*	*0.010*	*0.286*
Event 12	-1.2003	-0.6827	0.0674	1.1919	-0.6319	-1.5597	0.2487
	0.184	*0.431*	*0.852*	*0.248*	*0.441*	*0.189*	*0.784*
Event 13	0.1217	0.0594	-0.1802	1.3735	1.8639**	1.7167	1.5074
	0.896	*0.947*	*0.627*	*0.195*	*0.027*	*0.160*	*0.105*
Event 14	1.2534	2.69068***	-0.0672	2.5875**	1.51994*	0.1135	-1.5896*
	0.166	*0.002*	*0.853*	*0.012*	*0.064*	*0.924*	*0.079*
Event 15	-0.7018	0.7860	-1.12586***	-1.1875	0.4730	-0.6060	0.4167
	0.438	*0.365*	*0.002*	*0.250*	*0.565*	*0.611*	*0.646*
Event 16	2.5234***	-1.2019	1.3727***	1.3003	-0.2692	1.6653	2.3114**
	0.006	*0.171*	*0.000*	*0.214*	*0.746*	*0.167*	*0.012*
Event 17	0.2983	-0.7939	1.4629***	0.7836	1.0863	0.0907	1.8525**
	0.741	*0.359*	*0.000*	*0.447*	*0.186*	*0.939*	*0.041*

Table 2.9 reports the estimation of the event day abnormal returns for important announcements surrounding the financial crisis of 2007 and 2008 across seven sub-industries of the financial services sector: broker-dealers, depository institutions, holding-investment firms, insurance brokers, insurance carriers, non-depository credit institutions, and real estate firms. Many news events during the financial crisis pertained to specific types of assets or involved specific companies in specific segments of the financial industry. An analysis of the impact of financial crisis news events on the abnormal returns of specific types of financial institutions allows us to analyze potential differences in stock price reactions across financial sub-industries.

Similar to previous findings, many of the identified financial crisis event announcements correspond with negative estimated abnormal financial portfolio stock returns, and smaller financial firms are particularly impacted. The coefficients for Event 4 are negative and significant for smaller holding-investment companies and real estate firms, which correspond to negative abnormal returns in response to the downgrade of Countrywide's credit rating. The Event 6 dummy variable corresponds with the government rescue of Bear Sterns and is similarly negative and significant for small broker-dealer, holding-investment companies, insurance carriers, and real estate firms. The Event 6 coefficient is also negative an significant for the portfolio of large broker-dealer firms. The estimated abnormal returns in response to the Lehman Brothers bankruptcy announcement, Event 9, are negative and significant for small broker-dealer, and non-depository credit institutions. The coefficient for Event 10, the government bailout of AIG, is negative and significant for small broker-dealer and holding-investment companies, as well as larger holding-investment companies. The Event 11 dummy variables, corresponding to the conversion of Goldman Sachs and Morgan Stanley into investment companies, report negative and significant coefficients for the portfolios of small non-depository

credit and large broker dealers firms. The coefficient for Event 13, the initial rejection of the government bailout package by Congress, is negative and significant for the portfolio of small broker dealer firms. The impact of the eventual passing the revised bailout package, measured by the coefficient for Event 14, is negative and significant for large real estate firms. The reported abnormal returns for Event 15, the request by the major U.S. auto manufacturers to access TARP funds, are negative and significant for small holding-investment, insurance carriers, and non-depository firms, as well as large holding-investment companies. The coefficients for Event 16, which correspond to the government rescue of Citigroup, are negative and significant for small depository and real estate firm portfolios. Finally, the coefficients corresponding to Event 17, Congressional approval for TARP loans to the major U.S. auto manufacturers, are negative and significant for all small financial institutions, except holding-investment companies.

In contrast, consistent with prior evidence, we also estimate positive estimated abnormal portfolio returns in response to some financial crisis event announcements for certain portfolios of financial institutions, and these positive abnormal returns are generally yielded by larger financial institutions. Specifically, the coefficient for Event 4, corresponding to the downgrading of Countrywide's credit rating, is positive and significant for large depository institutions. The Event 9 dummy variables, which correspond to the Lehman Brothers bankruptcy announcement, also report positive and significant coefficients for the large broker-dealer, depository institution, and insurance carrier portfolios. The estimated abnormal returns in response to the government rescue of AIG, the coefficients for Event 10, are positive and significant for the large broker-dealer and depository firm portfolios. The coefficients associated with Event 11, the conversion of Goldman Sachs and Morgan Stanley into holding companies, are positive and significant for small broker dealer and insurance carriers, as well as the large non-depository credit institution

portfolio. The coefficients for Event 13, which corresponds to the initial rejection of the TARP program, are positive and significant for small depository and insurance brokers, and large insurance carriers. The Event 14 dummy variable coefficients, indicating abnormal returns in response to the passing of the TARP program, are positive and significant for small insurance carriers as well as the large depository institution, insurance broker, and insurance carrier portfolios. The reported coefficients for Event 16, the government rescue of Citigroup, are positive and significant for small holding-investment firms, as well as the large brokerage, holding-investment and real estate firm portfolios. Finally, the coefficients corresponding to Event 17, the approval of the inclusion of the major automakers into the TARP program, are positive and significant for large holding-investment and real estate firm portfolios.

8. Conclusion

The financial crisis began to present in the financial markets in February of 2007 with an increase in defaults in subprime mortgages, and the financial crisis spread throughout the economy as important news came to light throughout 2007 and 2008. In response to the crisis, the Federal Reserve and other Federal agencies and policymakers began to implement policies aimed at curtailing the crisis. The Fed enacted typical monetary policy to slow the crisis, but soon had to resort to unconventional approaches. The Fed began to create new facilities, changed its lending rules, and even injected large amounts of capital into financial institutions to overcome the crisis. The Fed’s interventions were established to improve the entire financial system and the U.S. economy in general. The impact of the financial crisis and the effect that policymakers had on its severity and duration is an important issue, and we add to the empirical literature on the subject.

In this paper, we examine the impact of news announcements related to the financial crisis on the abnormal stock returns of real sector and financial firms. We identify 17 important financial crisis events from the *USA Today* article "A Repeat of 2008? Not Impossible" that conveyed important information about the evolution of the financial crisis. On the event days under study, the value-weighted CRSP market return averages -0.78 percent per day, while, on non-event days, the market return averages 0.03 percent. Therefore, we test for whether the negative event day returns are explained by asset pricing models, or represent unexplained, or abnormal returns.

The empirical results presented in this paper add to the literature on the impact of financial crisis news and intervention announcements on the short-term stock price reactions in the financial markets. We show that financial crisis news significantly impacts the abnormal stock returns of most firms; however, such announcements have the least impact on large financial institutions, which actually achieve positive abnormal event interval returns. Positive abnormal portfolio returns for large financial firms in response to crisis event announcements are consistent with market perceptions of relatively lower risks for large financial institutions, despite the fact that many of these institutions were severely distressed, in part, due to the implicit understanding that the government would not allow the largest and most important financial institutions to fail. In addition, the negative impact of financial crisis event announcements on the real sector portfolios, especially those of small firms, illustrates the significant spillover effects that financial crisis news has on the returns of real sector stock returns and the importance of understanding and preventing financial crises. Finally, some individual events, such as the conversion of Morgan Stanley and Goldman Sachs into holding companies and the government bailout of Citigroup are met with positive abnormal returns, as

large financial firms and policymakers attempted to dampen the crisis, indicating that regulatory and policy intervention can positively impact the targeted firms. Therefore, our results shed light on the stock price reactions to financial crisis news in the literature and provide insights to firm managers, investors, and policymakers.

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