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# Bank diversification and systemic risk★

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ABSTRACT

One of the controversies of diversification is that it may not be necessarily beneficial to the banks as it leads to more severe systemic risk. Recent studies have modelled theoretical frameworks for the role of diversification in systemic risks faced by banks. As an alternative, we provide empirical evidence on this by examining the effects of bank diversification on systemic risk. Based on the sources of revenue of banks to measure diversification and using data of U.S. commercial banks from 2000 to 2013, we find that the bank diversification is associated with an increase in systemic risk. However, such effect of diversification on systemic risk is significant in larger- and medium sized banks. The effects are also significant during the 2007–2009 credit crunch and 2010–2013 European Debt crisis, supporting the idea that bank diversification plays a crucial role to influence systemic risk.



## 1. Introduction

Diversification is beneficial for an individual bank since it can increase the bank's resilience to shocks. However, if all banks diversify they may end up holding similar portfolios. Hence, when the economy is hit by a strong shock, all banks may be affected and fail or have difficulties at the same time. Thus, an unintended consequence of diversity at the individual bank level can be an increase in systemic risk. While we have theoretical papers in the literature that analyze this issue, we do not have many empirical studies. Therefore, we empirically answer the research question of whether the contagion risks among banks (propagated from the financial system) are influenced by individual bank's level of diversification.

Risks the financial institutions used to undertake were generally viewed as exclusive to each financial institution but the policy reforms in the 1990s and asset diversification strategies that followed have changed the state of the banking business (Ibragimov, Jaffee, & Walden, 2011). Theoretically, diversification of assets by financial institutions can decrease the individual risk embedded in their portfolios of financial assets, further preventing banks asset value from dropping below liabilities and reducing probability of failure (Acharya, Hasan, & Saunders, 2006; Beck, Demirguc-Kunt, & Levine, 2006; Beger & Ofek, 1995; Campa & Kedia, 2002; Demsetz & Strahan, 1997; Nguyen, Skully, & Perera, 2012). Although these earlier studies find benefits from diversification, Stiroh and Rumble (2006) suggests that diversification benefits are offset by the costs of the increased exposure to new volatile activities. Moreover, Slijkerman, Schoenmaker, and de Vries (2013) also address that diversification may benefit individual institutions, but often increases the systemic risk.

Diversification is viewed as a popular business strategy for banking institutions but it increases the interbank overlaps in related business activities because of similar portfolios, leading to larger risk exposure caused from external contagion[1] . Ibragimov et al.

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[1] Please refer to Freixas, Parigi, and Rochet, (2000); De Young and Roland (2001); Goldstein and Pauzner (2004); Elsas et al. (2010); Lepetit et al. (2008); Uhde and Heimeshoff (2009); Viale, Kolari, and Fraser, (2009); Liao et al. (2015).

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(2011) indicate that interdependence among banks caused by asset diversification may not only lead to risk contagion but may also contribute to systemic risk, which played a crucial role in the recent 2007–2009 credit crisis (Drakos & Kouretas, 2015). In addition, De Jonghe (2010) and Slijkerman et al. (2013) note that banks are exposed to diversification across financial institutions at the start of the credit crisis. Wagner (2010) also suggests that diversification may not be desirable as it also entails a cost that makes systemic risks more likely and the systemic risks entail additional costs, over and above individual failures. Therefore, the level of diversification seems to have contrasting effects and causes banking risks.

Several research have developed theoretical models of systemic risk in which the magnitude of diversification plays a crucial role. Allen and Gale (2005); Allen and Carletti (2006) and Bégin, Boudreault, Doljanu, and Gauthier (2017) indicated that following the transfer of credit risk, another financial institution's failure can spillback when it has invested in the same assets as others. Wagner (2010) and Slijkerman et al. (2013) provide theoretical arguments that the diversification of risks at financial institutions can be undesirable because it makes systemic crises more likely. Also, Ibragimov et al. (2011) developed a model in which the negative externality from diversification with moderately heavy-tailed idiosyncratic risks that are optimal for individual financial intermediaries and suboptimal for the overall financial system. A simple two-period model from Allen, Babus, and Carletti (2012) and argues that commonality of assets and maturity of short-term debt of banks interact to generate excessive systemic risk through a contagion effect among financial institutions, thereby causing groups of banks holding common asset portfolios to default together, and when most of the financial institutions fail simultaneously, systemic risk is more likely to have emanated from common risks or a contagion process (De Jonghe, 2010; De Young, 2012; Helwege, 2010). These theoretical arguments motivate this study by suggesting that systemic risk is more likely to occur when banks adopt diversified assets to swap similar portfolios containing idiosyncratic risk common to assets held by other banks.

The cause of systemic risk might also due to illiquidity spillover. Wagner (2008, 2010) considers the relationship between bank heterogeneity and systemic risk from illiquidity spillover. Diversification indeed decreases banks' idiosyncratic risk, further re-optimizing their portfolios. However, diversification, at the same time, also induces banks to decrease their liquidity holdings and to redistribute their illiquidity into the financial sector as a whole. This, in turn, increases the likelihood of illiquidity and systemic risk (Wagner, 2008). Since diversification decreases individual banks' risk by holding liquid assets, and other banks hold a combination of illiquidity. Therefore, diversification has negative effects on systemic stability.

Although theoretical models exploring diversification and systemic risk are widely discussed, little empirical evidence of interest seems to have been provided. Lopez-Espinosa, Moreno, Rubia, and Valderrama (2012) explore the determinants to systemic risk but do not consider the effect of diversification on systemic risk. By exploring the drivers of tail-risk interdependence, this study offers empirical support to justify these theoretical models that diversification is burdened with higher systemic risk.

To investigate the effects of diversification on systemic risk of the whole financial system, we follow prior research to adopt a conditional value-at-risk (CoVaR) model to measure systemic risk.[2] Using a sample of 275 U.S. listed banks from 2000 to 2013 we find that bank diversification is significantly related to larger systemic risk. Moreover, if we include bank size as regressor in the model, both of the effects of diversification and size on the increase in systemic risk are also significant. However, it is not the case for the subsamples of banks of different sizes. The effects of diversification on systemic risk are significant in the subsample of larger- and medium-sized banks, whilst the effects are insignificant in the subsample of small-sized banks. Moreover, in 2002–2006 when there was no crisis, in 2007–2009 credit crunch, and in 2010–2013 European Debt Crisis, the effects of diversification on systemic risk were significant. We explain our results by arguing that systemic risks are more likely to be larger when many of the banks in the financial system are larger and more diversified simultaneously, thereby leading to more complex influences from the effects of size–diversification interactions. This argument is similar to that of Rajan (2009); Walter (2012); Freixas and Rochet (2013), and Liao, Sojli, and Tham (2015), who suggested that too-systemic-to-fail applies simultaneously to too-big-to-fail and too-interconnected-to-fail. We also include examination on the squared term of diversification in empirical analysis to check whether there is any nonlinear effects. Consistent with Das and Uppal (2004) and Wagner (2008, 2010), the diversification can reduce systemic risk in the beginning. However, over-diversification, in contrast, cause severe systemic risk.

This study contributes to the literature in the following ways. Firstly, among different criteria of risk measures, our study is the first to provide empirical evidence on the relation between bank diversification and systemic risk. Previous literature has explored the effect of diversification on bank risks with several firm-specific markets or accounting data based risk measures, such as proportion of risky assets and nonperforming loans, *Z*-score ratio, market beta, idiosyncratic risk and standard deviation of performances (Baele, De Jonghe, & Vander Vennet, 2007; Demsetz & Strahan, 1997; Esho, Kofman, & Shapre, 2005; Lepetit, Nys, Rous, & Tarazi, 2008; Manthos & Kouretas, 2011; Mnasri & Abaoub, 2010). However, the diversification effects are rarely linked to systemic risk. Although several recent studies have tried to model the theories on the role of diversification in systemic risk (Allen et al., 2012; Wagner, 2011), related empirical analyses are still unrealized. Therefore, this is the first study to bridge the theory-evidence gap between diversification and systemic risk.

Second, although current conclusive evidence on determinants influencing systemic risk refers to too-big-to fail, we contribute to literature by arguing that diversification is also critical to systemic risk as big banks are burdened with higher level of diversification. Tarashev, Borio, and Tsatsaronis (2009); De Jonghe (2010); Gauthier, Lehar, and Souissi (2013) and Pais and Stork (2013) and Laeven, Ratnovski, and Tong (2014) note that large banks tend to have significantly higher systemic risk. Moreover, Demsetz and Strahan (1997) find that larger-sized banks are more likely to have diversified banking business, but such diversification leads to more risky lending. Based on the line of literature, both of bank size and diversification are intricately intertwined to influence systemic risk. We further explore such debate by showing that, after considering bank size, the marginal effects of diversification on systemic risk are significant. However, such effects are pronounced only in larger-sized banks, suggesting that size and diversification play complementary roles to increase systemic risk. Therefore, this study helps clarify the debate on size-diversification complementary roles in literature by arguing that the effects of banking diversification on systemic risk occur only in larger-sized banks.

The remainder of the paper is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 introduces variable measures and regression models. Section 4 shows the results and discussions. Finally, Section 5 concludes.

[2] Please refer to Adrian and Brunnermeier (2011); Lopez-Espinosa et al. (2012); Brunnermeier et al. (2012); Castro and Ferrari (2014); Drakos and Kouretas (2015), and Billio, Casarin, Costola, and Pasqualini, (2016).

## 2. Theoretical ground and hypothesis

We argue that banks with greater level of diversification will hold common assets and similar exposures, causing interdependence among banks. Such banking interconnectedness, accompanied with risk-taking incentives from too-big-to-fail moral hazard, exacerbates risk contagion in financial sector, finally leading to higher systemic risk. In the following, the above mechanisms through which diversification influence systemic risk are introduced with lines of literature.

The first line of literature suggests that banks with higher level of diversification hold similar assets and common exposures. The policy reforms for banking diversification contribute to common exposure in financial sector. The 1999 Gramm–Leach–Bliley Act released U.S. banks from restrictions imposed by the Glass–Steagall Act, which prohibited them from engaging in nonbanking activities and they began pursuing broader diversification. Since 2000, banks are allowed to operate more nonbanking financial businesses, and financial institutions turned their main business lines from originate-and-hold to originate-and-distribute markets and diversified even more. Allenspach and Monnin (2008) finds an increasing trend in asset to debt ratio correlation, as a proxy of common exposure. Allenspach and Monnin suggest that, after 2000, banks generalized their business in response to changes in banking sector environment. Banks further increased their common exposure by diversifying their portfolio and thus have become increasingly similar. Therefore, diversification leads different institutions to hold similar and correlated portfolios which implies increasing similarities between exposure profiles of different banks.

The second line of literature suggests that similar assets and common exposure make the banks more interdependent. Diversification is accompanied by a higher amount of overlap in separate banking business. Allenspach and Monnin (2009) argue that diversified banks are exposed to the same risk factors, and banking sector as a whole becomes more homogeneous. As a result, banks' common exposure to shocks increase. In addition, Bluhm and Krahnen (2014); Billio, Getmansky, Lo, and Pelizzon (2012); Kleinow and Moreira (2016) also argue that banking diversification has an implicit mechanism of inter-bank independence. Giudici, Sarlin, and Spelta (2017) further suggest that increasing asset similarity and common exposures is more pronounced to amplify interconnectedness in financial systems. Therefore, from diversification to interconnectedness, we argue that if financial intermediaries hold similarly diversified portfolios, any potential financial distress can disrupt all institutions simultaneously.[3]

The third line of literature suggests that banking interdependence allow banks be more aggressive in transferring risk to each other. Interdependence caused by diversification is one of the main reasons to risk distribution and negative externalities among banks. Bank diversifying away individual risks can transfer risk to their interconnected linkage (Jorion & Zhang, 2009; Zhou, 2009). Wagner (2010) argues that diversification may leads to costs in terms of more negative interbank externalities. When banks adopt diversification to insure each other against liquidity problems, the diversification itself imposes negative externalities by distributing their different idiosyncratic risks among institutions and increases the likelihood of joint failure. Thus, if most banks are essentially holding the same diversified portfolios, a shock may disrupt all the institutions simultaneously (Ibragimov et al., 2011). After trading in this joint market, each bank receives risks propagated from negative externalities in the system. In addition, Mistrulli (2011) indicate that the effect of diversification on larger interbank financial markets is due to market interconnectedness, which leads to the propagation of risk contagion (Bluhm & Krahnen, 2014; Kleinow & Moreira, 2016; Liao et al., 2015). Boot (2011) and Walter (2012) also notes that diversification creates risk herding behavior and interconnectedness. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) show that negative contagion from the interconnectedness among banks exacerbate financial stability. Therefore, although diversification lowers the probability of failure, it exposes them to similar risks and this similarity raises the problem of interconnection, thereby generating a trade-off between diversification and risk contagion (Anand, 2011).

Moreover, such risk contagion from banking interdependence is the main cause to systemic risk and credit crisis. Ibragimov et al. (2011) and Allen, Babus, and Carletti (2010) consider a type of contagion where systemic risk arises from common asset exposures. Billio et al. (2012) note that the increasing interconnectedness among financial institutions can be taken as a significant systemic risk indicator. Thus, when looking at systemic risk, risk is propagated through the financial interdependence (Adrian & Shin, 2010; Bluhm & Krahnen, 2014; Cai, Saunders, & Steffen, 2011; Kleinow & Moreira, 2016). The mechanisms relating banking heterogeneity or common exposure to systemic risk is addressed by a small stream of studies, which treat the degree of diversification as bank heterogeneity (Butzbach, 2016; Wagner, 2007, 2008, 2010, 2011). In addition, diversification increases the risk of massive failure and further creates negative externalities in the form of systemic risk (Allen et al., 2012; Ibragimov et al., 2011; Shaffer & DiSalvo, 1994; Wagner, 2011). Therefore, externalities that arise from diversification are associated with systemic failures.

From another perspective to explain the systemic risk, moral hazard from government bailouts provides banks with incentives to use their interdependence for transferring their risks to others. Government bailouts induce moral hazard and further exacerbate banking independence. Banks may invest in diversified and correlated assets because they want to increase the likelihood of failing simultaneously in order to induce a regulator to bail them out (Acharya et al., 2006; Acharya & Yorulmazer, 2007). When faced with financial crises, government agencies are compelled to provide financial support, usually involving public resources. These support measures cause moral hazard and adversely impact market discipline (Dijkman, 2010; Hakenes & Schnabel, 2011). Since regulators provide bailout support to SIFIs in distress only if a significantly large part of the system is at risk, banks have more incentives to take a diversification strategy and to some degree maintain their interdependence within the entire banking system for ensuring rescue when a crisis occurs. Thus, banks have incentives to hold diversified portfolios to increase the financial system's dependence upon their health.

Overall, based on the three lines of literature, we bridge the relation between diversification and systemic risk by arguing that diversification cause common exposures, further leading to interdependence and risk contagion among banks. There are other research providing similar theoretical argument on the relation between diversification and systemic risk. When the banks form a joint mutual market portfolio through diversification, with each firm contributing its risky portfolio to the total and receiving back its proportional share of risks from the total (Billio et al., 2012; Bluhm & Krahnen, 2014; Huang, Zhou, & Zhu, 2012), they may succeed in eliminating the idiosyncratic risks embedded in their individual portfolios but the probability of risk to the entire financial system increases (Ibragimov et al., 2011). Moreover, Allenspach and Monnin (2008) provides a theoretical explanation to their findings of increasing asset to debt ratio correlation that diversification might be the reason to the positive relation between common

[3] These theoretical grounds on common exposures and asset similarities are to explain how diversification affects systemic risk. However, in our research, diversification is not proxy of common exposure. Instead, common exposure is to explain the diversification-risk relations, rather than the main determinants to systemic risk.

exposure and systemic risk. Overall, since banks hold diversified portfolios and become involved in similar business activities as other banks, risk caused by banks' common exposures lead to risk contagion among financial institutions (Claessens, Demirguc-Kunt, & Moshirian, 2009). The argument of Das and Uppal (2004) that systemic risk reduces the gains from diversification is similar to the perspectives of Wagner (2008, 2010) that diversification induces banks to decrease their liquidity holdings and to redistribute their illiquidity into the financial sector as a whole. Shaffer and DiSalvo (1994) and Wagner (2011) show that diversification is good for each bank individually but can lead to greater systemic risk as banks' business lines become more similar. The lines of literature suggests that banking diversification causes common exposure, resulting more risk contagion and interdependence, further leading to severe systemic risk. We therefore hypothesize that more diversified banks have higher systemic risk.

**Hypothesis 1.** *Banks with higher degree of diversification are burdened with higher systemic risk.*

## 3. Measurement and model

### 3.1. Risk measurement

We model systemic risk by using the CoVaR model with time-varying, distribution-free tail-risk-event and costless properties. First, we follow Adrian and Brunnermeier (2011) to estimate the unconditional VaR of the overall stock market and financial system by using quantile regressions. To control for potential influences from macroeconomic and market variability, we regress daily returns of the S&P 500 index ($R^{S\&P}$) and the iShares Dow Jones U.S. Financial Sector Index ($R^{FIN}$) by interest rate, exchange rate and volatility index, correspondingly:

$$R_t^i = \theta_t^i + X\Theta + \varepsilon_t^i, \tag{1}$$

where $i$ indicates S&P 500 index (S&P) or Dow Jones U.S. Financial Sector Index (FIN). **X** is a vector of market-level state variables, including the lagged Volatility Index (VIX) of the Chicago Board Options Exchange; the lagged liquidity spread measured by the difference between the 3-month US repo rate and the 3-month US T-bill yield (IR); and the lagged credit spread between the 10-year Moody's seasoned Baa corporate bond and the 10-year US Treasury bond (ER).

After acquiring the quantile regression estimates from Eq. (1), we fit the historical variables to have predicted values, which are taken as the market level VaR of the S&P 500 index and the Financial Services Index ($VaR^{S\&P}$ and $VaR^{FIN}$, respectively): $VaR_t^i(q) = \hat{\theta}_t^i + X\hat{\Theta}^{t-1} + \varepsilon_t^i$, where $i$ = S&P or FIN; $q$ = 1 %, 5 %, or 10 %. The VaR of a financial institution $VaR_t{}^i(q)$, typically a negative number, is determined by the returns of the institution $j$, the macroeconomic condition and the specified quantile $q$. Because conditional risk needs information on market risk in different stable and extreme cases, we estimate the market-level VaRs for $q$ = 1 %, 5 % or 50 % levels of critical value. For example, $VaR^{S\&P}$ indicate that the overall stock market proxied by S&P 500 index is under a critical level of risk whereas $VaR^{S\&P}(50\ \%)$ suggests that the market is under a medium level of risk. The same holds for the financial system risks given $VaR^{FIN}$ and $VaR^{FIN}(50\ \%)$.

Next, we calculate the bank's comovement VaR, which is the individual VaR when the financial market is under distress. We regress the stock returns of bank $j$ by the returns of the S&P 500 index ($R^{S\&P}$) and the Financial Services Index ($R^{FIN}$). We also include as controls IR, ER and VIX. However, a systemically distressed system is likely to have greater spillover effects on individual intermediaries. Therefore, the asymmetries based on the sign of bank returns play an important role in capturing the sensitivity of systemic risk to individual banks' returns. In this study, the systemic risk values focus on the downward market. Thus, the model is likely to yield parameter estimates that significantly underestimate the impact of a negative shock in the financial system on the bank. We therefore follow Lopez-Espinosa et al. (2012) to apply the asymmetric CoVaR model to address the asymmetric patterns that may underlie tail dependence:

$$\begin{aligned} R_t^{j|S\&P,FIN} &= \delta_0 + \delta_{j|S\&P}^{-} R_t^{S\&P} \mathrm{I}_{(R_t^{S\&P}<0)} + \delta_{j|S\&P}^{+} R_t^{S\&P} \mathrm{I}_{(R_t^{S\&P}\geq 0)} \\ &+ \delta_{j|FIN}^{-} R_t^{FIN} \mathrm{I}_{(R_t^{FIN}<0)} + \delta_{j|FIN}^{+} R_t^{FIN} \mathrm{I}_{(R_t^{FIN}\geq 0)} \\ &+ \delta_1 IR_{t-1} + \delta_2 ER_{t-1} + \delta_3 VIX_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

where $\mathrm{I}_{(.)}$ is set up as an indicator function that equals 1 if the condition in the subscript is true, and zero otherwise as the asymmetric sensitivity of an individual bank to the financial system is based on the sign of bank returns.

The coefficients of δ are usually taken as the evidence of risk contagion in extant literature. It can reflect the average response of the conditional distribution of returns of a bank to the distribution of the whole financial system's returns. However, the significance of non-zero values of this parameter is that they indicate the existence of risk spillovers, whilst the coefficient values indicate the level of sensitivity to financial system, rather than the quantity of systemic risk.

Using the estimates from Model 3, we use the predicted values of market level VaR of the S&P 500 index and the Financial Services Index ($VaR^{S\&P}$ and $VaR^{FIN}$, respectively) and the historical variables of IR, ER and VIX to fit the predicted value of individual CoVaR ($CoVaR_t{}^{j|S\&P,FIN}$):

$$\begin{aligned} CoVaR_t^{j|S\&P,FIN}(q) &= \hat{\delta}_0 + \hat{\delta}_{j|S\&P}^{-} VaR_t^{S\&P}(q) + \hat{\delta}_{j|FIN}^{-} VaR_t^{FIN}(q) \\ &+ \hat{\delta}_1 IR_{t-1} + \hat{\delta}_2 ER_{t-1} + \hat{\delta}_3 VIX_{t-1} \end{aligned} \tag{3}$$

$$\begin{aligned} CoVaR_t^{j|S\&P,FIN}(50\%) &= \hat{\delta}_0 + \hat{\delta}_{j|S\&P}^{+} VaR_t^{S\&P}(50\%) + \hat{\delta}_{j|FIN}^{+} VaR_t^{FIN}(50\%) \\ &+ \hat{\delta}_1 IR_{t-1} + \hat{\delta}_2 ER_{t-1} + \hat{\delta}_3 VIX_{t-1} \end{aligned} \tag{4}$$

The CoVaR defined here is the expected maximum loss of an individual bank for a given confidence level and time horizon, given the maximum expected loss of the whole financial system. We estimate the CoVaR values for different levels of critical values (q = 1 %, 5 %, or 50 %). For example, CoVaR indicate that the bank's individual VaR is conditional upon extreme cases of a financial system under distress and CoVaR(50 %) indicates individual VaR conditional upon an ordinary situation within the financial system.

To understand the additional risks the bank needs to consider, we take the difference between the risky CoVaR and the ordinary financial systems in which the market returns are at their median, CoVaR(50 %):

$$\begin{aligned} \Delta CoVaR_t^{j|S\&P,FIN} &= CoVaR_t^{j|S\&P,FIN}(q) - CoVaR_t^{j|S\&P,FIN}(50\%) \\ &= \left[\hat{\delta}_{j|S\&P}^{-} VaR_t^{S\&P}(q) - \hat{\delta}_{j|S\&P}^{+} VaR_t^{S\&P}(50\%)\right] \\ &+ \left[\hat{\delta}_{j|FIN}^{-} VaR_t^{FIN}(q) - \hat{\delta}_{j|FIN}^{+} VaR_t^{FIN}(50\%)\right] \end{aligned} \tag{5}$$

The definition of CoVaR denotes the VaR of institution $j$ conditional upon the financial market's performance. That is, for $\Delta CoVaR_t{}^{j|S\&P,FIN}$, the VaR of financial institution $j$ under distress is conditional not only on the extreme case of poor overall market performance (S&P 500 index) but also on the financial market itself (FIN). The systemic risk measurement suggests that if the difference ($\Delta CoVaR_t{}^{j|S\&P,FIN}$) is greater, the additional contagion risk propagated from the financial system is higher. It can also be taken as the amount of additional risk that the financial system inflicts upon a certain bank when other banks are in distress or reach their

VaR. Such systemic risk is conditional upon the markets being under distress and the individual banks' inability to diversify.

### 3.2. Regression model

Since banking diversifying strategy would be affected by different levels of diversification of other banks or banking system, we include year and bank fixed effect in panel-data regression estimation. In addition, decision on banking diversification should be endogenous (Campa & Kedia, 2002; Elsas, Hackethal, & Holzhauser, 2010). Wagner (2010) note that bank diversification is to maximize bank value. If shareholders make diversification choices which do not internalize its effects on depositors, equilibrium diversification may rise beyond the efficient level. we reduce potential endogenous problem of diversification by adopting instrumental variables.

Firstly, we follow Campa and Kedia (2002) and Leaven and Levine (2007) to select instrumental variables of diversification. The instruments are bank characteristics. Bank-specific characteristics influence the decision of banks to diversify. Campa and Kedia (2002) and Leaven and Levine (2007) suggest that banks with low profitability in their current operations may diversify in search of more development opportunities. To control for current and past profitability, the ratio of EBIT to Sales (EBIT) and its lagged values (EBIT(-1) and EBIT(-2) respectively) are also taken as instruments. We also control for firm size (SIZE) by including the log of total assets and its lagged values (SIZE(-1) and SIZE(-2) respectively).

However, other sets of instruments for diversification in Campa and Kedia (2002) are not included since industry factor is limited to financial institutions only, and the time variable is controlled as the fixed effects in regression model. In addition, capital expenditures as instrument used in Campa and Kedia (2002) is not suitable for banking sectors. Other regressors in the second stage estimation are also included. The first-stage regression is specified as following.

$$\begin{aligned}&Diversification_{i,t} = \alpha + \gamma_1 Diversification_{i,t-1}\\&+\gamma_2 EBIT_{i,t}+\gamma_3 EBIT_{i,t-1}+\gamma_4 EBIT_{i,t-2}\\&+\gamma_5 Asset_{i,t}+\gamma_6 Asset_{i,t-1}+\gamma_7 Asset_{i,t-2}\\&+\beta_1 LLRR_{i,t} + \beta_2 LAR_{i,t} + \beta_3 EAR_{i,t} + \beta_4 CIR_{i,t} + \beta_5 PMR_{i,t}\\&+\beta_6 LIQ_{i,t} + \beta_7 SDR_{i,t} + \beta_8 MA_{i,t} + \beta_9 EM_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{6}$$

$Diversification_{i,t}$ is the bank $i$'s asset, funding, or revenue diversification. Following Mercieca, Schaeck, and Wolf (2007) and Stiroh and Rumble (2006), and Elsas et al. (2010), $Diversification_{i,t}$ is measured by bank $i$'s asset, funding, and revenue diversification.

Asset diversification ('*Diversification*' in Model (7)) considers bank operating, such as interbank loans (IBLOAN), customer loans (CLOAN), government securities (GSEC), fixed income securities (FISEC) and other securities (OSEC), including shares, participation and other variable income securities. The asset diversification, ADIV, is calculated as the following.

$$\begin{aligned}ADIV_{i,t} = 1 - \Bigg[&\left(\frac{IBLOAN_{i,t}}{ER_{i,t}}\right)^2 + \left(\frac{CLOAN_{i,t}}{ER_{i,t}}\right)^2\\&+\left(\frac{GSEC_{i,t}}{ER_{i,t}}\right)^2 + \left(\frac{FISEC_{i,t}}{ER_{i,t}}\right)^2 + \left(\frac{OSEC_{i,t}}{ER_{i,t}}\right)^2\Bigg]\end{aligned} \tag{7}$$

Funding diversification considers bank funding from different equity and debt sources, including equity (EQUI), short-term interbank deposits (IBDEP), customer deposits (CDEP), short-term money market funds, such as certificates of deposit (CERDEP), and long-term capital market funding, such as subordinated debts (SDEBT). The funding diversification, FDIV, is calculated as the following.

$$\begin{aligned}FDIV_{i,t} = 1 - \Bigg[&\left(\frac{EQUI_{i,t}}{FUND_{i,t}}\right)^2 + \left(\frac{IBDEP_{i,t}}{FUND_{i,t}}\right)^2\\&+\left(\frac{CDEP_{i,t}}{FUND_{i,t}}\right)^2 + \left(\frac{CERDEP_{i,t}}{FUND_{i,t}}\right)^2 + \left(\frac{SDEBT_{i,t}}{FUND_{i,t}}\right)^2\Bigg]\end{aligned} \tag{8}$$

Revenue diversification considers different (non-)interest income origins, including net interest revenue (*NIR*), fees and commissions (*NFC*), net gains on trading (*NGT*), and other operations income (*OOI*). The revenue diversification, RDIV, is calculated as the following.

$$\begin{aligned}RDIV_{i,t} = 1 - \Bigg[&\left(\frac{NIR_{i,t}}{TOR_{i,t}}\right)^2 + \left(\frac{NFC_{i,t}}{TOR_{i,t}}\right)^2\\&+\left(\frac{OOI_{i,t}}{TOR_{i,t}}\right)^2 + \left(\frac{NGT_{i,t}}{TOR_{i,t}}\right)^2\Bigg]\end{aligned} \tag{9}$$

where *TOR* is the total operating revenue equaling the sum of *NIR*, *NFC*, *OOI* and *NGT*. In addition, we also include *DHHI*, the adjusted Herfindahl–Hirshman index, as another proxy of revenue diversification.

$$DHHI_{i,t} = 1 - \left[\left(\frac{NON_{i,t}}{TOR_{i,t}}\right)^2 + \left(\frac{NIR_{i,t}}{TOR_{i,t}}\right)^2\right] \tag{10}$$

where *NON* is the noninterest income and equal to the sum of *NFC*, *OOI* and *NGT* which have been found causing higher systemic risk contribution (Brunnermeier, Dong, & Palia, 2012).

The diversification proxies include different sources of income and measure the extent of revenue diversification. Staikouras, Mamatzakis, and Koutsomanoli-Filippaki (2008) use the diversification index to capture differences in structures of exposure of banks to external risks. Stiroh (2004) also classified financial activity diversification in various ways including revenue diversification, noninterest income diversification and loans diversification. For example, interest income is the conventional income from originate-and-hold financial business, whereas noninterest income captures the originate-and-distribute income streams from a broad array of financial services, ranging from underwriting and distributing securities, underwriting and distributing insurance policies, securitizing assets, selling mutual funds to providing payments and cash related services.

Control variables are selected based on the related literature to reduce potential exogenous influences from other company-level determinants of systemic risk.[4] LLPR is the ratio of loan loss provision to loans and is used to proxy the quality of bank credit portfolios; LAR is the ratio of total loans to total assets; and EAR is the ratio of total equity to total assets. Both LAR and EAR are both used to identify in part whether banks profit is from taking greater funding risks. CIR is the ratio of operating cost to operating income; PMR is the pretax margin ratio, measured by the proportion of profit before tax to operating income; LIQ is the ratio of cash

[4] Please refer to Gambacorta and Mistrulli (2004); Stiroh (2006); Baele et al. (2007); Lepetit et al. (2008); Hauner (2008); Uhde and Heimeshoff (2009); Buch, Eickmeier, and Prieto, (2010); Altunbas, Gambacorta, and Marques-Ibanez, (2010); Fiordelisi, Marques-Ibanez, and Molyneux, (2011); Delis, Tran, and Tsionas, (2012); Lopez-Espinosa et al. (2012).

and dues from banks to total customer deposits; SDR is the ratio of short-term borrowings to total assets.

In addition, the level of opaqueness of a bank is taken as control variable as it would cause variation in systemic risk. Thus, we take earnings management as proxy of bank's disclosure. Following Cornetta, McNutt, and Tehranian (2009), bank's earnings management of bank $i$ at year $t$ ($EM_{i,t}$) is measured by the difference between discretionary component of realized security gains and losses of bank $i$ at year $t$ ($DRSGL_{i,t}$) and discretionary component of loan loss provisions of bank $i$ at year $t$ ($DLLP_{i,t}$): $EM_{i,t}$ = $DRSGL_{i,t}$ - $DLLP_{i,t}$.

In accordance with the argument of Cornett et al. (2009), higher banking earnings management refers higher levels of discretionary realized-securities gains and underreporting discretionary loan-loss-provisions., and such discretionary components can bring higher income. However, in contrast, lower banking earnings management suggests fewer realized-security gains and over-reported-loan loss provisions, which decreases operating income.

The discretionary component of realized security gains and losses of bank $i$ at year $t$ ($DRSGL_{i,t}$) is measured by the error term from a model in which the realized security gains or and losses of bank $i$ at year $t$ is regressed and the coefficients are estimated by year fixed-effects OLS re*gression:* $RSGL_{i,t} = \alpha_t + \beta_1\ LASSET_{i,t} + \beta_2\ URSGL_{i,t} + \varepsilon_{i,t}$ where $RSGL_{i,t}$ is the ratio of sum of realized security gains and losses, available-for-sale securities, and held-to-maturity securities to total assets; $LASSET_{i,t}$ is the natural log of total assets; $URSGL_{i,t}$ is the ratio of sum of unrealized security gains and losses to total assets; $\varepsilon_{i,t}$ is the error term.

The discretionary component of loan loss provisions of bank $i$ at year $t$ ($DLLP_{i,t}$) is measured by transforming the error term: $DLLP_{i,t} = \varepsilon_{i,t} \times LOANS_{i,t} / ASSETS_{i,t}$. The error term is from a model in which the loan loss provisions of bank $i$ at year $t$ is regressed and the coefficients are estimated by time-region fixed-effects OLS regression: $LOSS_{i,t} = \alpha_{i,t} + \beta_1\ LASSET_{i,t} + \beta_2\ NPL_{i,t} + \beta_3\ LLR_{i,t} + \beta_4\ LOANR_{i,t} + \beta_5\ LOANC_{i,t} + \beta_6\ LOAND_{i,t} + \beta_7\ LOANA_{i,t} + \beta_8\ LOANI_{i,t} + \beta_9\ LOANF_{i,t} + \varepsilon_{i,t}$ where $LOSS_{i,t}$ is the ratio of loan loss provisions to total loans; r is the U.S. Department of Commerce defined region index; $LASSET_{i,t}$ is the natural log of total assets; $NPL_{i,t}$ is the ratio of nonperforming loans including loans past due 90 days or more, still accruing interest, and loans in nonaccrual status to total loans; $LLR_{i,t}$ is the ratio of loan loss allowance to total loans; $LOANR_{i,t}$ is the ratio of real estate loans to total loans; $LOANC_{i,t}$ is the ratio of commercial and industrial loans to total loans; $LOAND_{i,t}$ is the ratio of loans to depository institutions to total loans; $LOANDA_{i,t}$ is the ratio of agriculture loans to total loans; $LOANI_{i,t}$ is the ratio of consumer loans to total loans; $LOANF_{i,t}$ is the ratio of loans to foreign governments to total loans; $LOANS_{i,t}$ is the total loans; $ASSETS_{i,t}$ is the total assets.

Moreover, we follow Demerjian, Lev, and McVay (2012) to measure managerial ability of a bank as control variable as it would cause risk-taking behavior of a bank. We derive a measure of managerial ability (MA) as the residual from a Tobit regression model in which bank profit efficiency score is regressed by bank-specific explanatory variables and year fixed effects: $\pi\text{-}eff_{SFA,i,t} = \alpha + \beta_1\ BKSIZE_{i,t} + \beta_2\ NUMEMP_{i,t} + \beta_3\ AGE_{i,t} + \beta_4\ LEVRAG_{i,t} + \beta_5\ FCF_{i,t} + \Sigma^{T}_{t=1}\ \theta_t\ d_t + \varepsilon_{i,t}$ where BKSIZE is the log of gross total assets; NUMEMP is the log of the number of full-time equivalent employees (in thousands); AGE is the log of the age of the bank (in years), LEVRAG represents leverage, FCF is an indicator variable that takes the value one when cash flow for the year is positive and zero otherwise, and $d_t$ represents the year dummies. The MA captures all operating-efficiency effects that can be attributed to the managers' ability and not the bank characteristics.

The independent variable, $\pi\text{-eff}_{SFA,i,t}$, represents profit efficiency as computed by stochastic frontier analysis (SFA) which does not require the data to be observed without errors. Higher profit efficiency indicates well-operated bank can generate profits by using inputs and outputs relative to best practice. To parametrize the efficient frontier by utilizing information about how a bank use the resources (inputs and outputs) available to them, we estimate bank-level profit efficiency by employing Translog functional form with homogeneity in prices imposed.

Following Andreou, Philip, and Robejsek (2016), variables used in SFA are as following. Bank profit is proxied by the economic value added (EVA) which is defined as net operating profits after tax minus cost of capital, multiplied by capital invested. Inputs of a bank include labor, financial capital, and core deposits. Equity and fixed assets are fixed inputs. Outputs of a bank include consumer loans, business loans, real estate loans, loan for securities, and off-balance-sheet items. All parameters are estimated by maximum likelihood estimation, and are obtained through gradient-descent-based maximization of the log likelihood function. Larger profit efficiency score, $\pi\text{-eff}_{SFA,i,t}$, indicates that managers of a bank can adopt fewer inputs and make the bank to be more profitable.

Secondly, the results of the first-stage regression are used in the instrumental variable estimation[5] . In the second stage, we introduce fixed firm effects to control for unobservable bank characteristics and fixed year effects to control for effects which affect the diversification decision

$$\Delta CoVaR_{i,t} = \alpha + \gamma_1 Divers\widehat{ification}_{i,t}$$

$$+\beta_1 LLRR_{i,t} + \beta_2 LAR_{i,t} + \beta_3 EAR_{i,t} + \beta_4 CIR_{i,t} + \beta_5 PMR_{i,t}$$

$$+\beta_6 LIQ_{i,t} + \beta_7 SDR_{i,t} + \beta_8 MA_{i,t} + \beta_9 EM_{i,t} + \varepsilon_{i,t} \tag{11}$$

where $\Delta CoVaR$ is the systemic risk of bank $i$ at year $t$. The variable definitions are provided in Table 1.

Based on the previous discussion, we expect that a higher level of diversification leads to more severe systemic risk. As the value of *ADIV*, *FDIV*, *DIV*, or *DHHI* increases, the bank focuses more on non-traditional financial businesses, and diversified sources of income (Baele et al., 2007). These financial institutions become more similar to others and systemically more risky. Therefore, the parameters of $\gamma_1$ in Eq. (11) can be explained as the degree to which an increase of one percentage point in diversification leads to an increase in the systemic risk.

## 4. Empirical analyses

### 4.1. Data and discrepancy

Before 2000, banks specialized and thus reduced their common exposure to shocks. However, after 2000, banks appear to diversify in response to changes in the banking sector environment, having become increasingly similar and their common exposure has increased (Allenspach & Monnin, 2008). To explore the effects of bank diversification on systemic risks in financial institutions during the post-Gramm–Leach–Bliley periods and credit crunch, we employ data from U.S. listed commercial and investment banks for 2000–2013, during which the 2000–2001. com bubble, 2002–2006 growth in financial market, 2007–2009 credit crunch, and 2010–2013 European debt crisis are included.

The stock indices, repo and corporate bond yield data are from Thomson Reuters Datastream and Federal Reserve Board's Release; the firm-level variables of individual financial institutions are from CRSP, WorldScope and Bankscope database. After discarding data with incomplete variables of systemic risk and diversification, the data set covers 275 banks. However, due to

[5] The results on first-stage regression are provided in the Appendix.

**Table 1**
Variable Definition.

| Variable | Definition |
|---|---|
| ΔCoVaR | ΔCoVaR is a systemic risk measured by the conditional value-at-risk approach (CoVaR) with 5 % critical value (Adrian & Brunnermeier, 2011; Brunnermeier et al., 2012) |
| ADIV | ADIV is asset diversification, a proxy of diversification. |
| FDIV | FDIV is funding diversification, a proxy of diversification. |
| RDIV | RDIV is revenue diversification, a proxy of diversification. |
| DHHI | DHHI is Herfindahl-Hirschman Index, a proxy of diversification. |
| SIZE | Size is the natural log of total assets |
| AGE | Age is the number years since the financial institutions established |
| LLRR | Loan loss reserve ratio is the ratio of loan loss provision to loans |
| LAR | Loan to asset ratio is the ratio of total loans to total assets |
| EAR | Equity ratio is the ratio of total equity to total assets |
| CIR | Cost to income ratio is the ratio of operating cost to operating income |
| PMR | Profit margin ration is the ratio of profit before tax to operating income |
| LIQ | Liquidity ratio is the ratio of cash and due from banks to total customer deposit |
| SDR | Short-term debt ratio is the ratio of short-term borrowings to total assets |
| MA | Managerial ability measured by SFA-based alternative profit efficiency. |
| EM | Earnings management as a percent of total assets |

**Table 2**
Descriptive Summary and Correlation Coefficients.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Mean | | 0.36 | 0.55 | 0.38 | 0.34 | 0.67 | 0.62 | 0.10 | 0.67 | 0.23 | 0.05 | 0.07 | −0.07 | 0.87 | 6.55 | −1.50 |
| Median | | 0.36 | 0.55 | 0.38 | 0.35 | 0.31 | 0.66 | 0.09 | 0.65 | 0.29 | 0.03 | 0.04 | −0.07 | −2.05 | 6.33 | −1.51 |
| Maximum | | 0.76 | 0.72 | 0.75 | 0.50 | 10.29 | 0.94 | 0.94 | 3.85 | 1.26 | 9.41 | 0.78 | 208.5 | 116.0 | 9.51 | 0.07 |
| Minimum | | 0.00 | 0.00 | 0.00 | 0.00 | −2.05 | 0.00 | 0.00 | 0.00 | −3.84 | 0.00 | 0.00 | −20.70 | −22.16 | 4.33 | −4.56 |
| ADIV | (1) | 1.00 | | | | | | | | | | | | | | |
| FDIV | (2) | 0.07 | 1.00 | | | | | | | | | | | | | |
| RDIV | (3) | 0.12 | −0.10 | 1.00 | | | | | | | | | | | | |
| DHHI | (4) | 0.07 | 0.10 | 0.84 | 1.00 | | | | | | | | | | | |
| LLPR | (5) | 0.23 | 0.02 | 0.13 | 0.11 | 1.00 | | | | | | | | | | |
| LAR | (6) | 0.07 | 0.30 | −0.20 | 0.11 | 0.06 | 1.00 | | | | | | | | | |
| EAR | (7) | 0.02 | −0.31 | −0.12 | −0.27 | −0.09 | −0.26 | 1.00 | | | | | | | | |
| CIR | (8) | 0.22 | −0.07 | 0.15 | 0.06 | 0.25 | −0.10 | 0.07 | 1.00 | | | | | | | |
| PMR | (9) | −0.26 | 0.04 | −0.10 | −0.05 | −0.63 | −0.03 | 0.02 | −0.81 | 1.00 | | | | | | |
| LIQ | (10) | 0.01 | −0.01 | −0.03 | −0.03 | 0.01 | −0.03 | −0.02 | −0.01 | 0.00 | 1.00 | | | | | |
| SDR | (11) | −0.25 | −0.38 | 0.22 | 0.07 | −0.03 | −0.33 | −0.14 | −0.09 | 0.11 | 0.02 | 1.00 | | | | |
| MA | (12) | −0.04 | −0.01 | −0.03 | −0.02 | −0.06 | −0.04 | 0.02 | −0.16 | 0.20 | 0.01 | 0.03 | 1.00 | | | |
| EM | (13) | −0.12 | 0.05 | −0.06 | −0.02 | −0.09 | −0.30 | −0.07 | −0.13 | 0.13 | −0.02 | 0.06 | 0.04 | 1.00 | | |
| LTA | (14) | 0.04 | −0.06 | 0.44 | 0.29 | 0.14 | −0.33 | −0.14 | −0.13 | 0.04 | 0.03 | 0.39 | 0.01 | 0.01 | 1.00 | |
| ΔCoVaR | (15) | 0.01 | 0.10 | −0.25 | −0.16 | −0.20 | 0.14 | −0.05 | −0.01 | 0.09 | −0.02 | −0.19 | 0.02 | 0.12 | −0.49 | 1.00 |

the reasons that the diversification is lagged one-year as regressors and that some of the control variables are not complete, there are 2380 firm-year observations used in different regression settings. Compared to balanced-panel data with fewer observations, such unbalanced-panel data with more diversification-risk information would enhance estimation sufficiency. Table 2 provides the descriptive summaries and correlation coefficients. The minimum of diversification is 0 and the mean of diversification is 0.36 for ADIV, 0.55 for FDIV, 0.38 for RDIV, and 0.34 for DHHI. These variables are consistent with measure results in prior research.

Because we also look at the downside risk in distribution of changes in stock returns, the systemic risk of a financial sector is measured based on the probability of being under distress at a given confidence level. The critical value indicates that banks with systemic risk under the one-tailed 95 % confidence level will be sound and well-functioning when financial market is in distress.

We further examine whether the systemic risks are different in different time periods. We take the average of systemic risk for every year; Table 3 provides the trends of the changes in different criteria of risks. The results show that the marginal contribution of financial system's distress to the 5 % quantile of an individual bank's downside risk (*ΔCoVaR*) increases from−1.09 percent in 1998 to−1.59 percent in 2009, a year characterized by the credit crunch. On average across banks, systemic risk contributions are particularly higher during the credit crisis years of 2007–2009, relative to the pre-crisis periods from 2002 to 2006. This suggests that the measurements of systemic risk are verifiable and convincing, consistent with the notion that systemic risk was increasing during the 2007–2009 credit crisis.

The conventional view suggests that during the period of deregulation following the Gramm–Leach–Bliley Act, larger banks had higher systemic risks. Although the size of a financial institution should not be considered as a proxy of its systemic risk (Drehmann & Tarashev, 2011; Liu & Staum, 2010; Staum, 2010), prior study addresses bank size as a crucial role in systemic risk (Liao et al., 2015). Iragorri and Ferrari (2010) propose that size is strongly associated with systemically important risk. Lopez-Espinosa et al. (2012) further find evidence of the effect of size on systemic risk. Su and Wen (2018) find that larger sized individual banks have higher system risk, as they are hit and go down jointly in shocking events. Since research argues that SIFIs are large-sized banks and size contributes to systemic risk, we further explore the effects of the size of banks. Using median as the threshold for the subsample decomposition, we further decompose the risks by the two dimensions of size and diversification into four criteria: large size and greater diversification, large size and lower diversification, smaller size and greater diversification and smaller size and lower diversification. Table 4 shows the value of systemic risk measures for these different criteria.

The average of ΔCoVaR values for larger-sized and higher-diversified banks are −1.84 for ADIV, −1.81 for FDIV, −1.89 for RDIV, and −1.87 for DHHI respectively, whilst the value is smaller for

**Table 3**
Systemic Risk during the Sample Years.

| Year | ΔCoVaR |
|---|---|
| 1998 | −1.09 |
| 1999 | −1.22 |
| 2000 | −1.29 |
| 2001 | −1.36 |
| 2002 | −1.34 |
| 2003 | −1.41 |
| 2004 | −1.40 |
| 2005 | −1.43 |
| 2006 | −1.47 |
| 2007 | −1.51 |
| 2008 | −1.56 |
| 2009 | −1.59 |
| 2010 | −1.50 |
| 2011 | −1.48 |
| 2012 | −1.53 |
| 2013 | −1.51 |


smaller-sized or lower-diversified banks (−1.13 for ADIV, −1.10 for FDIV, −1.04 for RDIV, and −1.05 for DHHI respectively). The difference between values of systemic risk between samples of larger-sized and higher-diversified banks and smaller-sized and lower-diversified banks are particularly pronounced. This suggests that the systemic risk is higher not only in larger-sized banks, but also for the highly-diversified ones. Besides ADIV as diversification proxy, we find similar results when FDIV, RDIV, or DHHI is taken as the diversification proxy. Overall, using parametric *t*-test and non-parametric Wilcoxon signed rank test, the systemic risk in larger-sized banks (−1.82) and the one for smaller-sized banks (−1.10) are significantly different (t=−36.71; z = 29.97), suggesting that systemic risk is higher in banks with larger size.

When controlling the dimension of size, the systemic risks (ΔCoVaR) changes from −1.45 (−1.41, −1.27, and −1.31 respectively) to −1.47 (−1.51, −1.64, and −1.60 respectively) when the diversification increases. Most of the evidence from Table 4 indicates that both the size and the level of diversification play complementary roles to increase banks' systemic risk. Although Table a shows that the systemic risk is higher for larger-sized and higher-diversified banks, we adopt the regression models to further examine the hypothesis.

### 4.2. Regression results

Besides the OLS estimation, we use the fixed effects model with instrumental variables estimation to control for unobserved time variant firm-specific effects. We regress systemic risk (ΔCoVaR) by four proxies of diversification (ADIV, FDIV, RDIV, and DHHI respectively). The regression models specified in Eqs. (7) and (8) are found to have no significant multicollinearity problem after performing a variance inflation factor test. Table 5 provides the results of the effects of $\Delta CoVaR$. Using the OLS estimation, we find that coefficients of asset and funding diversification (ADIV and FDIV) are insignificantly positive (ADIV = 0.0735 and FDIV = -0.2770 for $\Delta CoVaR$). However, the effects of revenue diversification and Herfindahl-Hirschman index is significantly negative (RDIV= -1.0035 and DHHI = -1.0808). When using the panel data model with instrumental variables estimation, we find that effects of funding and revenue diversification and Herfindahl-Hirschman index is significantly negative (FDIV = -3.7602; RDIV= -1.3402; DHHI = -1.1123). The facts from Table 5 show that, funding and revenue diversification and Herfindahl-Hirschman index lead to more severe systemic risk, suggesting that asset diversification exacerbates systemic risks.

Too-big-to-fail is another important issue in the bank risk control during credit crunch years. For considering potential effect of bank size on systemic risk, we include bank size (SIZE) as regressor. Panel A, Table 6 shows that when examining the relation between bank size and systemic risk, the coefficient is significantly negative (SIZE= −0.1201; – 0.1105; −0.1108; – 0.1173 for ΔCoVaR). Thus, we suggest that larger-sized banks are faced with more severe systemic risks.

When taking both size and diversification as regressors, consistent with results in Table 5, the effect of ADIV is insignificant. Other proxies of diversification are significantly negative for ΔCoVaR (FDIV = -2.2655; RDIV = -0.0014; DHHI = -1.2962). The evidence

**Table 4**
Discrepancies for Diversification and Systemic Risk.

| | | ΔCoVaR | | | | |
|---|---|---|---|---|---|---|
| | | Size | | | Difference | |
| | | High | Low | All | mean | median |
| ADIV | High | −1.84 | −1.08 | −1.47 | −0.02 | −0.00 |
| | Low | −1.79 | −1.13 | −1.45 | (−1.03) | (0.76) |
| FDIV | High | −1.81 | −1.10 | −1.51 | −0.00 | 0.01* |
| | Low | −1.82 | −1.10 | −1.41 | (−0.11) | (1.81) |
| RDIV | High | −1.89 | −1.21 | −1.64 | −0.36*** | −0.34*** |
| | Low | −1.67 | −1.04 | −1.27 | (−18.60) | (17.43) |
| DHHI | High | −1.87 | −1.17 | −1.60 | −0.28*** | −0.22*** |
| | Low | −1.71 | −1.05 | −1.31 | (−13.96) | (13.06) |
| Average | | −1.82 | −1.10 | −1.46 | | |
| Difference | mean | −0.72***<br>(−36.71) | | | | |
| | median | −0.77***<br>(29.97) | | | | |

Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

**Table 5**
Diversification and Systemic Risk.

| | ΔCoVaR | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | OLS Estimation | | | | Panel Data with Instrumental Variables Estimation | | | |
| ADIV | 0.0735 | | | | −0.5947 | | | |
| | (1.32) | | | | (−1.92) | | | |
| FDIV | | −0.2770 | | | | −3.7602$^{***}$ | | |
| | | (−1.73) | | | | (−3.78) | | |
| RDIV | | | −1.0035$^{***}$ | | | | −1.3402$^{***}$ | |
| | | | (−12.16) | | | | (−3.59) | |
| DHHI | | | | −1.0808$^{***}$ | | | | −1.1123$^{**}$ |
| | | | | (−11.15) | | | | (−2.67) |
| LLPR | −0.1294$^{***}$ | −0.1264$^{***}$ | −0.0972$^{***}$ | −0.1049$^{***}$ | −0.2243$^{**}$ | −0.1662$^{*}$ | −0.1691 | −0.2098$^{*}$ |
| | (−8.74) | (−8.52) | (−6.58) | (−7.12) | (−2.67) | (−1.98) | (−1.95) | (−2.44) |
| LAR | 0.5532$^{***}$ | 0.5442$^{***}$ | 0.3694$^{***}$ | 0.5906$^{***}$ | 0.5791 | 0.5370 | 0.3618 | 0.6535 |
| | (7.78) | (7.55) | (5.15) | (8.34) | (1.56) | (1.47) | (0.97) | (1.76) |
| EAR | −0.5402$^{**}$ | −0.7690$^{***}$ | −1.0079$^{***}$ | −1.0983$^{***}$ | −1.5104 | −2.6177$^{**}$ | −1.3987 | −1.1812 |
| | (−3.22) | (−4.27) | (−6.00) | (−6.43) | (−1.78) | (−2.92) | (−1.70) | (−1.42) |
| CIR | 0.3750$^{***}$ | 0.3976$^{***}$ | 0.6224$^{***}$ | 0.5562$^{***}$ | 1.9629$^{**}$ | 2.4966$^{***}$ | 2.3731$^{***}$ | 1.9205$^{**}$ |
| | (3.54) | (3.73) | (5.85) | (5.25) | (2.98) | (3.74) | (3.60) | (2.98) |
| PMR | 0.1374 | 0.1428 | 0.2736$^{**}$ | 0.2453$^{**}$ | 0.9843 | 1.6581$^{**}$ | 1.2759$^{*}$ | 0.9929 |
| | (1.62) | (1.66) | (3.22) | (2.89) | (1.81) | (2.92) | (2.38) | (1.87) |
| LIQ | −0.0431 | −0.1122 | −0.1440$^{*}$ | −0.1338$^{*}$ | −0.1522 | −0.2685 | −0.3172 | −0.2957 |
| | (−0.69) | (−1.86) | (−2.43) | (−2.25) | (−0.48) | (−0.86) | (−1.01) | (−0.93) |
| SDR | −1.3087$^{***}$ | −1.5165$^{***}$ | −1.1906$^{***}$ | −1.3205$^{***}$ | −3.3126$^{***}$ | −3.5460$^{***}$ | −2.2885$^{**}$ | −2.7212$^{**}$ |
| | (−9.40) | (−10.12) | (−8.78) | (−9.78) | (−3.82) | (−4.23) | (−2.72) | (−3.25) |
| MA | −0.0003 | −0.0003 | −0.0002 | −0.0003 | 0.0033 | 0.0007 | 0.0033 | 0.0028 |
| | (−0.94) | (−0.80) | (−0.63) | (−0.74) | (1.10) | (0.23) | (1.10) | (0.94) |
| EM | 0.0066$^{***}$ | 0.0067$^{***}$ | 0.0057$^{***}$ | 0.0066$^{***}$ | 0.0061 | 0.0065 | 0.0059 | 0.0076$^{*}$ |
| | (9.72) | (9.89) | (8.42) | (9.94) | (1.74) | (1.94) | (1.74) | (2.25) |
| constant | −1.9286$^{***}$ | −1.7278$^{***}$ | −1.5879$^{***}$ | −1.6672$^{***}$ | −2.6862$^{***}$ | −1.2231 | −2.7260$^{***}$ | −2.6500$^{***}$ |
| | (−16.16) | (−11.68) | (−13.29) | (−14.01) | (−3.75) | (−1.49) | (−3.88) | (−3.72) |
| fixed | – | – | – | – | YES | YES | YES | YES |
| N | 2380 | 2380 | 2380 | 2380 | 2380 | 2380 | 2380 | 2380 |
| Adj $R^2$ | 0.120 | 0.123 | 0.154 | 0.149 | | | | |

Note: $^{***}$, $^{**}$, and $^{*}$ indicate significance at the 0.01, 0.05, and 0.1 levels, respectively. fixed indicates year*bank fixed effect.

indicates that diversification still play important roles in increasing systemic risk. We suggest that when considering potential influence of 'too-big-to-fail', i.e. bank size (SIZE), systemic risk increases when bank diversification, while asset diversification can help reduce such risk.

Elderly banks are also more likely to suffer from greater systemic risk. For clarifying whether younger banks diversify more to have more profitability and further leading to greater systemic risk, we include firm age (AGE), defined as number of years since the bank was established, as refressor. The results show insignificant results of bank age. We also decompose banks into different subsamples, including younger, medium, and elderly banks for robustness. The empirical findings show insignificant results on bank age, regardless of the results from full sample or subsample.

We further decompose our dataset into three subsamples based on different levels of bank size, including the largest-sized (High 30 %), the median-sized (Medium 40 %) and the smallest-sized (Low 30 %) banks. Regarding to the asset diversification, ADIV, Panel B, Table 6 show that its significant relations to systemic risk in full sample examination disappear in the small-sized banks. However, the effects of diversification on increasing systemic risk are significant only in larger- and medium-sized banks. The results also show that asset diversification still provide insignificant results.

Taking Tables 5 and 6 together, asset diversification provide inconclusive results, while the effects of funding and revenue diversification and Herfindahl-Hirschman index are consistent. The results on funding and revenue diversification and Herfindahl-Hirschman index (FIDV, RDIV, and DHHI) are consistent in Tables 5 and 6 that diversification is found to significantly increase systemic risk.

The effect of diversification might be nonlinear. Das and Uppal (2004) and Wagner (2008, 2010) argue that systemic risk reduces the gains from diversification as diversification indeed decreases banks' idiosyncratic risk and re-optimizing their portfolios. However, diversification, at the same time, also induces banks to decrease their liquidity holdings and to redistribute their illiquidity into the financial sector as a whole. Therefore, we also include examination on the squared term of diversification in empirical analysis to clarify whether over-diversification leads to different results. Using the full sample, we find the squared terms of FDIV, RDIV, and DHHI on systemic risk are significant. Consistent with Das and Uppal (2004) and Wagner (2008, 2010), the diversification can reduce systemic risk in the beginning. However, over-diversification, in contrast, cause severe systemic risk (Table 7).

When using subsample of different bank size, the significant effects of diversification on increasing systemic risk are similar. There are nonlinear effects that diversification can reduce systemic risk, and over-diversification leads to contrast effects. Such phenomenon is also supported only in subsample of larger- and medium-sized banks.

Since the empirical data used in this study is from 2000 to 2013 which covers varied levels of risk changes and different financial crises, the effects of diversification on systemic risk may be influenced by such time-series intervening factor. We therefore decompose our data into different subsample periods, and using the same subsample, the regression model is used to explore the same effects in different time periods, including 2002–2006 non-crisis years, 2007–2009 credit crunch, and 2010–2013 European debt crisis. Table A of Table 8 show the effect of diversification on systemic risk during 2000–2001. com bubble years. The results are insignificant. From 2002–2006, it is a period of prosperous growth in capital market. Panel A of Table 8 provides empirical results from the subsample of 2002–2006 non-crisis years. It shows that diversification brings more severe systemic risk.

**Table 6**
The Role of Bank Size and Age in Diversification–Systemic Risk Relation.

Panel A: Full Sample

| | ΔCoVaR | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ADIV | −0.1531 | | | | −0.5609 | | | |
| | (−0.51) | | | | (−1.79) | | | |
| FDIV | | −2.2655* | | | | −3.6926*** | | |
| | | (−2.32) | | | | (−3.68) | | |
| RDIV | | | −0.5035 | | | | −1.3151*** | |
| | | | (−1.31) | | | | (−3.46) | |
| DHHI | | | | −0.2393 | | | | −1.0718* |
| | | | | (−0.57) | | | | (−2.55) |
| SIZE | −0.1201*** | −0.1105*** | −0.1108*** | −0.1173*** | | | | |
| | (−6.23) | (−5.74) | (−5.44) | (−5.86) | | | | |
| AGE | | | | | −0.0005 | −0.0004 | −0.0002 | −0.0004 |
| | | | | | (−0.69) | (−0.54) | (−0.34) | (−0.61) |
| LLPR | −0.1565* | −0.1245 | −0.1466 | −0.1631* | −0.2248** | −0.1674* | −0.1707* | −0.2114* |
| | (−1.98) | (−1.56) | (−1.79) | (−2.02) | (−2.68) | (−1.99) | (−1.97) | (−2.46) |
| LAR | −0.0495 | −0.0385 | −0.0795 | −0.0115 | 0.5569 | 0.5195 | 0.3543 | 0.6301 |
| | (−0.14) | (−0.11) | (−0.22) | (−0.03) | (1.49) | (1.41) | (0.95) | (1.69) |
| EAR | −2.3635** | −3.0445*** | −2.2506** | −2.2317** | −1.5438 | −2.6306** | −1.4192 | −1.2256 |
| | (−2.94) | (−3.58) | (−2.83) | (−2.79) | (−1.82) | (−2.93) | (−1.71) | (−1.46) |
| CIR | 1.1826 | 1.6365* | 1.3553* | 1.1142 | 1.9702** | 2.4988*** | 2.3694*** | 1.9286** |
| | (1.88) | (2.53) | (2.08) | (1.80) | (2.99) | (3.74) | (3.59) | (2.99) |
| PMR | 0.8647 | 1.3062* | 0.9377 | 0.8091 | 1.0107 | 1.6685** | 1.2830* | 1.0150 |
| | (1.70) | (2.42) | (1.84) | (1.62) | (1.85) | (2.93) | (2.39) | (1.90) |
| LIQ | −0.2735 | −0.3248 | −0.3216 | −0.3016 | −0.1693 | −0.2787 | −0.3223 | −0.3054 |
| | (−0.92) | (−1.11) | (−1.08) | (−1.01) | (−0.53) | (−0.89) | (−1.02) | (−0.96) |
| SDR | −1.8321* | −2.2217** | −1.5922* | −1.7141* | −3.2952*** | −3.5402*** | −2.3034** | −2.7337** |
| | (−2.17) | (−2.69) | (−1.98) | (−2.14) | (−3.79) | (−4.21) | (−2.73) | (−3.26) |
| MA | 0.0025 | 0.0011 | 0.0027 | 0.0025 | 0.0032 | 0.0007 | 0.0033 | 0.0028 |
| | (0.91) | (0.39) | (0.95) | (0.87) | (1.08) | (0.23) | (1.08) | (0.92) |
| EM | 0.0066* | 0.0063* | 0.0064* | 0.0070* | 0.0063 | 0.0066* | 0.0060 | 0.0077* |
| | (2.00) | (1.99) | (2.00) | (2.22) | (1.79) | (1.96) | (1.76) | (2.27) |
| constant | −0.3742 | 0.3645 | −0.5120 | −0.3749 | −2.6554*** | −1.2222 | −2.7070*** | −2.6188*** |
| | (−0.49) | (0.44) | (−0.66) | (−0.49) | (−3.70) | (−1.49) | (−3.83) | (−3.66) |
| fixed | YES | YES | YES | YES | YES | YES | YES | YES |
| N | 2380 | 2380 | 2380 | 2380 | 2380 | 2380 | 2380 | 2380 |

Panel B: Subsample of Different Bank Size

| | ΔCoVaR | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High 30 % | | | | Medium 40 % | | | | Low 30 % | | | |
| ADIV | −0.6939 | | | | −0.2671 | | | | 0.1190 | | | |
| | (−1.55) | | | | (−0.76) | | | | (0.17) | | | |
| FDIV | | −0.1796* | | | | −5.2857 | | | | −0.9537 | | |
| | | (−2.04) | | | | (−1.44) | | | | (−0.54) | | |
| RDIV | | | −2.0981** | | | | −1.3573* | | | | 0.1498 | |
| | | | (−3.02) | | | | (−2.45) | | | | (0.19) | |
| DHHI | | | | −2.2754** | | | | −1.2342* | | | | 0.6013 |
| | | | | (−2.80) | | | | (−1.97) | | | | (0.69) |
| LLPR | −0.1835* | −0.1571 | −0.1589 | −1.7451 | 0.0070 | −0.0422 | 0.0918 | 0.0625 | −0.1312 | −0.1642 | −0.2591 | −0.2783 |
| | (−2.11) | (−1.68) | (−1.79) | (−0.92) | (0.04) | (−0.26) | (0.54) | (0.37) | (−0.70) | (−0.84) | (−1.12) | (−1.30) |
| LAR | 0.4460 | 0.4014 | 0.3807 | 0.5356 | −1.1865* | −1.2521* | −1.1823* | −1.1440* | −1.9968* | −2.0257* | −1.8489 | −1.8631 |
| | (1.13) | (1.01) | (0.97) | (1.32) | (−2.06) | (−2.18) | (−2.09) | (−2.01) | (−2.01) | (−2.04) | (−1.87) | (−1.89) |
| EAR | −0.9802 | −0.3317 | −2.0389 | −1.7184 | −3.6662 | −1.0900 | −4.3138* | −4.2551* | −1.5713 | −2.2760 | −1.7520 | −1.7973 |
| | (−0.44) | (−0.14) | (−0.89) | (−0.73) | (−1.77) | (−0.40) | (−2.11) | (−2.07) | (−1.24) | (−1.33) | (−1.43) | (−1.47) |
| CIR | 0.7438 | 0.8197 | 0.8794 | 0.5903 | 1.0557 | 0.7429 | 2.0183 | 1.7311 | 3.0322 | 3.0149 | 1.9929 | 1.9653 |
| | (0.97) | (0.97) | (1.10) | (0.77) | (1.02) | (0.76) | (1.86) | (1.61) | (1.93) | (1.93) | (1.32) | (1.40) |
| PMR | 0.7499 | 0.9854 | 0.9140 | 0.7639 | 0.7164 | 0.5151 | 1.3943 | 1.2037 | 2.3611 | 2.3204 | 1.3004 | 1.3842 |
| | (1.19) | (1.40) | (1.43) | (1.20) | (0.74) | (0.54) | (1.40) | (1.21) | (1.65) | (1.63) | (1.06) | (1.17) |
| LIQ | −0.1350 | −0.1746 | −0.2555 | −0.2460 | −1.5597 | −1.5796 | −1.3117 | −1.4433 | −2.0102* | −2.0950* | −1.8962 | −1.7973 |
| | (−0.44) | (−0.57) | (−0.83) | (−0.78) | (−1.28) | (−1.31) | (−1.10) | (−1.20) | (−1.97) | (−2.03) | (−1.84) | (−1.74) |
| SDR | −2.0666* | −1.8099* | −1.3668 | −1.5305 | −2.7879** | −2.9391** | −2.7165** | −2.7840** | −2.0823 | −2.1729 | −1.9141 | −1.9687 |
| | (−2.22) | (−1.96) | (−1.62) | (−1.80) | (−2.71) | (−2.88) | (−2.77) | (−2.81) | (−1.15) | (−1.20) | (−1.06) | (−1.09) |
| MA | 0.0001 | −0.0009 | −0.0002 | −0.0005 | 0.0109 | 0.0105 | 0.0090 | 0.0094 | −0.0041 | −0.0047 | −0.0010 | −0.0033 |
| | (0.04) | (−0.29) | (−0.05) | (−0.15) | (1.44) | (1.40) | (1.21) | (1.26) | (−0.40) | (−0.46) | (−0.09) | (−0.28) |
| EM | 0.0067 | 0.0061 | 0.0058 | 0.0070 | 0.0072 | 0.0075 | 0.0067 | 0.0071 | −0.0051 | −0.0066 | −0.0053 | −0.0051 |
| | (1.63) | (1.43) | (1.40) | (1.70) | (1.70) | (1.81) | (1.63) | (1.72) | (−0.62) | (−0.88) | (−0.71) | (−0.69) |
| cons. | −2.0727** | −1.5554 | −2.0944** | −2.1119** | −0.9235 | 2.0048 | −1.3612 | −1.2005 | −2.0032 | −1.2928 | −1.0857 | −1.1989 |
| | (−2.83) | (−1.56) | (−2.90) | (−2.88) | (−0.89) | (0.90) | (−1.31) | (−1.16) | (−1.10) | (−0.59) | (−0.62) | (−0.70) |
| fixed | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| N | 714 | 714 | 714 | 714 | 952 | 952 | 952 | 952 | 714 | 714 | 714 | 714 |

Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively. fixed indicates year*bank fixed effect.

**Table 7**
Nonlinear Effect in Diversification−Systemic Risk Relation.

Panel A: Full Sample

| | ΔCoVaR | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ADIV | −2.3797 | | | | 0.7140 | | | |
| | (−1.29) | | | | (0.40) | | | |
| ADIV$^2$ | 2.1917 | | | | −1.0889 | | | |
| | (0.98) | | | | (−0.50) | | | |
| FDIV | | 0.4737* | | | | 0.2506** | | |
| | | (2.13) | | | | (2.97) | | |
| FDIV$^2$ | | −4.0744** | | | | −1.0740*** | | |
| | | (−3.10) | | | | (−7.86) | | |
| RDIV | | | 0.1979* | | | | −0.7547 | |
| | | | (2.31) | | | | (−0.40) | |
| RDIV$^2$ | | | −7.7971*** | | | | −1.0223*** | |
| | | | (−8.04) | | | | (−6.10) | |
| DHHI | | | | 0.7632* | | | | 2.3504*** |
| | | | | (2.35) | | | | (5.40) |
| DHHI$^2$ | | | | −2.4469*** | | | | −5.6697*** |
| | | | | (−5.63) | | | | (−8.09) |
| SIZE | | | | | −0.1222*** | −0.1023*** | −0.1114*** | −0.1244*** |
| | | | | | (−6.14) | (−4.70) | (−5.41) | (−5.89) |
| LLPR | −0.2292** | −0.1744* | −0.1652 | −0.2071* | −0.1525 | −0.1284 | −0.1481 | −0.1717* |
| | (−2.71) | (−2.03) | (−1.91) | (−2.42) | (−1.92) | (−1.61) | (−1.79) | (−2.08) |
| LAR | 0.6077 | −0.5265 | 0.3359 | 0.6158 | −0.0768 | −0.2696 | −0.0735 | 0.0031 |
| | (1.62) | (−1.04) | (0.90) | (1.65) | (−0.21) | (−0.57) | (−0.20) | (0.01) |
| EAR | −1.7253* | 3.4037 | −1.3952 | −1.0918 | −2.2849** | −1.4979 | −2.2545** | −2.4521** |
| | (−1.97) | (1.58) | (−1.70) | (−1.30) | (−2.78) | (−0.67) | (−2.82) | (−2.92) |
| CIR | 2.0540** | 1.2657 | 2.3548*** | 1.9051** | 1.1351 | 1.4005 | 1.3476* | 1.0448 |
| | (3.08) | (1.60) | (3.58) | (2.98) | (1.77) | (1.92) | (2.06) | (1.65) |
| PMR | 1.0248 | 0.9101 | 1.2944* | 1.0087 | 0.8467 | 1.1556* | 0.9279 | 0.7501 |
| | (1.87) | (1.45) | (2.42) | (1.91) | (1.66) | (1.98) | (1.81) | (1.47) |
| LIQ | −0.1528 | −0.3040 | −0.2984 | −0.2502 | −0.2738 | −0.3314 | −0.3248 | −0.3561 |
| | (−0.48) | (−0.96) | (−0.95) | (−0.78) | (−0.92) | (−1.13) | (−1.09) | (−1.15) |
| SDR | −3.3492*** | −3.3608*** | −2.1736* | −2.5970** | −1.8093* | −2.2863** | −1.6205 | −1.8883* |
| | (−3.84) | (−3.91) | (−2.52) | (−3.02) | (−2.13) | (−2.77) | (−1.96) | (−2.26) |
| MA | 0.0031 | 0.0032 | 0.0032 | 0.0027 | 0.0026 | 0.0017 | 0.0027 | 0.0026 |
| | (1.03) | (1.01) | (1.06) | (0.89) | (0.94) | (0.57) | (0.95) | (0.90) |
| EM | 0.0053 | 0.0037 | 0.0058 | 0.0074* | 0.0069* | 0.0056 | 0.0064* | 0.0073* |
| | (1.48) | (1.05) | (1.71) | (2.20) | (2.04) | (1.69) | (2.00) | (2.26) |
| cons. | −2.4711** | −8.1477*** | −2.8990*** | −2.8981*** | −0.4341 | −1.4958 | −0.4598 | 0.1445 |
| | (−3.29) | (−3.41) | (−3.81) | (−3.56) | (−0.56) | (−0.57) | (−0.54) | (0.15) |
| fixed | YES | YES | YES | YES | YES | YES | YES | YES |
| N | | | | | | | | |

Panel B: Subsample of Different Bank Size

| | ΔCoVaR | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High 30 % | | | | Medium 40 % | | | | Low 30 % | | | |
| ADIV | −0.7996 | | | | −0.2283 | | | | −0.5279 | | | |
| | (−1.02) | | | | (−0.09) | | | | (−1.64) | | | |
| | 1.8630 | | | | 0.0346 | | | | 0.3629 | | | |
| | (0.57) | | | | (0.01) | | | | (1.73) | | | |
| FDIV | | 1.7775* | | | | 0.8977** | | | | 4.9061 | | |
| | | (2.33) | | | | (2.67) | | | | (0.92) | | |
| | | −4.8429*** | | | | −1.6035** | | | | −9.9717 | | |
| | | (−5.15) | | | | (−2.85) | | | | (−1.24) | | |
| RDIV | | | 1.5563* | | | | 2.5215** | | | | 0.9401 | |
| | | | (2.28) | | | | (2.75) | | | | (1.95) | |
| | | | −4.0719*** | | | | −6.4489*** | | | | −0.8689* | |
| | | | (−4.34) | | | | (−4.30) | | | | (−2.21) | |
| DHHI | | | | 1.8350*** | | | | 1.5650** | | | | 0.2153 |
| | | | | (3.39) | | | | (3.12) | | | | (1.62) |
| | | | | −1.2026*** | | | | −1.6234*** | | | | −2.2671* |
| | | | | (−3.59) | | | | (−5.69) | | | | (−2.33) |
| LLPR | −0.0873 | −0.0145 | −0.0656 | −0.0288 | −0.2168 | −0.4897** | −0.1690 | −0.2944 | −1.0262** | −0.7370* | −0.6737* | −0.7080* |
| | (−0.69) | (−0.11) | (−0.54) | (−0.22) | (−1.59) | (−3.07) | (−1.07) | (−1.95) | (−3.20) | (−2.38) | (−2.02) | (−2.09) |
| LAR | 0.1867 | 0.5162 | −0.0293 | 0.5436 | 0.5288 | −1.7630* | 0.4191 | 0.1915 | −0.4693 | −3.1865** | −1.1343 | −0.4528 |
| | (0.30) | (0.87) | (−0.05) | (0.92) | (0.88) | (−2.23) | (0.70) | (0.30) | (−0.43) | (−2.65) | (−1.14) | (−0.43) |
| EAR | −0.5412 | 2.8415 | −2.3073 | −1.3514 | −6.5222** | −2.2697 | −5.8779* | −5.2730* | −3.0916* | 5.6758 | −2.1314 | −0.9179 |
| | (−0.25) | (1.07) | (−1.07) | (−0.58) | (−2.58) | (−0.75) | (−2.33) | (−2.05) | (−1.99) | (1.33) | (−1.48) | (−0.55) |
| CIR | 2.2396* | 1.8419 | 2.3422* | 2.2637* | 1.2068 | −1.1979 | 1.4813 | 0.6109 | −2.1603 | −3.1940 | −0.4571 | −0.3656 |
| | (2.18) | (1.84) | (2.25) | (2.23) | (1.11) | (−0.91) | (1.20) | (0.52) | (−1.06) | (−1.64) | (−0.22) | (−0.17) |
| PMR | 0.6678 | 0.2080 | 0.9951 | 1.0900 | 1.0253 | −2.5244 | 1.3734 | 0.6635 | −3.6703* | −3.1422 | −2.0311 | −1.9552 |
| | (0.80) | (0.24) | (1.19) | (1.28) | (1.14) | (−1.71) | (1.40) | (0.70) | (−2.00) | (−1.80) | (−1.08) | (−1.01) |
| LIQ | −0.9394 | −1.2102 | −0.4342 | −0.6409 | −0.3443 | 0.0248 | −0.2852 | −0.2746 | −1.6703 | −2.8523* | −1.6776 | −0.5372 |

Table 7 (*Continued*)

Panel B: Subsample of Different Bank Size

| | ΔCoVaR | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | High 30 % | | | | Medium 40 % | | | | Low 30 % | | | |
| | (−0.51) | (−0.64) | (−0.25) | (−0.36) | (−0.95) | (0.07) | (−0.79) | (−0.77) | (−1.41) | (−2.41) | (−1.44) | (−0.40) |
| SDR | −4.4785** | −4.3569** | −1.7047 | −2.5949 | −2.8022* | −2.1543 | −2.1503 | −2.3830 | −4.4775* | −4.4293* | −2.9184 | −2.0930 |
| | (−2.92) | (−2.93) | (−1.21) | (−1.74) | (−2.18) | (−1.66) | (−1.67) | (−1.87) | (−2.05) | (−2.24) | (−1.33) | (−0.90) |
| MA | 0.0038 | 0.0227 | 0.0035 | 0.0006 | −0.0012 | 0.0572** | −0.0006 | −0.0019 | 0.0064 | 0.0071 | 0.0070 | 0.0022 |
| | (0.47) | (1.78) | (0.45) | (0.07) | (−0.28) | (2.92) | (−0.12) | (−0.39) | (0.67) | (0.79) | (0.75) | (0.23) |
| EM | 0.0079 | 0.0096 | 0.0061 | 0.0100 | 0.0054 | −0.0017 | 0.0050 | 0.0046 | 0.0002 | −0.0095 | −0.0003 | 0.0035 |
| | (1.36) | (1.73) | (1.12) | (1.83) | (1.10) | (−0.34) | (1.01) | (0.94) | (0.03) | (−1.16) | (−0.04) | (0.46) |
| cons. | −2.1060 | 2.0791 | −3.1589** | −3.7189** | −1.9069 | −1.3088*** | −3.1539* | −2.9238* | 3.4480 | −7.3600 | 0.9607 | −0.6744 |
| | (−1.75) | (0.55) | (−2.84) | (−2.59) | (−1.47) | (−3.33) | (−2.19) | (−2.12) | (1.47) | (−1.48) | (0.39) | (−0.23) |
| fixed | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| N | 714 | 714 | 714 | 714 | 952 | 952 | 952 | 952 | 714 | 714 | 714 | 714 |

(Panel A) Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively fixed indicates year*bank fixed effect.
(Panel B) Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively. fixed indicates year*bank fixed effect.

The 2007–2009 credit crunch year are characterized as the illiquidity caused by systemic risk, and one of the reasons of such phenomenon is due to banking diversification. The results from Panel B of Table 8 show that diversification cause more severe systemic risk. The credit crisis impact indicates how banks are simultaneously affected by the financial system and how banks face the risk propagated from the shock and its subsequent contagion (De Nicolo, Bartholomew, Zaman, & Zephirin, 2004). Allen et al. (2012); Ibragimov et al. (2011) and Wagner (2010) have proposed theoretical models of effects of banks' diversification on stability of the financial system and conclude that diversification in financial institutions decreases each individual bank's probability of failure but increases systemic risk. Namely, one specific event of a financial institution can trigger and subsequently become a systemic crisis due to common exposures to similar assets, suggesting that a downward event can affect many institutions with similar exposures and thus trigger a systemic crisis in the entire financial system (De Nicolo & Kwast, 2002; Hawkesby, Marsh, & Stevens, 2007). We posit that these results are consistent with the too-interconnected-to-fail argument that banks are under distress in credit crunch if they are closely linked in similar financial businesses as other banks Billio et al. (2012).

Consistent with Panel A of Table 8, Panel B also show that diversification can cause more severe systemic risk during the 2010–2013 European debt crisis periods. The 2010–2013 European debt crisis caused illiquid banks more problematic in post-credit-crisis years.

Overall, our empirical results show that bank diversification is significantly related to larger systemic risk. However, such effects of diversification on systemic risk are significant only in the subsample of larger- and medium-sized banks. When we include bank size as an regressor, both of the effects of diversification and size on the increase in systemic risk are significant. The results are also significant in 2002–2006 when there was no crisis, in 2007–2009 credit crunch, and in 2010–2013 European Debt Crisis.

Theoretical implications from our evidence suggest that, besides banking size of too-big-to-fail, diversification provides marginal effect to influence systemic risk. It is similar to the argument that individual banking diversification leads to decrease in systemic diversity, but simultaneously, an increase in systemic risk (Haldane, 2009; Michie, 2011). Theoretical papers of Wagner (2008, 2010) considers the relationship between bank heterogeneity and systemic risk from illiquidity spillover. Diversification indeed decreases banks' idiosyncratic risk, further re-optimizing their portfolios. However, diversification, at the same time, also induces banks to decrease their liquidity holdings and to redistribute their illiquidity into financial sector as a whole. This, in turn, increases the likelihood of illiquidity and systemic risk (Wagner, 2008). Thus, from the theoretical perspectives, the benefits of diversification are ambiguous since banks are 'too interconnected' or 'too diversified' under laissez-faire.

Practical implications from our exploration provide supports to the argument of too-interconnected-to-fail. Due to the trend of more complicated financial activities existing in the marketplace, financial business integration enhances diversification but exposes more entities to similar risks. Moreover, SIFIs usually have incentives to internalize the benefits of banking diversification and export its negative consequences to external sectors, and these negative externalities may spill over to the overall financial system. Since bank's privately optimal portfolio features diversification, over-diversification in individual financial sector results in systemic fragility, exposing each bank to runs on others (Ahnert & Nelson, 2012). Thus, any shock or crisis hitting one large institution can spread to those who are interconnected very quickly, and such increase in their interconnectedness enhance possibility of being bailed out when crises occur (Acharya & Yorulmazer, 2007; Acharya, Engle, & Richardson, 2012). We find that, besides bank size, diversification also cause greater systemic risk, and the effects diversification on systemic risk is significant only in larger– and medium–sized banks. Our analyses provide insightful explanation to the controversial arguments too-big-to-fail and too-interconnected-to-fail from the perspective of diversification.

Policy implications suggest that current reforms on macro-prudential regulation focus on liquidity and capital reserves, and diversification per se is not critically attached. From the practical perspectives, although the regulation reforms on systemic liquidity buffer uses prudential tools to limit systemic risk and might endogenously help reduce diversification, current studies on the diversification-risk relations do not support adequate evidence to help deal with making policies on diversification-related causes of systemic risk. Acharya and Yorulmazer (2007) shows diversification inducing banks to herd ex-ante to increase the likelihood of being bailed out. Thus, banks herd by mimicking each other's diversification strategies, further leading to high degree of asset correlation, which constitutes systemic risk. The adequacy of macro-prudential regulation reveal the key role of policy instruments in shaping policy outcomes (Blundell-Wignall & Roulet, 2014; Howlett & Lejano, 2013). Given the fact that the degree of diversification is associated with other different banking business models and bank characteristics (Ahnert, 2016), we argue that diversification is another suitable starting point for macro-prudential regulation looking beyond prudential risk regulation at just liquidity and capital reserves in single financial institution.

**Table 8**
Diversification-Systemic Risk Relation in Different Periods.

Panel A: Subsample of 2000 to 2006

| | ΔCoVaR | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2000–01 Tech Bubble | | | | 2002–06 Non−Crisis Years | | | |
| ADIV | 0.3235 | | | | −0.2375 | | | |
| | (0.52) | | | | (−0.54) | | | |
| FDIV | | −0.5584 | | | | −2.4367 | | |
| | | (−0.31) | | | | (−1.34) | | |
| RDIV | | | −0.7204 | | | | −1.9635*** | |
| | | | (−1.46) | | | | (−4.25) | |
| DHHI | | | | −0.4531 | | | | −2.1907*** |
| | | | | (−0.79) | | | | (−3.92) |
| LLPR | −0.1465 | −0.1201 | 0.1673 | 0.1624 | −0.1602 | −0.1565 | −0.1769 | −0.2039 |
| | (−0.38) | (−0.32) | (0.45) | (0.43) | (−1.19) | (−1.17) | (−1.38) | (−1.57) |
| LAR | 0.3097 | 0.2297 | 0.2236 | 0.5193 | −0.3508 | −0.3017 | −0.6360 | −0.3822 |
| | (0.45) | (0.32) | (0.34) | (0.78) | (−0.55) | (−0.48) | (−1.05) | (−0.63) |
| EAR | −0.0116 | 0.4583 | −3.0565 | −2.9367 | 0.9099 | 3.0586 | −0.6018 | −0.3826 |
| | (−0.00) | (0.08) | (−0.72) | (−0.69) | (0.45) | (1.25) | (−0.31) | (−0.20) |
| CIR | 2.9930 | 3.2976 | 4.8526 | 4.9200 | 1.0002 | 0.9533 | 0.6329 | 0.6333 |
| | (0.89) | (1.01) | (1.54) | (1.55) | (0.72) | (0.70) | (0.48) | (0.48) |
| PMR | 2.1725 | 2.3415 | 3.2977 | 3.5885 | −0.3337 | −0.4168 | −0.7490 | −0.7715 |
| | (0.64) | (0.69) | (1.04) | (1.12) | (−0.28) | (−0.35) | (−0.65) | (−0.66) |
| LIQ | −1.7850 | −1.3773 | 1.9674 | 1.2766 | −1.2117 | −0.7157 | −0.2458 | −1.3376 |
| | (−0.50) | (−0.40) | (0.56) | (0.36) | (−0.52) | (−0.30) | (−0.11) | (−0.60) |
| SDR | −2.4755* | −2.6505* | −1.6479 | −2.0537* | −3.7747*** | −4.0845*** | −3.0695*** | −3.2251*** |
| | (−2.36) | (−2.45) | (−1.58) | (−2.01) | (−4.26) | (−4.48) | (−3.57) | (−3.74) |
| MA | 0.0004 | −0.0005 | 0.0092 | 0.0044 | 0.0102 | 0.0128 | 0.0142 | 0.0142 |
| | (0.03) | (−0.03) | (0.59) | (0.29) | (0.94) | (1.17) | (1.37) | (1.36) |
| EM | 0.0129* | 0.0115* | 0.0090 | 0.0104* | 0.0070 | 0.0073 | 0.0038 | 0.0051 |
| | (2.51) | (2.37) | (1.94) | (2.25) | (1.41) | (1.53) | (0.82) | (1.10) |
| cons. | −4.0834 | −3.9233 | −4.7892 | −5.0477 | −1.4052 | −0.3042 | −0.0953 | −0.2084 |
| | (−1.23) | (−1.09) | (−1.52) | (−1.58) | (−0.99) | (−0.19) | (−0.07) | (−0.15) |
| fixed | YES | YES | YES | YES | YES | YES | YES | YES |
| N | 210 | 210 | 210 | 210 | 724 | 724 | 724 | 724 |

Panel B: Subsample of 2007 to 2013

| | ΔCoVaR | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2007–2009 Credit Crunch | | | | 2010–2013 European Debt Crisis | | | |
| ADIV | −0.2236 | | | | 0.0680 | | | |
| | (−0.51) | | | | (0.20) | | | |
| FDIV | | −6.0641*** | | | | −4.4181*** | | |
| | | (−3.79) | | | | (−4.30) | | |
| RDIV | | | −1.2667** | | | | −1.7582*** | |
| | | | (−2.93) | | | | (−4.99) | |
| DHHI | | | | −1.2071* | | | | −1.6234*** |
| | | | | (−2.29) | | | | (−3.95) |
| LLPR | −0.1724** | −0.0960 | −0.1423* | −0.1444* | −0.1494* | −0.1296* | −0.0939 | −0.1163 |
| | (−2.94) | (−1.66) | (−2.55) | (−2.54) | (−2.25) | (−2.01) | (−1.43) | (−1.75) |
| LAR | 0.2173 | 0.2394 | −0.4054 | 0.0382 | 0.8516* | 0.7119* | 0.3825 | 0.7797* |
| | (0.44) | (0.52) | (−0.77) | (0.08) | (2.41) | (2.08) | (1.09) | (2.26) |
| EAR | −4.8130** | −1.9185 | −5.2866*** | −5.0395** | −0.6472 | −2.4818** | −0.8638 | −0.5820 |
| | (−2.99) | (−1.12) | (−3.35) | (−3.18) | (−0.77) | (−2.78) | (−1.10) | (−0.73) |
| CIR | 1.0527* | 1.3689** | 1.1970* | 1.2680* | 0.7336 | 1.1101* | 1.2891** | 0.9708* |
| | (2.13) | (2.86) | (2.48) | (2.57) | (1.50) | (2.34) | (2.71) | (2.04) |
| PMR | 0.8740* | 1.6435*** | 0.9020* | 0.9771** | 0.2477 | 0.7050 | 0.5546 | 0.3589 |
| | (2.28) | (3.90) | (2.43) | (2.59) | (0.67) | (1.89) | (1.54) | (0.99) |
| LIQ | −0.4107 | −0.3720 | −1.1326 | −0.9077 | −0.0329 | −0.1671 | −0.2919 | −0.2466 |
| | (−0.53) | (−0.51) | (−1.43) | (−1.15) | (−0.11) | (−0.56) | (−0.97) | (−0.81) |
| SDR | −1.6366 | −3.0609** | −1.6429 | −1.6984 | −1.9107 | −1.8323 | −2.1250 | −2.7504* |
| | (−1.55) | (−2.98) | (−1.73) | (−1.77) | (−1.51) | (−1.50) | (−1.75) | (−2.20) |
| MA | 0.0063 | −0.0019 | 0.0079 | 0.0070 | −0.0006 | −0.0004 | −0.0004 | −0.0007 |
| | (1.02) | (−0.30) | (1.30) | (1.16) | (−0.53) | (−0.38) | (−0.40) | (−0.61) |
| EM | −0.0004 | 0.0003 | −0.0027 | −0.0008 | 0.0072* | 0.0056 | 0.0048 | 0.0071* |
| | (−0.08) | (0.08) | (−0.57) | (−0.17) | (2.10) | (1.69) | (1.47) | (2.15) |
| cons. | −1.5420* | 1.1224 | −0.7742 | −1.2329* | −2.3668*** | 0.0876 | −1.8258*** | −1.9261*** |
| | (−2.39) | (1.20) | (−1.17) | (−1.99) | (−4.18) | (0.11) | (−3.37) | (−3.49) |
| fixed | YES | YES | YES | YES | YES | YES | YES | YES |
| *N* | 526 | 526 | 526 | 526 | 920 | 920 | 920 | 920 |

(Panel A) Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively fixed indicates year*bank fixed effect.
(Panel B) Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively. fixed indicates year*bank fixed effect.

## 5. Conclusion

Prior research explores the issue of diversification which has been taken as a popular business strategy for financial institutions from the perspectives of individual-risk effects. However, recent theoretical works argue that diversification increases the interbank overlaps in related business activities because of similar portfolios, leading to larger risk exposure caused from external contagion. Such interdependence among banks caused by asset diversification may not only lead to risk contagion but may also be burdened with systemic risk, which played a crucial role in the recent 2007–2009 credit crisis.

Although theoretical models exploring diversification and systemic risk are widely discussed (Allen & Carletti, 2006; Allen & Gale, 2005; Allen et al., 2012; De Young, 2012; Ibragimov et al., 2011; Slijkerman et al., 2013; Wagner, 2010), little empirical evidence of interest seems to have been provided. We therefore empirically answer the research question of whether the contagion risks propagated from the financial system are influenced by individual bank's level of diversification.

For measuring the micro-level systemic risk, we use $\Delta$CoVaR to estimate the level of risk propagated from the financial market and other institutions (Adrian & Brunnermeier, 2011; Brunnermeier et al., 2012; Castro & Ferrari, 2014; Lopez-Espinosa et al., 2012). Using a sample of 275 U.S. listed banks from 2000 to 2013, we find that revenue diversification is significantly related to larger systemic risk. However, results from other proxy of asset diversification are inconsistent. Considering potential mediating effect of banking size, if we include bank size as regressor in the model, both of the effects of revenue diversification and size on the increase in systemic risk are also significant, and the effects of diversification are significant in the subsample of larger- and medium-sized banks. In addition, in the subsample of 2000–2001. com bubble, 2002–2006 growth in financial market, 2007–2009 credit crunch, and 2010–2013 European debt crisis, the effects of revenue diversification on systemic risk were significant.

Our research contributes to the literatures by arguing that larger and medium-sized banks contribute to systemic risk through the level of diversification. Although the role of diversification in systemic risk has been discussed theoretically in the literature, little empirical evidence is provided to focus on other determinants influencing systemic risk. And we are the first to explore effects of diversification on systemic risk, among different other criteria of institutional risks. We also contribute to literature by understanding the controversy on the effects of baking diversification that there are nonlinear relation between diversification and systemic risk. Diversification in the beginning indeed reduce the risk. However, over-diversification is suffered from severe systemic risk.

The capability to identify systemic risk and SIFIs should be largely improved in a more disciplined manner as a means to foresee potential financial shocks (Castro & Ferrari, 2014). Institutions providing regulating policies are currently designing new regulatory frameworks for SIFIs to ensure global financial stability and to prevent—or at least mitigate—future episodes of systemic contagion. Allen and Saunders (2004) and Slijkerman et al. (2013) note that current regulatory framework does not recognize explicitly the negative effects of diversification on systemic stability. In addition, banks holding more diversified assets that are highly correlated with the portfolios of other banks are supposed to be subject to higher capital charges (Wagner, 2010). Thus, based on our empirical findings, it is imperative that authorities should outline the level of over-diversification which triggers to systemic risks and set up regulations to motivate financial institutions to stay away from being overly systemically risky.

## Declaration of Competing Interest

None.

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## Appendix A

See Table A1

**Table A1**
First-stage Results on Panel Data with Instrumental Variables Estimation.

| | ADIV | FDIV | RDIV | DHHI |
|---|---|---|---|---|
| ADIV(-1) | 0.7820*** | | | |
| | (65.05) | | | |
| FDIV(-1) | | 0.8776*** | | |
| | | (87.31) | | |
| RDIV(-1) | | | 0.8758*** | |
| | | | (89.49) | |
| DHHI(-1) | | | | 0.8847*** |
| | | | | (91.58) |
| EBIT | −0.1477*** | −0.0394*** | −0.1439*** | −0.0422*** |
| | (−3.90) | (−6.66) | (−3.67) | (−5.65) |
| EBIT(-1) | −0.0136*** | −0.0133* | −0.0002*** | −0.0027*** |
| | (−4.15) | (−2.41) | (−3.79) | (−4.43) |
| EBIT(-2) | −0.0223 | 0.0063 | −0.0152 | 0.0046 |
| | (−0.96) | (1.75) | (−1.38) | (0.50) |
| ASSET | 0.0223*** | 0.0056*** | 0.0052*** | 0.0031*** |
| | (3.89) | (6.35) | (6.15) | (23.21) |
| ASSET(-1) | 0.0058*** | 0.0042*** | 0.0704*** | 0.0100*** |
| | (6.16) | (3.54) | (3.63) | (3.31) |
| ASSET(-2) | 0.0053 | 0.0010* | 0.0287 | −0.0004 |
| | (1.79) | (2.16) | (1.67) | (−0.03) |
| LLPR | 0.0103 | 0.0003 | 0.0024 | 0.0019 |
| | (1.84) | (0.53) | (1.52) | (1.47) |
| LAR | −0.0272* | −0.0205* | −0.0003** | −0.0005* |
| | (−2.24) | (−2.04) | (−3.11) | (−2.55) |
| EAR | 0.1349 | 0.0212 | 0.0008 | 0.0006 |
| | (1.79) | (1.69) | (1.83) | (1.63) |
| CIR | −0.0380 | 0.0123 | 0.0013 | 0.0005 |
| | (−1.53) | (1.59) | (0.92) | (0.42) |
| PMR | 0.0008 | 0.0031 | 0.0150 | 0.0140 |
| | (0.21) | (1.00) | (1.61) | (1.79) |
| LIQ | −0.0019 | −0.0002 | 0.0202 | 0.0113 |
| | (−0.05) | (−0.29) | (1.20) | (0.80) |
| SDR | 0.0079* | 0.0034*** | 0.1336*** | 0.1020*** |
| | (2.04) | (23.19) | (3.69) | (3.36) |
| MA | −0.0007 | −0.0005 | 0.0000 | 0.0000 |
| | (−1.83) | (−1.63) | (1.01) | (0.73) |
| EM | −0.0001 | −0.0000 | −0.0009 | −0.0031 |
| | (−1.83) | (−1.29) | (−0.33) | (−1.38) |
| constant | 0.0000 | 0.0020 | 0.0111 | 0.0027 |
| | (1.00) | (0.86) | (0.60) | (0.18) |
| $N$ | 2380 | 2380 | 2380 | 2380 |
| $R^2$ | 0.715 | 0.844 | 0.842 | 0.827 |

Note: ***, **, and * indicate significance at the 0.01, 0.05, and 0.1 levels, respectively.

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