How Loan Portfolio Diversification Affects U.S. Banks' Return and Risk: Correlation and Contagion Perspectives.

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Abstract

This paper adopts the dependence structure perspective to investigate how loan portfolio diversification affects banks' return and risk. We argue that the dependence structure of bank loan portfolios, namely, the correlation among loan assets within a portfolio and the presence of contagion channels due to contractual relationships across the border of the portfolio, affects the degree of diversification. Based on the U.S. bank loan data collected from 1987-2014, our empirical study employs the Herfindahl-Hirschman Index (HHI), intra-portfolio correlation and contagion as proxies for diversification. We find that diversification exhibit a positive effect on the performance of U.S. banks during tranquil periods. During periods of turmoil, however, banks should lend to specific groups of industry that have the fewest connections with other industries in order to reduce risk and improve return. In other words, in times of crisis, banks should choose a suitable loan portfolio concentration strategy rather than focus on selected industries as determined solely by the HHI.

1   Introduction

A fundamental tenet of traditional portfolio theory is that diversification can help minimize idiosyncratic risk in a given portfolio. It does so by reducing the variance of returns for a portfolio of assets. By drawing on this principle, banking theory suggests that diversification reduces the potential for bank failure, and that, according to delegated monitoring theory, it is optimal for financial intermediaries to be as diversified as possible (Diamond, 1984; Diamond and Dybvig, 1986; Boyd and Prescott, 1986). However, recent studies have found that aggressive diversification strategies can be responsible for banks' increased risk and impaired return, implying that the benefits of diversification need to be more carefully assessed (Acharya, Hasan, and Saunders, 2006; Berger, Hasan, and Zhou, 2010; Tabak, Fazio, and Cajueiro, 2011).

It is noteworthy that the existing literature on diversification has shown no consensus on a proper definition for diversification. For example, subject to returns and risk forecasts as inputs to Mean Variance Optimization (MVO), traditional portfolio theory argues that the MVO portfolio is engineered to achieve the best diversification. On the other hand, a growing proportion of the literature on asset allocation with a focus on risk and diversification rather than on estimating expected returns, collectively known as risk-based asset allocation approaches,[1] has been documented. One common characteristic across all risk-based portfolios is their tendency to be highly weighted on assets that have low volatilities and/or low correlation with other assets. Therefore, it does not necessarily suggest that the portfolio is diversified only from the standpoint of portfolio weights. In other words, whether a portfolio is indeed a diversified one is subject to different definitions of diversification. Due to the lack of knowledge of a bank's true underlying objective ex-ante, one should not judge a portfolio as poorly diversified solely based on its resulting weight distribution,[2] ex-post.

This study provides an alternative means of assessing the degree of diversification in the presence of dependent relationships, namely, the correlation among loan assets within a portfolio and the contagion effect due to contractual relationships across the border of a portfolio. Based on data collected from the syndicated loan portfolios of individual U.S. banks from 1987 to 2014, we examined how loan portfolio diversification, in the presence of correlation and contagion, affects bank profitability and risk.

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[1] Lee (2011) shed some light on what these risk-based approaches, i.e., global minimum variance portfolio, maximum diversification (Choueifaty and Coignard, 2008) or risk parity, attempt to achieve.

[2] Many papers have studied the effects of loan portfolio diversification on banks' profitability and riskiness (e.g., Acharya et al., 2006; Rossi, Schwaiger and Winkler, 2009; and Tabak et al., 2011). All of these studies adopted the Herfindahl-Hirschman Index (HHI) to measure the extent of diversification. While the HHI considers diversification as equal exposure to every sector, the measurement of the extent of diversification is mainly focused on the weight distribution of assets.

The dependent relationships under consideration are important for several reasons. First, the Herfindahl-Hirschman Index (HHI) is limited because it neglects asset correlation. Diez-Canedo (2005) concluded that asset correlation affects diversification and recommended a correlation adjusted concentration index as an alternative to HHI. Second, while the integration of interbank markets in recent decades allows greater scope for risk sharing, it provides greater opportunity for cross-border contagion (Bonfiglioli, 2008; Fecht, Gruner and Hartmann, 2012). Cross-border contagion results in the amplification of a bank's idiosyncratic risk exposure which is usually assumed to be fully diversifiable under the Asymptotic Single Risk Factor (ASRF) framework (Vasicek, 1987; Gordy, 2003) used in the Basel II Internal Ratings Based (IRB) guidelines. The conditional independence assumption that underlies the ASRF model attributes the source of default clustering to observable macroeconomic factors. However, Das, Duffie, Kapadia, and Saita (2007) found evidence that the ASRF framework fails to fully explain default clustering, suggesting the presence of contagion or frailty.

A channel of credit contagion may occur due to contractual linkages. This effect arises when the default of a counterparty causes a ripple effect on its business partners. To empirically examine contractual linkage contagion, Jorion and Zhang (2009) used bankruptcy files to identify creditors of the filing firms. They found that bankruptcy announcements induce negative abnormal equity returns and an increase in the Credit Default Swap (CDS) spread of creditors. Hertzel, Li, Officer, and Rodgers (2008) examined the contagion effects of pre-filing distress and bankruptcy filing along the supply chain. Suppliers showed abnormal returns (significantly negative on average) around both the pre-filing distress and bankruptcy filing of a major customer. That is, under the framework of contractual linkages, subsequent to a bankruptcy announcement or financial distress of a firm, its creditors suffer a direct loss in credit exposure. In addition, market participants change their perceptions about the financial condition of the creditors. They expect that a default by a client will also impact their future earnings due to the spread of negative information about sales prospects. These studies implied that idiosyncratic shocks from one particular asset are propagated to other assets via contractual linkages. Therefore, since a complex web of contractual relationships is always present in any asset, contractual relationships can bring about directional contagion effects. We argue in this paper that contractual relationships play a role in the dependence structure of bank loan portfolios and affect banks' risk-return profiles.

To sum up, assets are correlated because they are jointly exposed to the same macroeconomic factors as well as a number of other factors, which may include firm-specific business relationships. Hence, dependent relationships may be the result of both systemic and idiosyncratic structures. The idiosyncratic dependence structure can be used as a proxy to depict the contractual relationships between assets.

Intra-portfolio correlation [3] is a common indicator for identifying the dependence characteristics or an inverse measure of the diversification of a portfolio. Correlation is calculated by the covariance between assets normalized by the square root of the variance of the individual assets involved. The covariance specifically captures the dependence between assets arising from correlated factors, for example, where a portfolio is composed of two assets and the dependence between these two assets is a result of macroeconomic factors only. We also assumed that each underlying asset has its own distinct counterparties, which are not included in the portfolio.[4] The portfolio covariance only measures the strength of the relationship between these two underlying assets arising from macroeconomic factors, and thus excludes the idiosyncratic dependence structure of each underlying asset. However, if the connection between an underlying asset and its counterparty is strong, it will not influence the portfolio covariance measure, but it will result in a higher volatility of return on that underlying asset and a lower level of correlation. Hence, the intra-portfolio correlation used as a singular measure may overestimate the extents of diversification, and ignore the role of contagion-induced volatilities, which can decrease the degree of diversification. Assessing the idiosyncratic dependence structure is important especially for those underlying assets with extensive contractual linkages which tend to be more prone to external shocks than assets with fewer cross-border relationships.

Our paper consists of two parts. First, the standard factor model is extended to include additional latent factors, which are used to depict the idiosyncratic infectious effect. Additionally, we divided the idiosyncratic dependence structures into the inner and the outer transmission channels, depending on whether the underlying asset's counterparties are included in the portfolio or not. Under this framework, we are able to show the impact of different types of idiosyncratic transmission channels on the measures of correlation and the degree of diversification.

In the second part, we undertook an empirical investigation of how loan diversification affects banks' profitability and risk. To fully measure the degree of diversification, particularly from the perspective of the asset dependence structure, we divided the dependence measure into two categories. The first category examined intra-portfolio correlation, which measures the dependence between assets within the portfolio. The second category aimed to investigate the unidirectional contagion effect, which is the risk that the fluctuations of an asset which is not included in the portfolio trigger the co-movement of its counterparty within the portfolio through the contractual linkages (outer transmission channel).

Each measure defines diversification somewhat differently. For example, the HHI considers diversification as equal exposure to every industry, while the

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[3] Campbell, Lettau, Malkiel and Xu (2001) used the equally weighted average pairwise correlation across stocks held in the portfolio to measure the portfolio correlations.

[4] We further assumed that there exists no contractual relationship between assets that are outside the scope of the portfolio.

intra-portfolio correlation measure uses the equally weighted average pairwise correlation across assets held in the portfolio to construct a proxy of diversification. In this paper, we followed the definition of contagion as excess correlation, that is, correlation over and above what one would normally expect according to macro fundamentals (Bekaert, Harvey, and Ng, 2005; Phylaktis and Xia, 2009; Bekaert, Hodrick, and Zhang, 2009; Bekaert, Ehrmann, Fratzscher, and Mehl, 2014). We adopted the approach of Bekaert et al. (2009) and employed the Fama-French Three Factor model to capture movements in asset return. This model allows for separating the empirical correlation of asset return into 1) the correlation between risk factors, which represents the fundamental co-movements between assets, and 2) the correlation between idiosyncratic shocks, which captures the co-movements that are beyond expectation. Hence, we used the residual correlation to assess the correlations that come from the idiosyncratic dependence structure and to provide a single measure of the extent of the contagion effect. Furthermore, in order to specify the direction of the contagion effect, we gathered information about the contractual relationships of the underlying industry's customers from Compustat's Segment Database. Using the supply chain framework, we hypothesized that the stronger the connection between the underlying industry and its external customers due to idiosyncratic dependence, the higher the risk of contagion borne by the underlying industry. In summary, portfolios that have higher HHI, greater intra-portfolio correlation, or a higher level of contagion measures face more concentration risk.

This paper makes a number of contributions to the literature. First, we provided a theoretical framework to link dependence structure to diversification. We found that underlying assets that have more counterparties in common (indicating a higher degree of overlap in transmission channels) will lower the degree of diversification in the portfolio. Additionally, the higher the overlap of the outer transmission channels, the more information about the outer transmission mechanism is contained in the intra-portfolio correlation. This implied that the accuracy of estimating diversification measured by intra-portfolio correlation is affected by the extent of the overlap ratio of outer transmission channels.

Second, an actual portfolio of bank syndicated loans was used to investigate the issue of concentration versus diversification and to verify the inference that we deduced from the model. Our results suggested that during tranquil periods, a more concentrated weight distribution in a bank portfolio or higher intra-portfolio correlation will decrease the bank's return and increase its risk. With regard to the contractual structure of the portfolio assets, we found that the contagion estimated based on the outer transmission channels has significant explanatory power for the bank's return and risk. This signified the importance of using supply chains to understand how external shocks are propagated and how they affect a bank's levels of return and risk. These findings are consistent with the policy of the Basel Concordat that requires banks to implement diversification.

Another interesting aspect of our study is that we limited the sample period to a

period of turmoil in response to the impact of increased correlation in stressed market conditions[5] on the measurement of diversification. We found that during a period of crisis, the selection of portfolio assets by banks should focus on several specific industries that have a low connection with other industries. As we have pointed out, if the HHI is used as an indicator of the degree of portfolio diversification, the model suggests that a higher concentration could improve the bank's return and decrease risk during a crisis period. This is inconsistent with the effects in a tranquil period. Once the dependence structure is incorporated in the analysis, lending to industries with a low connection to other industries will reduce the degree of portfolio concentration. This implied that if we only use the HHI to measure portfolio diversification, it will overestimate the degree of the overall portfolio concentration and lead to a biased interpretation.

The remainder of this paper is structured as follows. In Section 2, we construct a theoretical model to illustrate the role of the dependence structure in the measurement of bank diversification. In Section 3, we define the variables of interest, and describe the data sources and the regression approaches taken. Section 4 presents our empirical results. Finally, Section 5 provides concluding remarks.

2   The Models

From traditional portfolio theory, we know that diversification increases the central tendency of the distribution of a loan portfolio. In this section we propose that both the weight distribution among assets within a portfolio, and the dependence structure of assets which stimulates co-movement of asset returns can play a critical role in diversification.

2.1 *A Factor Model Including Sector-specific Latent Factors*

Our model is an extension of the standard factor model as it is used by CreditMetrics and the Basel II Capital Accord. First we will set up a single-factor model. We consider a portfolio of loans to n distinct sectors. Sectors are defined in the following as industries..

In the standard factor model, sector i's standardized asset return is driven by a common factor and an idiosyncratic factor, that is:

$$r_i = \sqrt{\rho}M + \sqrt{1-\rho}\xi_i \tag{1}$$

where M and ξ_i are assumed to have independent standard normal distributions. M is a systematic factor which represents global economic factors that may affect sectors' return in a systemic way. ξ_i is the idiosyncratic (sector-specific) risk factor. Factor loading $\sqrt{\rho}$ measures sector i's sensitivity to systemic risk.

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[5] Recent research presents the notion of correlation asymmetry, i.e. the correlation among equity return tend to be much greater on the downside than on the upside (Longin and Solnik, 2001; Ang and Chen, 2002).

Our model builds on previously documented evidence that the unexpected shocks from a particular sector, or group of sectors, are propagated to other sectors. This has implications for sectors that are connected by contractual relationships. Therefore, we divided the sectors in the portfolio into two distinct types, the first n_1 sectors are primary sectors and the next n_2 sectors belong to secondary sectors. Thus, a fluctuation in the primary sector's asset return will cause fluctuations in the returns of the secondary sector via the contractual relationships. We refer to this as the idiosyncratic transmission channels.[6]

However, there might be some sectors not included in the bank loan portfolio, that may still have an influence on the sectors within the portfolio through idiosyncratic transmission channels. We further assume that there are m outer primary sectors (primary sectors that are outside the border of the portfolio) and that the performance of m sectors may have an impact on the portfolio. This strict ex-ante segmentation, is also used by Jarrow and Yu (2001) in their default intensity model which describes counterparty risk and suggests that the shock is transmitted from primary sectors to secondary sectors but not vice versa.

First, we construct the asset return for primary sectors, that is rough the same as standard factor model, besides the idiosyncratic term. According to the definition, contagion occurs when a sector-specific shock becomes regional or common. Hence, in this paper we further separate the idiosyncratic structure into a latent variable and a residual idiosyncratic risk factor. Thus, primary sector-specific shocks cause a jump in the conditional distribution of latent variable, as well as a subsequent jump in any other secondary sectors whose value depends on the same latent variable. In other words, the latent variable can be interpreted as a form of transmission channel that allows the sector-specific signal to travel through the contractual relationship. This concept is illustrated by the following factor model. The asset return process for the primary sector is given by ($i \in$ primary sectors):

$$r_i = \sqrt{\rho}M + \sqrt{1-\rho}\xi_i \tag{2}$$

$$\xi_i = \sqrt{\theta}\eta_i + \sqrt{1-\theta}\varepsilon_i \tag{3}$$

where η_i is the standardized normally distributed latent factor and $\varepsilon_i \sim N(0,1)$ depicts the residual idiosyncratic risk. M, η_i and ε_i are independent from each other.

For secondary sectors, we assume that their asset return processes have the following form ($j \in$ secondary sectors):[7]

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[6] In analogy to the literature of contagion effect on equity market, contagion occurs when a country-specific shock becomes regional or common. Contagion is defined as the shocks from a particular market are propagated to other markets via the idiosyncratic channel. (e.g., Corsetti et al., 2005; Phylaktis and Xia, 2009; and Bekaert et al., 2009)

[7] Similar latent factor models of contagion are used by Dungy, Fry, González-Hermosillo, and Martin (2002, 2005).

$$r_j = \sqrt{\rho}M + \sqrt{1-\rho}\,\xi_j \tag{4}$$

$$\xi_j = \sqrt{\alpha}\zeta_j + \sqrt{1-\alpha}\,\varepsilon_j \tag{5}$$

$$\zeta_j = \sum_{l=1}^{n_1} \omega_{jl}\delta_{jl}\eta_l + \sum_{k=(n+1)}^{(n+m)} \omega_{jk}\delta_{jk}\,\eta_k \tag{6}$$

where $\zeta_j \sim N\left(0, \sum_{l=1}^{n_1} \omega_{jl}^2 \delta_{jl}^2 + \sum_{k=(n+1)}^{(n+m)} \omega_{jk}^2 \delta_{jk}^2\right)$ is a composite factor. We define ω_{jl} as the relative exposure of the sector j to sector l and δ_{jl} measures sector j's original sensitivity to sector l-specific shock. This means the transmission of shock from the primary sector to the secondary sector is mainly through the latent factor η_i $(i = 1, \cdots, n_1, n+1, \cdots, n+m)$. $\sqrt{(1-\rho)\alpha}\,\omega_{jl}\delta_{jl}$ and $\sqrt{(1-\rho)\alpha}\,\omega_{jk}\delta_{jk}$ measure the secondary sector's sensitivity to the transmission effect from the primary sector within and across the portfolio, respectively. So, the dependence between sectors is not only built on a common factor but latent factors also exist that play a key role in propagating shocks. In the rest of the paper, as we refer to transmission channels that are specific to dependent sectors we refer to those which originate form idiosyncratic latent factors rather than common factors.

2.2 *Correlation to the Extent of Diversification*

We investigated the effect of correlation on the level of portfolio diversification. In order to avoid cumbersome notations and simplify our analysis, we assumed that each secondary sector has the same number of primary sectors which consist of $\bar{n}$ and $\bar{m}$ sectors, within and outside the portfolio, respectively. We further assumed that each secondary sector has n' inner primary sectors and m' outer primary sectors in common. The underlying sectors' original sensitivity to inner and outer primary sector l-specific shock is δ_I and δ_O, respectively.

The correlation coefficient is computed as follows:

Proposition 1

(1) If sector i and sector $j \in$ primary sector, the correlation between the two sectors equals:

$$\rho \tag{7}$$

(2) If sector $i \in$ primary sector and sector $j \in$ secondary sector, the correlation between the two sectors equals:

$$\rho' = \begin{cases} \dfrac{\rho + (1-\rho)\sqrt{\alpha\theta}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)\delta_I}{\sqrt{1 + (1-\rho)\alpha\left[\bar{n}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]}}, & \text{for } i = \begin{matrix} 1,\cdots,n' \\ \bar{n}'_{j-1}+1,\cdots,\bar{n}'_j \end{matrix} \\[6ex] \dfrac{\rho}{\sqrt{1 + (1-\rho)\alpha\left[\bar{n}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]}}, & \text{otherwise} \end{cases}$$

(8)

where sector $i = \{1,\cdots,n',\bar{n}'_{j-1}+1,\cdots,\bar{n}'_j\}$ are secondary sector $j's$ corresponding inner primary sectors.

(3) If sector i and sector $j \in$ secondary sector, the correlation between the two sectors equals:

$$\rho'' = \frac{\rho + (1-\rho)\alpha\left[n'\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + m'\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2\right]}{1 + (1-\rho)\alpha\left[\bar{n}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]}$$

(9)

Proof: see Appendix A

The proposition is very intuitive. It states that correlations can be classified into three types. The first type is the correlation between primary sectors that only arises from the common factor. The second type shows that the existence of transmission channels induces a higher correlation between primary and secondary sectors. The third type, indicates that secondary sectors in the portfolio may have a much higher correlation due to the overlap of transmission channels within or across the portfolio.

After constructing the dependence structure, we used it for deriving the correlation between sectors. Below we clarify how the dependence structure affects the extent of diversification, which is measured by the dispersion of portfolio return.

Corollary 1

Holding the number of primary and secondary sectors constant, increasing correlations $(\rho, \rho' \text{ or } \rho'')$ increases the volatility of portfolio return.

$$Var[r_p] = \left(\frac{1}{n}\right)^2 \{n_1 + n_2\sigma_s^2 + n_1(n_1 - 1)\rho + 2n_2\sigma_s[\bar{n}\rho'_1 + (n_1 - \bar{n})\rho'_2] \\ + n_2(n_2 - 1)\sigma_s^2\rho''\}$$

(10)

where ρ'_1 and ρ'_2 are the correlations between the secondary sector and the primary sector with or without contractual relationships, respectively. σ_s is the

standard deviation of secondary sector.

Proof: see Appendix B

In Corollary 1, the dispersion of the portfolio is an increasing function of the level of correlation and the standard deviation of secondary sector. However, we can also observe that the dispersion decreases as the number of sectors n increases in the portfolio.

By integrating the above, the dependence structure of underlying sectors can be seen to have two ways of influencing the extent of portfolio diversification. The first is if the portfolio is highly concentrated towards several highly correlated secondary sectors and especially if the high correlation of these secondary sectors originates from the high overlap of their transmission channels. The other influence is related to the underlying secondary sectors' specific idiosyncratic structure which they may be overexposed to a variety of inner or outer primary sectors. This increases the volatility of the underlying secondary sector's return and may also induce higher return dispersion of the portfolio. This implies that we should not only focus on the dependence structure between assets within the portfolio but also the aggregate dependence structure.

Below, we investigate whether the outer non-overlapping part of the transmission channels between secondary sectors will affect the precision of using correlation measures to depict diversification.

Proposition 2

(1) If sector i and sector $j \in$ primary sector, then the first-order derivative of the correlation coefficient with respect to strength of outer connection is:

$$\frac{\partial Corr(r_i, r_j)}{\partial \delta_O} = \frac{\partial \rho}{\partial \delta_O} = 0 \tag{11}$$

(2) If sector $i \in$ primary and sector $j \in$ secondary sector, then the first-order derivative of the correlation coefficient with respect to strength of outer connection is:

$$\frac{\partial \rho'}{\partial \delta_O}$$

$$= \begin{cases} \dfrac{-\left\{\left[\dfrac{1}{\sqrt{Var(r_j)}}(1-\rho)\alpha\bar{m}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O\right]\left[\rho+(1-\rho)\sqrt{\alpha\theta}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)\delta_I\right]\right\}}{Var(r_j)} & \text{for} \\[3em] \dfrac{-\left\{\left[\dfrac{1}{\sqrt{Var(r_j)}}(1-\rho)\alpha\bar{m}\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O\right]\rho\right\}}{Var(r_j)} & , \text{otherwise} \end{cases}, i = \begin{matrix} 1,\cdots,n' \\ \bar{n}'_{j-1}+1,\cdots,\bar{n}'_j \end{matrix}$$

$$\leq 0 \tag{12}$$

where $0 \leq \rho, \alpha, \theta \leq 1$

(3) If sector i and sector $j \in$ secondary sector, then the first-order derivative of the correlation coefficient with respect to strength of outer connection is:

$$\frac{\partial \rho''}{\partial \delta_O}$$
$$= \frac{\left[2(1-\rho)\alpha\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_O\right]\left\{m'[1-(1-\rho)\alpha]-\bar{m}\rho+(m'\bar{n}-\bar{m}n')(1-\rho)\alpha\left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2\right\}}{Var(r_i)^2}$$

$$\begin{matrix} < \\ =0 \\ > \end{matrix} \tag{13}$$

where $0 \leq \rho, \alpha \leq 1$

Proof: see Appendix C.1

We know that the linkages between primary sectors are derived only from systematic factors, therefore, the strength of the connection between underlying secondary sectors and outer primary sectors will not affect the correlation between primary sectors. Similarly, because of the dependence between secondary sector and primary sector within the portfolio outer connection channels are excluded. Hence, the strength of outer connections will not have any influence on the covariance, but will increase the return dispersion of the secondary sector and lower the correlation between secondary and primary sectors within the portfolio. The dependence between secondary sectors includes the overlap of transmission channels with inner and outer primary sectors. The higher the strength of outer connections the greater the simultaneous increase in covariance between secondary sectors and the return volatility of an individual secondary sector. This implies that the increase or decrease of the correlation will be the net result of these two elements.

In order the have a more explicit relation between correlation and the strength of outer connection, we attempt to construct sequences of portfolios with increasing the overlap of outer transmission channels.

Corollary 2

If sector i and sector $j \in$ secondary sector, and m' is the number of overlap of outer transmission channel, then the derivative of $\frac{\partial \rho''}{\partial \delta_O}$ with respect to strength of outer connection is:

$$\frac{\partial \rho''}{\partial \delta_O \partial m'} = \frac{\left[2(1-\rho)\alpha\left(\frac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O\right]}{Var(r_i)^2}\left[1-(1-\rho)\alpha+\bar{n}(1-\rho)\alpha\left(\frac{1}{\bar{n}+\bar{m}}\right)^2 \delta_I\right] \geq 0 \quad (14)$$

where $0 \leq \rho, \alpha \leq 1$

From equation (14), it appears that $\frac{\partial \rho''}{\partial \delta_O}$ is an increasing function of the extent of overlap of outer transmission channel m'. This result indicates that the higher the overlap of the outer transmission channels, the more the information is contained in the correlation measure. This include the strength of influence of outside primary sectors and the channels through which they influence sectors within the portfolio. Interestingly, taking the extreme case by assuming that no outer overlapping transmission channels exist (i.e., $m' = 0$), the corresponding covariance in the portfolio contains information about linkages between sectors that originate from systemic factors and inner overlapping transmission channels without describing other non-overlapping outer transmission channels that increase the return dispersion of the secondary sector and lower the correlation between secondary sectors within the portfolio.

Finally, we further examine the relationship between the strength of the outer connection, intra-portfolio correlation, and portfolio dispersion. The intra-portfolio correlation measure uses the equally weighted average pairwise correlation across sectors held in the portfolio.

Corollary 3

(1) The partial derivative of the return dispersion of the portfolio with respect to strength of outer connection is:

$$\frac{\partial Var[r_p]}{\partial \delta_O} = \sum_{i=1}^{n} \omega_i^2 \frac{\partial Var[r_i]}{\partial \delta_O} + \sum_{\substack{i=1 \\ i \neq j}}^{n} \sum_{j=1}^{n} \omega_i \omega_j \frac{\partial Cov(r_i, r_j)}{\partial \delta_O} \geq 0 \quad (15)$$

(2) The partial derivative of the average correlation of the portfolio with respect to strength of outer connection is:

$$\frac{\partial \bar{\rho}}{\partial \delta_O} = \frac{2}{n(n-1)}\left[\frac{n_1(n_1-1)}{2}\frac{\partial \rho}{\partial \delta_O} + n_2\bar{n}\frac{\partial \rho_1'}{\partial \delta_O} + n_2(n_1-\bar{n})\frac{\partial \rho_2'}{\partial \delta_O} + \frac{n_1(n_1-1)}{2}\frac{\partial \rho''}{\partial \delta_O}\right]\substack{< \\ =0 \\ >} (16)$$

where $\bar{\rho}$ is the equally weighted average pairwise correlation across sectors held in the portfolio, which is given by:

$$\bar{\rho} = \frac{2}{n(n-1)} \left[\frac{n_1(n_1-1)}{2}\rho + n_2\bar{n}\rho_1' + n_2(n_1-\bar{n})\rho_2' + \frac{n_1(n_1-1)}{2}\rho'' \right] \quad (17)$$

where ρ_1' and ρ_2' are the correlations between secondary sectors and primary sectors that have or do not have contractual relationships, respectively.

Proof: see Appendix C.2

According to equation (15), we see that no matter what the level of transmission channels overlap is, the higher the degree of dependence between an underlying sector and its corresponding outer primary sectors, and the higher the return dispersion of the portfolio. According to Corollary 2, the relationship between intra-portfolio correlation and strength of outer connection is determined by the extent of overlap of outer transmission channels. In equation (16), the lower the overlap of the outer transmission channels, the higher the probability that the intra-portfolio correlation will be negatively related to the strength of the outer connection. Under the extreme condition that all of the underlying secondary sectors have no outer transmission channels in common, the higher the extent that underlying sectors connect with outer primary sectors, the lower the average correlation of the portfolio. This implies that using intra-portfolio correlation as a singular measure will bias the measurement of the extent of diversification.

It is noteworthy that the inclusion of the transmission channels in the measurement of correlation in our model led us to address the question of whether the correlation measure of the portfolio is able to accurately depict the extent of diversification, especially when the overlap ratio of the outer transmission channels of the portfolio is low. In the next section, we provide an empirical procedure to examine this question.

3 Variable Definition and Methodology

3.1 Measuring Loan Portfolio Diversification

Since diversification increases the central tendency of the distribution of a loan portfolio, we use three proxies to describe the diversifying characteristics of each bank's loan portfolio: (i) the HHI; (ii) the average pairwise correlation across industries held in the portfolio; and (iii) the residual correlation as a contagion measure as proposed by Bekaert et al. (2009). Each of these measures is described below.

A. Lending HHI

HHI is used to measure a bank's relative exposure to each industry.[8] For each

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[8] In addition, we also seek to establish the robustness of our results with the following measures of the extent of diversification that focus on the characteristic of exposure weight distribution. We consider a traditional diversification measure and two distance measures: the Shannon Entropy (SE), an absolute distance measure (Da) and a relative distance measure (Dr). We find that the results lead

bank loan portfolio, DealScan provides information about the identities of borrower's industry through the Standard Industrial Classification (SIC) Code. We then used the classification of Fama and French (1997) to classify all bank loan exposures into 49 industries. Thus, the *Lending HHI* at time t for a loan portfolio i is defined as the sum of the squares of loan exposures to industry j (q_{ijt}) as a fraction of total loan exposures (Q_{it}) under a given 49 different industrial classifications:

$$Lending\ HHI = \sum_{j=1}^{49} \left(\frac{q_{ijt}}{Q_{it}}\right)^2 \tag{18}$$

Note that the inferior limit of the HHI is 1/49, which represents a perfectly diversified portfolio (i.e. an equal share of exposure to each industry). On the other hand, if the HHI is equal to 1, the bank loans to only one industry.

After calculating the HHI, we introduced two other variables, the intra-portfolio correlation (*CORR*), and contagion effect (*Contagion*), to measure the degree of portfolio diversification. All these variables are calculated at the industry level.

B. Intra-portfolio Correlation (CORR)

To measure portfolio correlation, we adopt the approach of Campbell, Lettau, Malkiel, and Xu (2001) and Demirer and Lien (2004) which uses the equally weighted average pairwise correlation across stocks held in the portfolio as a proxy for portfolio correlation. For each portfolio in a given quarter, we estimated pairwise industry correlations using industry returns from the prior 12 months. Therefore, the intra-portfolio correlation (*CORR*) is calculated by averaging over all possible pairs of industries held in the portfolio:

$$CORR = \frac{1}{W} \sum_{\substack{p=1 \\ p \neq q}}^{49} \sum_{q=1}^{49} Corr_{[t-12,t-1]}\left(Return_p, Return_q\right) \tag{19}$$

where W indexes the number of pair industries in a loan portfolio. $Return_j$ is the value-weighted industry return for industry j.

C. Contagion

To better understand how external disturbances are propagated through the outer transmission channels into the portfolio, we investigate the supply-chain relationship to identify the customers of underlying industries of the bank loan portfolio. We used supplier-customer data from COMPUSTAT's Segment Customer database to identify major customers of underlying industries.[9][10]

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to the same conclusions.

[9] The unit of observation in the Segment database is a supplier-customer pairs.

[10] The database reports all customers that represent more than 10% of a firm's total sales. We employ

We then constructed a measure of industry contagion (*Contagion*) in a bank portfolio using a residual correlation as proposed by Bekaert et al. (2009).[11] The method breaks the sample correlation into two components: explained correlation and idiosyncratic correlation. We define the average portfolio-level correlation between the underlying industries and its outer customer industries as:

$$CORR_{supply-chain} = \frac{1}{N}\sum_{\substack{s=1 \\ s \neq c}}^{49}\sum_{c=1}^{49} Corr_{[t-12,t-1]}(Return_s, Return_c)$$

$$= \frac{1}{N}\sum_{\substack{s=1 \\ s \neq c}}^{49}\sum_{c=1}^{49} Corr_{[t-12,t-1]}(\beta_s' F, \beta_c' F) + \frac{1}{N}\sum_{\substack{s=1 \\ s \neq c}}^{49}\sum_{c=1}^{49} Corr_{[t-12,t-1]}(\epsilon_s, \epsilon_c)$$

$$= \rho_{risk,\tau}^{CORR} + \rho_{idio,\tau}^{CORR} \tag{20}$$

where

$$Return_s - R_f = \alpha_s + \beta_s^{MKT}MKT + \beta_s^{SMB}SMB + \beta_s^{HML}HML + \epsilon_s \tag{21}$$

$$Return_c - R_f = \alpha_c + \beta_c^{MKT}MKT + \beta_c^{SMB}SMB + \beta_c^{HML}HML + \epsilon_c \tag{22}$$

N indicates the number of industry pairs between underlying industries (*s*) and its outer customer industry (*c*). As there is no consensus on the common factors for asset pricing, we use the Fama and French (1992) Three-factor Asset Pricing model to estimate the residual ϵ. F is a vector of three factors: the market factor (*MKT*), the size factor (*SMB*), and the value factor (*HML*). ϵ indicates the idiosyncratic term.

According to equations (20) - (22), both the expected correlation ($\rho_{risk,\tau}^{CORR}$) and the contagion ($\rho_{idio,\tau}^{CORR}$) are obtained from the factor model. Thus, the residual correlation ($\rho_{idio,\tau}^{CORR}$) can be viewed as a time-varying contagion measure.[12] Contagion is measured by the correlation of idiosyncratic shocks. Any significant correlation among those shocks would indicate that sector residuals are correlated beyond what is captured in our model, suggesting evidence of contagion. The following is the correlation measure for industry contagion:

$$Contagion = \frac{1}{N}\sum_{\substack{s=1 \\ s \neq c}}^{49}\sum_{c=1}^{49} Corr_{[t-12,t-1]}(\epsilon_s, \epsilon_c) \tag{23}$$

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a text-matching program to match the text abbreviation for the customer's name and industry. We define important customer relations as recurring customer and exclude customers that appear for less than three times in the sample period.

[11] The literature on contagion has shown no consensus as to the exact definition of contagion. Bekaert et al. (2005) and Phylaktis and Xia (2005) define contagion as excess correlation, that is, correlation over and above what one would expect from economic fundamentals.

[12] For this application, we use the 3-Factors Model to capture the industry residual term as our contagion factor.

where *N* indicates the number of industry pairs between an underlying industry (*s*) and an outer customer industry (*c*).

D. Measuring Outer Overlap Ratios (Overlap)

To corroborate our argument that the importance of outer transmission channel is associated with a lower overlap ratio, we examine the relation between the outer overlap ratio and contagion. We define the outer overlap ratio as follows:

$$
\begin{aligned}
Overlap &= \frac{1}{W} \sum_{\substack{p=1 \\ p \neq q}}^{n} \sum_{q=1}^{n} Overlap(Channel_p, Channel_q) \\
&= \frac{1}{W} \sum_{\substack{p=1 \\ p \neq q}}^{n} \sum_{q=1}^{n} \frac{OverlapChannel_{p,q}}{Channel_p + Channel_q - OverlapChannel_{p,q}} \quad (24)
\end{aligned}
$$

where $Channel_j$ is the number of underlying industry *j*'s corresponding to outer customer transmit channels. $OverlapChannel_{p,q}$ is the number of overlaps in outer customer transmit channels between underlying industry p and q.

A high level of *Overlap* means a large proportion of outer customer transmission information is contained in intra-portfolio correlations. Accordingly, for a loan portfolio with a lower outer overlap ratio, the contagion effect originates from outer transmission channels, becoming increasingly important, and thus cannot be ignored.

3.2 Sample Selection

To test our assertions, we use a sample of U.S. bank's syndicated loan portfolio from 1987 to 2014 between corporate borrowers domiciled in the United States as reported by LPC DealScan. The LPC DealScan contains detailed information on corporate loan contracts. Using the loan dataset allows us to identify borrowers for which loan contracts exist. Moreover, we can compute the share of loans for each participating lender in a syndicated loan. We define the quarterly loan portfolio as a deal that not matures at the end of the quarter. Bank financial statement variables were obtained from the COMPUSTAT database. Finally, we assigned each borrowing firm to one of the 49 industries categorized by Fama and French (1997). To calculate the intra-portfolio correlation and the contagion effect, we use Ken French's Website data for industry return, market return, and the Fama-French Three-factor model.

3.3 Methodology

We regressed bank performance on variables that capture distribution of exposure (*LendingHHI*), intra-portfolio correlation (*CORR*), and contagion effect

(*Contagion*) under tranquil period and turmoil period conditions, respectively.[13] For our analyses, data was collected from the period 1987 to 2014. This period includes two banking crises and three market crises, as defined by Berger and Bouwman (2013).[14] Specifically, we used the following equation to estimate bank performance:

$$
\begin{aligned}
Bank\ Performance_{i,t} \\
= \alpha_0 + \alpha_1 Lending\ HHI_{i.t-1} + \alpha_2 CORR_{i.t-1} + \alpha_3 Contagion_{i.t-1} \\
+ \alpha_4 Size_{i.t-1} + \alpha_5 Equity\ Ratio_{i.t-1} + \alpha_6 Employee_{i.t-1} + \sum_{j=1}^{2} BankSIC_j \\
+ \sum_{qtr=1988Q1}^{2014Q4} Year - quarterly_{qtr} \tag{25}
\end{aligned}
$$

where *Bank Performance* $\in \{ROA_{i,t}, NPL_{i,t}\}$.[15] $ROA_{i,t}$ is the return of bank i at time t measured by the return on assets. $NPL_{i,t}$, a risk measure, represents the ratio of non-performing loans to total assets. To partially address the issue of the endogeneity of diversification measures, we considered the relationship between loan portfolio diversification in year-quarterly *t*-1 on performance measures in year-quarterly *t*. To assess the impact of the loan portfolio diversification on bank performance, we controlled for other factors that might also affect performance. These factors include bank size, equity ratio, number of employees, bank-specific fixed effects and year-quarterly fixed effects. Bank size (*Size*) is measured by the natural log of total assets. Equity ratio (*Equity Ratio*) is defined as the book value of equity divided by the book value of assets, the approximate equivalent of a bank's Tier 1 capital ratio. Employee ratio (*Employee*) is defined as the number of employees divided by total assets. We used dummy variables to control for the bank type (*BankSIC*), i.e., a savings bank, commercial bank, or another type. All regressions are estimated with robust standard errors, clustered by bank, to control for heteroscedasticity as well as possible correlation between observations of the same bank in different periods. Time dummies (*Year-quarterly*) are used to capture macroeconomic conditions in each period of our analysis.

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[13] As a robustness check, we also replicate all analyses under full sample period. To examine whether the diversification effects on bank return and risk would differ under asymmetry correlations, we introduce interaction terms between the diversification measures and the crisis dummy variable, which is equal to one if the observation takes place during crisis. We find that our main inferences remain unchanged.

[14] Banking crises that originated in the banking sector like 1990s credit crunch and recent subprime lending crisis. The market crises that originated outside banking in the financial markets like 1987 stock market crash, 1998 LTCM bailout and early 2000s dot.com bubble and 911 terrorist attacks.

[15] As a robustness check, however, we re-estimated the model using return on equity (ROE) rather than ROA as our profit measure. In addition, we also employ standard deviation of ROA and ROE as another two measures of bank riskiness. We find that the conclusions remain unchanged.

We examined whether a diversified loan portfolio (indicated by a lower *Lending HHI*, lower *CORR*, or less *Contagion*) leads to better returns than a concentrated one. If $a_1 < 0$, $a_2 < 0$, or $a_3 < 0$, diversification appears to be more advantageous than concentration. Otherwise, if $a_1 > 0$, $a_2 > 0$, or $a_3 > 0$, bank returns are higher if they have a concentrated loan portfolio. Our analysis also takes into account the relationship between diversification and risk. Therefore, among other things, we evaluated the bank's risk taking. An increase in concentration increases the bank risk only if $a_1 > 0$, $a_2 > 0$, or $a_3 > 0$.

Based on Corollary 2 and 3, we find that the higher the outer overlap ratio the more information is contained within the intra-portfolio correlation measure. Hence, we argue that where the outer transmission channels have a high overlap ratio, the intra-portfolio correlation is able to quite accurately illustrate the overall dependence structure and explain the degree of portfolio diversification. In order to verify the inference of the model, we further partition our bank loan portfolio into sub-samples with higher outer overlap ratios and lower outer overlap ratios, and carry out analyses to compare the findings between these two groups. Accordingly, we expect the sign of the coefficient a_3 to hold mainly among the group with lower outer overlap ratio.

3.4 Summary Statistics

[INSERT Table 1]

[INSERT Table 2]

Table 1 presents the summary statistics of the variables that we used in our research for the sample period 1987 to 2014. The banks' mean profitability value is approximately 0.929% and the mean ratio of nonperforming loans to total assets is 5.953%. The sample average for the traditional diversification measure (*Lending HHI*) is 0.529. The mean intra-portfolio correlation is 0.555, and the mean of the contagion effect is 0.382. In Table 2, we divide the total sample periods into tranquil and turmoil periods to investigate whether variables are affected by the macro-environment. From column (3) of Table 2, we can observe that the return, *ROA*, in a non-crisis period is superior to that in a crisis period. The risk measure *NPL* increases significantly during a turmoil period. On the other hand, bank loan diversification, as measured by *Lending HHI*, *CORR*, and *Contagion*, is significantly higher under a period of turmoil.

[INSERT Table 3]

Table 3 shows the correlation matrix for these variables. The measures of *Lending HHI*, *CORR*, and *Contagion* are all negatively correlated with bank profitability, and positively correlated with bank risk. These results indicate that a greater degree of diversification in a bank's loan portfolio will improve bank profitability and decrease risk. A bank with a higher equity ratio will have lower profitability and higher risk. We also found that the three measures of portfolio

diversification, HHI (*Lending HHI*), intra-portfolio correlation (*CORR*), and contagion effect (*Contagion*), are not highly correlated with each other. This suggests that, although these three measures are related to some extent, they actually capture different aspects of the extent of diversification of a bank's loan portfolio.

[INSERT Table 4]

Table 4 presents the correlation matrix for *CORR* and *Contagion* under different extent of outer overlap ratio. Notice that the correlation between intra-portfolio correlation and contagion (0.483) is higher in groups with higher outer overlap ratios than in groups with lower outer overlap ratios (0.068). Thus we can predict that if a portfolio has a high outer overlap ratio, its portfolio correlation might contain more information about the linkage between underlying industries and their corresponding outside customers. Therefore, a bank loan portfolio with a low outer overlap ratio might have a significant contagion effect.

4   Empirical Results

In this section, we use multivariate analysis to investigate the effect of loan portfolio diversification on bank return and risk. In the first subsection, we analyze the effect of loan portfolio diversification on bank returns using three different diversification measures. We also verify whether contagion is the major factor that underlies the transmission effect to the portfolio return. In Section 4.2, we investigate whether the degree of the overlap ratio of outer transmission channels will affect the explanatory ability of contagion for the bank return. In Section 4.3 and 4.4, risk measures are substituted for measures of return in order to examine the effects of diversification on risk.

4.1 The Relationship Between Bank Return and Loan Portfolio Diversification

[INSERT Table 5]

Table 5 contains the results of ordinary least-squares regressions examining the effects of diversification on bank return, while controlling for the bank's size, the equity ratio and employee ratio. The dependent variable in all regressions is the *ROA*. The key independent variables of interest are the diversification measures, which include HHI, intra-portfolio correlation and contagion. We next examined whether these effects differ under different market conditions by considering two sample periods, one that is characterized by the absence of crisis referred to as a tranquil period and the other as a turmoil period. In particular, we searched for the existence of correlation asymmetry under a crisis period.

First, from columns (1) and (4) we note that the coefficients of traditional diversification measures (i.e. HHI) are all negatively correlated with bank returns during a tranquil period, showing that this concentration of portfolio assets reduces bank returns. This suggests that uniformly diversifying loan portfolios to include more industries is more profitable than concentrating assets. In column (2), the

coefficients of intra-portfolio correlation are negatively significant at 1%. As we replaced the correlation with contagion in column (3), the estimated coefficients of contagion are negatively significant at the 1% level. With regard to contagion, which indicates the extent of co-movement across the portfolio, column (3) shows that contagion affects banks' returns. Taking all of the diversification measures into account, column (4) shows that the coefficients of these three measures are all negative and significant. The inclusion of the intra-portfolio correlation and contagion in column (4) significantly enhances the explanatory power of equation (25), especially when compared to using HHI as the sole proxy for bank diversification (in column (1)). These results imply that the all three measures of portfolio diversification negatively affect banks' returns.

Next, we restricted the sample period to a crisis period and provide our analyses in columns (5) to (8). In Table 5, columns (5) and (8), the coefficients for HHI are positive, in contrast to the negative coefficients found in columns (1) and (4) for a tranquil period. The results indicate that during turmoil periods, banks experience greater profitability from portfolio concentration than portfolio diversification. In fact, this result is consistent with the work of Acharya, et al. (2006), which suggests that diversification across industries is not necessary beneficial for bank returns, especially for banks facing high downside risk. They also conclude that bank managers have less incentive to monitor their loans during periods of market stress, and might benefit from focusing, rather than diversifying, their bank loan portfolio.

The coefficients of intra-portfolio correlation and contagion are all negative and statistically significant, suggesting that these variables are not dependent on the market environment. In columns (7) and (8), the contagion coefficients for the turmoil period are statically significant at the 1% level, and are even higher than the coefficients during the tranquil period. To summarize, with respect to the structure of a loan portfolio, banks should distribute their funds to an industry with low connection to other industries. Moreover, bank should pay closer attention to asset's potential idiosyncratic transmission channels, especially during a period of turmoil.

4.2 The Role of the Outer Overlap Ratio on Contagion Effect on Bank Return

[INSERT Table 6]

This section is mainly to verify the inference made in the model in Section 2, namely, whether the overlap ratio relevant to the outer transmission channels affects the role of contagion in explaining bank return.

Banks were divided into two groups - higher and lower outer overlap ratio groups, where the outer overlap ratio is above or below 0.5, respectively. Columns (1) and (3) of Table 6, show that when the bank portfolio has high outer overlap ratios, in different sample periods, the intra-portfolio correlation has a significant negative impact on bank return. However, although the contagion coefficients also show

some negative impact, this is not significant. Next, in columns (2) and (4), if the bank portfolio has a low outer overlap ratio, there is evidence of a negative relationship between contagion and return, which is significant. This finding implies that when a loan portfolio has a higher outer overlap ratio, the intra-portfolio correlation measure captures more information about the dependence structure, including information about the transmission channels of underlying industries. Turning to the findings for the sub-sample with lower outer overlap ratios, we find that the contagion effect from transmission channels becomes increasingly important and should not be ignored.

4.3 The Relationship Between Bank Risk and Loan Portfolio Diversification

[INSERT Table 7]

Table 7 presents the results of testing equation (25). The objective of this regression is to evaluate the effect of loan portfolio diversification on bank risk, measured by nonperforming loan to assets ratio. Columns (1) and (4) show that in tranquil periods the HHI is significantly positively related to bank risk. Columns (2) and (3) show the respective effects of intra-portfolio correlation and contagion on bank risk. The effects of both intra-portfolio correlation and contagion on bank risk are positive and statistically significant. In column (4), we take all three measures into consideration simultaneously and the coefficients of these measures are all positive and significant. Thus, for all measures of loan portfolio diversification there is strong evidence to suggest portfolio concentration positively influences bank risk.

Because the sample period is restricted to a crisis period, in columns (5) and (8) of Table 7, the HHI coefficients are negative and significant. This is the opposite of the results we observe from tranquil periods, which suggests that more diversified banks have riskier portfolios. In the case of intra-portfolio correlation, columns (6) and (8), show that the coefficients of intra-portfolio correlation are positive and significant. With respect to the contagion effect, the coefficients in columns (7) and (8) are still economically significant. This implies that the positive relationship between dependence structure and banks' risk is not affected by different market conditions.

These results also imply that during times of turmoil, the correlations within the portfolio structure should be as low as possible. This is especially true for the contagion measure, because as our results imply, bank risk might suffer due to contagion effect across the portfolio. The results also highlight that (if the conventional weight distribution is used as the indicator of portfolio diversification) a higher degree of concentration will more effectively reduce portfolio risk in a turmoil period. Noteworthy, banks load up on industries that have low connection with other industries. This means that banks are more likely to build loan portfolios that are moderately concentrated.

4.4 The Role of Outer Overlap Ratio on Contagion Effect on Bank Risk

[INSERT Table 8]

In Table 8, columns (1) and (3) show that for portfolios with high outer overlap ratios (i.e. *Overlap* ≥0.5), the coefficients of intra-portfolio correlation are both significantly positive in NPL estimations. The coefficients of contagion are positively correlated with risk, but not significant. Columns (2) and (4), demonstrate that when the portfolio has less outer overlapping (i.e., *Overlap* <0.5), the higher the intra-portfolio correlations, and the higher the bank risk. However, compared to the high outer overlap ratio, the coefficients on contagion associated with low outer overlap ratio are positive and are statistically significantly. This supports the inference made earlier in this paper on the correlation coefficients, that is, when the overlap ratio of outer transmission channels is high, most of the information between the underlying industry and its connections to corresponding outside customer industries will be included in the correlation measure. In this case, the role of correlation in diversification will reduce the explanatory power of contagion effect.

It is generally believed that the higher the overlap ratio of outside customers, the more attention should be paid to the extent of the linkage between the outside customer industry and the inside supplier industry. However, the model shows that the higher the outer overlap ratio, the higher the information contained in the correlation measure of the portfolio. In such cases, the intra-portfolio correlation can adequately depict the overall dependence structure and explain the degree of portfolio diversification.

5 Conclusion

The benefits of diversification in a portfolio of securities is a primary tenet of modern portfolio theory. Yet, the tools we used to measure and understand diversification remain imprecise. Investors tend to think "more is better," without paying enough attention to the declining value of diversification. This is especially so when increasing correlations among assets groups diminish the benefits of diversification.

In this paper, characteristics such as exposure weight distribution, intra-portfolio correlation and strength of connection between assets across the border of the portfolio are used to interpret the degree of portfolio diversification and to reexamine the effect of diversification on the return and risk of U.S. banks from 1987 to 2014. Understanding the effects of these three factors enables us to make conclusions about the overall effects of diversification on a bank's profitability and risk.

Based on the proposed model, two hypotheses were developed: 1) According to the position of each underlying secondary sector's corresponding primary sectors which are included in the portfolio or not, we divide the idiosyncratic channels into inner and outer transmission channels, respectively. Furthermore, we suggest that it is important to consider the outer transmission channels as a measurement of portfolio diversification; and 2) The higher the overlap ratio of the outer

transmission channels, the more the relevant information will be contained in the intra-portfolio correlation, thus reducing the explanatory ability of the extent of the connection via outer transmission channels (i.e. the contagion effect).

Given the asymmetric correlations that exist in the market, the role of idiosyncratic transmission channels is particularly important. This paper estimates the extent of idiosyncratic connections using residual correlation to capture the idiosyncratic dependence structure that triggers correlations between assets that are a result of factors beyond the common factors. Particularly when the market is in turmoil, a higher degree of residual correlation implies that the volatility of outside asset values is more likely to affect the performance of the assets inside a portfolio through outer transmission channels.

Our empirical results show that under tranquil period conditions, all diversification measures have a negative effect on the performance of U.S. banks. Thus, when banks build portfolios, they should uniformly distribute their exposure across industries, or choose industries with low correlations to each other to reduce risk and improve return. The contagion effect, which is estimated based on the supply chain, has a significant impact on a bank's performance. However, during a turmoil period we find that banks should focus on certain groups of industries, construct a lower intra-portfolio correlation or select industries which have low levels of connection with their outer corresponding customer industries to improve their performance. Here, the distribution of portfolio exposure is measured by the HHI. Low intra-portfolio correlation reduces the occurrence of co-movement of portfolio. The lower the degree of connection with outer customer industries of an underlying industry, the lower the probability that external shocks will be propagated from the customer industries to the portfolio. This implies that the performance of a portfolio is less likely to be affected by fluctuations in the value of outer industries during crisis. That is to say, during crisis, banks should choose an appropriate concentration strategy rather than focus on selected industries as determined solely by the HHI.

With regard to the transmission channels of the underlying industry, the outer overlap ratio is the key factor that affects the ability of the contagion effect to explain bank performance. Especially when the outer channels are highly overlapping, the intra-portfolio correlation contains most of the outside connection information, and dramatically reduces the importance of the contagion effect. Nevertheless, 72.73% of the bank portfolios are characterized by a zero outer overlap ratio. Therefore, the role of the external connections of the underlying industries cannot be overlooked and it is strongly indicated that when banks build investment portfolios, the effect of outer industries through idiosyncratic transmission channels should not be ignored.

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Table 1: Summary Statistics

Variable	N	Mean	Med.	Std.	Min.	Max.
ROA: Return on assets (%)	6,338	0.929	0.936	1.030	-3.963	6.734
NPL: Nonperforming loans to total assets ratio (%)	6,338	5.953	2.549	1.896	0.000	62.280
Lending HHI	6,338	0.529	0.504	0.119	0.177	1.000
CORR	6,338	0.555	0.599	0.255	-0.562	0.973
Contagion	6,338	0.382	0.187	4.622	-1.683	2.537
Size: Natural log of total assets ($millions)	6,338	11.457	11.389	1.814	6.191	15.108
Equity ratio: Equity to total assets ratio (%)	6,338	8.080	8.080	3.022	0.711	25.522
Employee: Number of employees to total assets ratio (%)	6,338	3.347	3.816	1.657	0.035	5.799

Note. This table shows the summary statistics of the bank performance measures, exposure weight, portfolio correlation, contagion measures, and bank characteristics variables. The loan portfolio sample spans the 1987 to 2014 window, featuring lead arrangers in the syndicated loan market that have available bank characteristics and our key variables. *Lending HHI*, a Herfindahl-Hirschman index, measures the exposure of a bank's loan portfolio. *CORR* indicates the average portfolio correlation by using Pearson correlation for each pair-industry. *Contagion* captures the contagion effect by employing residual correlation for each pair-industry with supplier-customer connections. The definitions of all variables appear in Section 3.

Table 2: Tranquil and Turmoil Period

Variable	Tranquil Period (1) N=4,888	Turmoil Period (2) N=1,450	Difference (2)-(1)
ROA: Return on assets (%)	0.958	0.800	-0.158 ***
NPL: Nonperforming loans to total assets ratio (%)	4.943	6.963	2.029 ***
Lending HHI	0.849	0.861	0.012 *
CORR	0.490	0.619	0.129 ***
Contagion	-0.055	0.819	0.874 ***
Size: Natural log of total assets ($millions)	11.368	11.759	0.391 ***
Equity ratio: Equity to total assets ratio (%)	8.080	8.081	0.001
Employee: Number of employees to total assets ratio (%)	3.279	3.574	0.294 ***

Note. This panel tests for differences in means between the loan portfolio that are from tranquil and turmoil periods. ***, **, * indicate significantly different from zero at the 1%, 5%, and 10% levels, respectively. The definitions and calculations of all variables appear in Section 3.

Table 3: Correlation Coefficients

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	*ROA*	1.000							
(2)	*NPL*	**0.432**	1.000						
(3)	*Lending HHI*	-0.009	**0.042**	1.000					
(4)	*CORR*	-0.072	**0.144**	0.053	1.000				
(5)	*Contagion*	-0.005	0.013	0.005	0.052	1.000			
(6)	*Size*	-0.015	0.002	**-0.086**	**0.173**	0.063	1.000		
(7)	*Equity ratio*	**-0.077**	0.217	**-0.083**	0.000	0.026	**-0.119**	1.000	
(8)	*Employee*	0.003	-0.011	**-0.144**	**0.159**	0.049	**0.455**	**-0.039**	1.000

Note. The table presents Pearson correlation matrix for the bank performance measures, exposure weight, portfolio correlation, contagion measures, and bank characteristics variables. Bold text indicates significance at the 5% level and italic text indicates significance at the 10% level.

Table 4: The Role of Outer Overlap Ratio

Panel A: Lower Outer Overlap Ratio

	Variables	(1)	(2)
(1)	*CORR*	1.000	
(2)	*Contagion*	*0.068*	1.000

Panel B: Higher Outer Overlap Ratio

	Variables	(1)	(2)
(1)	*CORR*	1.000	
(2)	*Contagion*	**0.483**	1.000

Note. The table presents Pearson correlation matrix for the portfolio correlation, and contagion measures. Bold text indicates significant at 5% level and italic text indicates significant at 10% level.

Table 5: Diversification and Bank Return

Independent variables	Tranquil Period				Turmoil Period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lending HHI	-0.081**			-0.044***	0.111**			0.060*
	(-2.03)			(-2.64)	(2.03)			(1.82)
CORR		-0.118***		-0.113*		-0.122***		-0.151*
		(-3.16)		(-1.84)		(-2.38)		(-1.88)
Contagion			-0.105***	-0.111**			-0.240***	-0.309***
			(-3.03)	(-2.58)			(-4.05)	(-3.22)
Size	-0.138	-0.134***	-0.139	-0.133***	-0.148***	-0.123	-0.134**	-0.115
	(-0.79)	(-5.92)	(-0.80)	(-5.97)	(-2.67)	(-1.49)	(-2.42)	(-1.37)
Equity ratio	-2.378	-0.812**	-2.381	-0.889**	-2.433	-0.477	-1.896	-0.020
	(-0.50)	(-2.25)	(-0.49)	(-2.42)	(-1.37)	(-0.25)	(-1.04)	(-0.01)
Employee	0.141	0.148***	0.142	0.147***	0.147***	0.118	0.134***	0.117
	(0.88)	(7.06)	(0.89)	(7.09)	(2.95)	(1.56)	(2.69)	(1.52)
Intercept	1.834	1.123***	1.812	1.134***	1.025*	1.346*	0.787	1.289
	(0.76)	(6.09)	(0.75)	(6.19)	(1.89)	(1.67)	(1.49)	(-0.060)
Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank SIC Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,888	4,888	4,888	4,888	1,450	1,450	1,450	1,450
adj. *R²*	0.017	0.298	0.117	0.511	0.110	0.168	0.183	0.328

Note: This table presents the ordinary least squares regression results on the effect of loan portfolio diversification on bank performance. The loan portfolio sample spans the 1987 to 2014 window, featuring lead arrangers in the syndicated loan market that have available bank characteristics and our key variables. Columns (1) through (4) show the regression results for the tranquil period. Columns (5) through (8) show the regression results for the turmoil period. The dependent variable is the bank profitability (*ROA*). Our key diversification measures are *Lending HHI*, *CORR*, and *Contagion. Lending HHI* measures bank loan exposures by employing a Herfindahl-Hirschman index. *CORR* indicates the average portfolio correlation by using Pearson correlation for each pair-industry. *Contagion* captures the outer transmit channel by measuring a residual correlation for each pair-industry connections. The definitions of all variables and also a description of how they are computed appear in Section 3. All regressions use year-fixed effects and bank-fixed effects. Bank-fixed effect is classified as 2-digit SIC industry. The t-statistics in parentheses are corrected for heteroscedasticity using White's correction. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 6: Overlap Ratio and Bank Return

Independent variables	Tranquil Period		Turmoil Period	
	(1)	(2)	(3)	(4)
	High Outer Overlap Ratio	Low Outer Overlap Ratio	High Outer Overlap Ratio	Low Outer Overlap Ratio
Lending HHI	-0.010*	-0.009*	0.034*	0.029*
	(-1.82)	(-1.89)	(1.77)	(1.88)
CORR	-0.229**	-0.247**	-0.151**	-0.156*
	(-2.27)	(-2.23)	(-2.01)	(-1.82)
Contagion	-0.001	-0.029***	-0.001	-0.039***
	(-0.46)	(-2.88)	(1.05)	(-2.82)
Size	-0.509***	-0.160	-0.080***	-0.062
	(-10.26)	(-0.84)	(-3.22)	(-0.66)
Equity ratio	-2.472***	-1.941	-0.730*	-0.325
	(-3.70)	(-0.80)	(-1.88)	(-0.16)
Employee	0.501***	0.157	0.103***	0.072
	(10.66)	(0.84)	(4.46)	(0.85)
Intercept	4.550***	1.422	0.728***	0.897
	(10.01)	(0.84)	(3.70)	(1.02)
Year Control	Yes	Yes	Yes	Yes
Bank SIC Control	Yes	Yes	Yes	Yes
N	125	4,763	38	1,412
adj. R^2	0.634	0.508	0.497	0.436

Note: This table presents the ordinary least squares regression results on the effect of loan portfolio diversification on bank performance in different overlap levels. The loan portfolio sample spans the 1987 to 2014 window, featuring lead arrangers in the syndicated loan market that have available bank characteristics and our key variables. Columns (1) and (2) show the regression results for the tranquil period. Columns (3) and (4) show the regression results for the turmoil period. We use the level of overlap to proxy for the outer contagion effect. We classify loan portfolio as "higher", and "lower" overlap ratio by median value respectively. The dependent variable is the bank profitability (*ROA*). Our key diversification measures are *Lending HHI*, *CORR*, and *Contagion*. *Lending HHI* measures bank loan exposures by employing a Herfindahl-Hirschman index. *CORR* indicates the average portfolio correlation by using Pearson correlation for each pair-industry. *Contagion* captures the contagion effect by employing residual correlation for each pair-industry with supplier-customer connections. The definitions of all variables and also a description of how they are computed appear in Section 3. All regressions use year-fixed effects and bank-fixed effects. Bank-fixed effect is classified as 2-digit SIC industry. The t-statistics in parentheses are corrected for heteroscedasticity using White's correction. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 7: Diversification and Bank Risk

Independent variables	Dependent variable: *NPL*							
	Tranquil Period				Turmoil Period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lending HHI	0.426***			0.455***	-0.302***			-0.177**
	(3.71)			(4.25)	(3.34)			(-2.10)
CORR		0.204**		0.243***		0.281*		0.210**
		(2.19)		(2.62)		(1.87)		(2.05)
Contagion			0.030***	0.039***			0.044***	0.043**
			(2.61)	(2.67)			(2.92)	(2.37)
Size	0.637*	0.814***	0.671*	0.802***	0.585***	1.060***	0.558***	1.034***
	(1.70)	(6.90)	(1.82)	(6.97)	(3.67)	(5.07)	(3.42)	(4.97)
Equity ratio	25.995***	13.676***	25.846***	12.719***	24.243***	13.277**	22.868***	13.139**
	(2.65)	(6.21)	(2.62)	(5.75)	(5.54)	(2.29)	(5.04)	(2.33)
Employee	-0.524	-0.740***	-0.566	-0.729***	-0.488***	-0.968***	-0.464***	-0.949***
	(-1.45)	(-7.16)	(-1.60)	(-7.18)	(-3.44)	(-5.12)	(-3.19)	(-5.00)
Intercept	-10.317**	-5.914***	-10.073**	-5.984***	-2.734**	-9.180***	-2.073	-9.058***
	(-2.30)	(-6.15)	(-2.24)	(-6.32)	(-1.99)	(-4.53)	(-1.50)	(-4.50)
Year Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank SIC Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4,888	4,888	4,888	4,888	1,450	1,450	1,450	1,450
adj. R^2	0.331	0.455	0.329	0.563	0.306	0.458	0.401	0.558

Note: This table presents the ordinary least squares regression results on the effect of loan portfolio diversification on bank performance. The loan portfolio sample span the 1987 to 2014 window, featuring lead arrangers in the syndicated loan market that have available bank characteristics and our key variables. Columns (1) through (4) show the regression results for the tranquil period. Columns (5) through (8) show the regression results for the turmoil period. The dependent variable is the bank risk (*NPL*). Our key diversification measures are *Lending HHI*, *CORR*, and *Contagion. Lending HHI* measures bank loan exposures by employing a Herfindahl-Hirschman index. *CORR* indicates the average portfolio correlation by using Pearson correlation for each pair-industry. *Contagion* captures the outer transmit channel by measuring a residual correlation for each pair-industry connections. The definitions of all variables and also a description of how they are computed appear in Section 3. All regressions use year-fixed effects and bank-fixed effects. Bank-fixed effect is classified as 2-digit SIC industry. The t-statistics in parentheses are corrected for heteroscedasticity using White's correction. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Table 8: Overlap Ratio and Bank Risk

Independent variables	Dependent variable: *NPL*			
	Tranquil Period		Turmoil Period	
	(1)	(2)	(3)	(4)
	High Overlap Ratio	Low Overlap Ratio	High Overlap Ratio	Low Overlap Ratio
Lending HHI	0.170*	0.425***	-0.137*	-0.053*
	(1.85)	(3.67)	(-1.84)	(-1.91)
CORR	0.267***	0.291***	0.234**	0.143**
	(2.60)	(2.71)	(2.12)	(2.24)
Contagion	0.006	0.055**	0.009	0.065***
	(0.64)	(2.05)	(0.30)	(2.60)
Size	1.054***	0.673***	1.322***	0.914***
	(3.26)	(4.60)	(2.82)	(3.90)
Equity ratio	24.032***	10.554***	26.964**	12.209**
	(5.28)	(3.93)	(2.71)	(2.02)
Employee	-0.740**	-0.655***	-0.991**	-0.867***
	(-2.35)	(-5.04)	(-2.16)	(-4.17)
Intercept	-11.332***	-4.920***	-13.181***	-7.830***
	(-3.85)	(-4.49)	(-3.00)	(-3.67)
Year Control	Yes	Yes	Yes	Yes
Bank SIC Control	Yes	Yes	Yes	Yes
N	125	4,763	38	1,412
adj. R^2	0.719	0.497	0.722	0.436

Note: This table presents the ordinary least squares regression results on the effect of loan portfolio diversification on bank performance in different overlap levels. The loan portfolio sample span the 1987 to 2014 window, featuring lead arrangers in the syndicated loan market that have available bank characteristics and our key variables. Columns (1) and (2) show the regression results for the tranquil period. Columns (3) and (4) show the regression results for the turmoil period. We use the level of overlap to proxy for the outer contagion effect. We classify loan portfolio as "higher", and "lower" overlap ratio by median value respectively. The dependent variable is the bank risk (*NPL*). Our key diversification measures are *Lending HHI*, *CORR*, and *Contagion*. *Lending HHI* measures bank loan exposures by employing a Herfindahl-Hirschman index. *CORR* indicates the average portfolio correlation by using Pearson correlation for each pair-industry. *Contagion* captures the contagion effect by employing a residual correlation for each pair-industry with supplier-customer connections. The definitions of all variables and also a description of how they are computed appear in Section 3. All regressions use year-fixed effects and bank-fixed effects. Bank-fixed effect is classified as 2-digit SIC industry. The t-statistics in parentheses are corrected for heteroscedasticity using White's correction. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Appendix A: Proof of Proposition 1

(1) If sector i and sector $j \in$ primary sector, then each sector return can be presented as:

$$r_i = \sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_i + \sqrt{(1-\rho)(1-\theta)}\varepsilon_i$$

$$r_j = \sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_j + \sqrt{(1-\rho)(1-\theta)}\varepsilon_j$$

Then the correlation coefficient between r_i and r_j can be written as:

$$Corr(r_i, r_j) = \frac{Cov(r_i, r_j)}{\sqrt{Var(r_i)}\sqrt{Var(r_j)}}$$

$$= Cov\left(\sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_i + \sqrt{(1-\rho)(1-\theta)}\varepsilon_i, \sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_j\right.$$
$$\left. + \sqrt{(1-\rho)(1-\theta)}\varepsilon_j\right)$$

$$= \rho \qquad\qquad\qquad\qquad (A1)$$

where

$$Var(r_i) = Var\left(\sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_i + \sqrt{(1-\rho)(1-\theta)}\varepsilon_i\right) = 1 = Var(r_j)$$

(2) If sector $i \in$ primary sector and sector $j \in$ secondary sector, then each sector return can be presented as:

$$r_i = \sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_i + \sqrt{(1-\rho)(1-\theta)}\varepsilon_i$$

$$r_j = \sqrt{\rho}M + \sqrt{(1-\rho)\alpha}\left(\sum_{l=1}^{n'}\omega_{jl}\delta_{jl}\eta_l + \sum_{l'=\left(\bar{n}'_{j-1}+1\right)}^{\bar{n}'_j}\omega_{jl'}\delta_{jl'}\eta_{l'} + \sum_{k=(n+1)}^{(n+m')}\omega_{jk}\delta_{jk}\eta_k\right.$$
$$\left. + \sum_{k'=\left(\bar{m}'_{j-1}+1\right)}^{\bar{m}'_j}\omega_{jk'}\delta_{jk'}\eta_{k'}\right) + \sqrt{(1-\rho)(1-\alpha)}\varepsilon_j$$

where

$$\bar{n}'_j = n' + \sum_{i=n_1+1}^{j} n'_i$$

$$\bar{m}'_j = n + m' + \sum_{i=n_1+1}^{j} m'_i$$

where n' and m' are the number of overlap primary sectors within and across the portfolio, respectively. As for the number of n'_j and m'_j are the non-overlap primary sectors, which sector j invest within and across the portfolio, respectively.

For simplicity, we assume that each secondary sector has the same number

of primary sector within portfolio and across the portfolio and uniformly exposed to each primary sector. Namely, the number of primary sectors and relative exposure to each sector can be written as:

$$\bar{n} = n' + n'_j$$

$$\bar{m} = m' + m'_j$$

$$\omega_{jl} = \omega_{jl'} = \omega_{jk} = \omega_{jk'} = \frac{1}{\bar{n} + \bar{m}}$$

We further assume that sector j's primary sensitive to inner and outer primary sector l-specific shock is δ_I and δ_O, respectively.

Then the covariance of r_i and r_j is :

$$Cov(r_i, r_j) = \begin{cases} \rho + (1 - \rho)\sqrt{\alpha\theta}\left(\dfrac{1}{\bar{n} + \bar{m}}\right)\delta_I, & \text{for } i = 1, \cdots, n', \bar{n}'_{j-1} + 1, \cdots, \bar{n}'_j \\ \rho & , \text{otherwise} \end{cases}$$

The variance of r_i and r_j can be calculated as :

$$Var(r_i) = Var\left(\sqrt{\rho}M + \sqrt{(1-\rho)\theta}\eta_i + \sqrt{(1-\rho)(1-\theta)}\varepsilon_i\right) = 1$$

$$Var(r_j) = \rho + (1 - \rho)\alpha\left[n'\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_I^2 + (\bar{n} - n')\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_I^2 + m'\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_O^2\right.$$

$$\left. + (\bar{m} - m')\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_O^2\right] + (1 - \rho)(1 - \alpha)$$

$$= 1 + (1 - \rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_O^2 - 1\right]$$

Then

$$Corr(r_i, r_j)$$

$$= \begin{cases} \dfrac{\rho + (1 - \rho)\sqrt{\alpha\theta}\left(\frac{1}{\bar{n} + \bar{m}}\right)\delta_I}{\sqrt{1 + (1 - \rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_O^2 - 1\right]}}, & \text{for } i = \begin{matrix} 1, \cdots, n' \\ \bar{n}'_{j-1} + 1, \cdots, \bar{n}'_j \end{matrix} \\[30pt] \dfrac{\rho}{\sqrt{1 + (1 - \rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n} + \bar{m}}\right)^2\delta_O^2 - 1\right]}}, & \text{otherwise} \end{cases} \quad (A2)$$

(3) If sector i and sector $j \in$ secondary sector, t the correlation between r_i and r_j can be presented as:

$$Corr(r_i, r_j) = \frac{Cov(r_i, r_j)}{\sqrt{Var(r_i)}\sqrt{Var(r_j)}}$$

where

$$Var(r_i) = Var(r_j) = 1 + (1-\rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]$$

$$Cov(r_i, r_j) = \rho + (1-\rho)\alpha\left[n'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + m'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2\right]$$

Then,

$$Corr(r_i, r_j) = \frac{\rho + (1-\rho)\alpha\left[n'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + m'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2\right]}{1 + (1-\rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]} \qquad (A3)$$

Appendix B: Proof of Corollary 1

Let r_i denote return of sector i, and ω_i is the relative exposure of the bank to sector i in the total portfolio. The variance of the portfolio can be written as:

$$Var[r_p] = Var\left[\sum_{i=1}^{n}\omega_i r_i\right] = \sum_{i=1}^{n}\omega_i^2 Var[r_i] + \sum_{i}\sum_{\substack{j \\ i \neq j}}\omega_i\omega_j Cov(r_i, r_j) \qquad (B1)$$

To simplify analysis, we assume that each sector has exactly the same principal with standardize to 1, so that each sector has portfolio share of $1/n$.

(1) If sector i and sector $j \in$ primary sectors, then the portfolio-weighted pairwise covariance is given by:

$$\sum_{i}\sum_{\substack{j \\ i \neq j}}\omega_i\omega_j Cov(r_i, r_j) = \left(\frac{1}{n}\right)^2 n_1(n_1 - 1)\rho$$

(2) If sector $i \in$ primary sector and sector $j \in$ secondary sector, then the portfolio-weighted pairwise covariance is given by:

$$\sum_{i}\sum_{\substack{j \\ i \neq j}}\omega_i\omega_j Cov(r_i, r_j) = \left(\frac{1}{n}\right)^2 2n_2\sigma_s[\bar{n}\rho_1' + (n_1 - \bar{n})\rho_2']$$

where σ_s is the standard deviation of secondary sector.

$$\sigma_s = \sqrt{1 + (1-\rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]}$$

$$\rho_1' = \frac{\rho + (1-\rho)\sqrt{\alpha\theta}\left(\frac{1}{\bar{n}+\bar{m}}\right)\delta_I}{\sqrt{1 + (1-\rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]}}, \text{ for } i = \begin{matrix} 1,\cdots,n' \\ \bar{n}_{j-1}' + 1,\cdots,\bar{n}_j' \end{matrix}$$

$$\rho_2' = \frac{\rho}{\sqrt{1 + (1-\rho)\alpha\left[\bar{n}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_I^2 + \bar{m}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2\delta_O^2 - 1\right]}}, \text{ for } i \neq \begin{matrix} 1,\cdots,n' \\ \bar{n}_{j-1}' + 1,\cdots,\bar{n}_j' \end{matrix}$$

(3) If sector i and sector $j \in$ secondary sectors, then the portfolio-weighted pairwise covariance is given by:

$$\sum_{\substack{i \\ i \neq j}}\sum_j \omega_i\omega_j Cov(r_i, r_j) = \left(\frac{1}{n}\right)^2 n_2(n_2 - 1)\sigma_s^2\rho''$$

where σ_s is the standard deviation of secondary sector. Then the return dispersion of the portfolio is given by

$$Var[r_p] = \left(\frac{1}{n}\right)^2 n_1 + \left(\frac{1}{n}\right)^2 n_2\sigma_s^2 + \left(\frac{1}{n}\right)^2 n_1(n_1 - 1)\rho + \left(\frac{1}{n}\right)^2 2n_2\sigma_s[\bar{n}\rho_1' + (n_1 - \bar{n})\rho_2']$$
$$+ \left(\frac{1}{n}\right)^2 n_2(n_2 - 1)\sigma_s^2\rho''$$

$$= \left(\frac{1}{n}\right)^2 \{n_1 + n_2\sigma_s^2 + n_1(n_1 - 1)\rho + 2n_2\sigma_s[\bar{n}\rho_1' + (n_1 - \bar{n})\rho_2']$$
$$+ n_2(n_2 - 1)\sigma_s^2\rho''\} \tag{B2}$$

Appendix C.1: Proof of Proposition 2

(1) If sector i and sector $j \in$ primary sector, then the first-order derivative of the correlation coefficient with respect to strength of outer connection is

$$\frac{\partial Corr(r_i, r_j)}{\partial \delta_O} = \frac{\partial \rho}{\partial \delta_O} = 0 \tag{C1}$$

(2) If sector $i \in$ primary sector and sector $j \in$ secondary sector, then the first-order derivative of the correlation coefficient with respect to strength of outer connection is

$$\frac{\partial \rho'}{\partial \delta_O} = \left[\frac{\frac{\partial Cov(r_i, r_j)}{\partial \delta_O} \sqrt{Var(r_j)} - \frac{\partial \sqrt{Var(r_j)}}{\partial \delta_O} Cov(r_i, r_j)}{Var(r_j)} \right]$$

$$= \begin{cases} \dfrac{-\left\{ \left[\dfrac{1}{\sqrt{Var(r_j)}} (1-\rho)\alpha\bar{m} \left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O \right] \left[\rho + (1-\rho)\sqrt{\alpha\theta} \left(\dfrac{1}{\bar{n}+\bar{m}}\right) \delta_I \right] \right\}}{Var(r_j)}, & \text{for } i = \begin{matrix} 1, \cdots, n' \\ \bar{n}'_{j-1} + 1, \cdots, \bar{n}'_j \end{matrix} \\[4em] \dfrac{-\left\{ \left[\dfrac{1}{\sqrt{Var(r_j)}} (1-\rho)\alpha\bar{m} \left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O \right] \rho \right\}}{Var(r_j)}, & \text{, otherwise} \end{cases}$$

$$< 0 \qquad\qquad (C2)$$

(3) If sector i and sector $j \in$ secondary sectors, then the first-order derivative of the correlation coefficient with respect to strength of outer connection is

$$\frac{\partial \rho''}{\partial \delta_O} = \frac{\left[2(1-\rho)\alpha \left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O \right] \left[m' Var(r_i) - \bar{m} Cov(r_i, r_j) \right]}{Var(r_i)^2}$$

$$= \frac{\left[2(1-\rho)\alpha \left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O \right] \left\{ m'[1-(1-\rho)\alpha] - \bar{m}\rho + (m'\bar{n} - \bar{m}n')(1-\rho)\alpha \left(\dfrac{1}{\bar{n}+\bar{m}}\right)^2 \delta_I^2 \right\}}{Var(r_i)^2}$$

$$\begin{matrix} < \\ = 0 \\ > \end{matrix} \qquad\qquad (C3)$$

Appendix C.2: Proof of Corollary 3

(1) The partial derivative of the return dispersion of the portfolio with respect to strength of outer connection is:

$$\frac{\partial Var[r_p]}{\partial \delta_O} = \sum_{i=1}^{n} \omega_i^2 \frac{\partial Var[r_i]}{\partial \delta_O} + \sum_{\substack{i=1 \\ i \neq j}}^{n} \sum_{j=1}^{n} \omega_i \omega_j \frac{\partial Cov(r_i, r_j)}{\partial \delta_O}$$

where

$$\frac{\partial Var[r_i]}{\partial \delta_O} = \begin{cases} 0 & , \text{for } i \in \text{primary sector} \\ 2(1-\rho)\alpha\bar{m}\left(\frac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O \geq 0 & , \text{for } i \in \text{secondary sector} \end{cases}$$

a. If sector i and sector $j \in$ primary sectors, the partial derivative of the covariance of r_i and r_j with respect to strength of outer connection is:

$$\frac{\partial Cov(r_i, r_j)}{\partial \delta_O} = \frac{\partial \rho}{\partial \delta_O} = 0$$

b. If sector $i \in$ primary sector and sector $j \in$ secondary sector, the partial derivative of the covariance of r_i and r_j with respect to strength of outer connection is:

$$\frac{\partial Cov(r_i, r_j)}{\partial \delta_O} = \begin{cases} \dfrac{\partial\left[\rho + (1-\rho)\sqrt{\alpha\theta}\left(\frac{1}{\bar{n}+\bar{m}}\right)\delta_I\right]}{\partial \delta_O} = 0, & \text{for } i = \begin{matrix} 1, \cdots, n' \\ \bar{n}'_{j-1}+1, \cdots, \bar{n}'_j \end{matrix} \\ \dfrac{\partial \rho}{\partial \delta_O} = 0 & , \text{ otherwise} \end{cases}$$

c. If sector i and sector $j \in$ secondary sectors, the partial derivative of the covariance of r_i and r_j with respect to strength of outer connection is:

$$\frac{\partial Cov(r_i, r_j)}{\partial \delta_O} = \frac{\partial\left\{\rho + (1-\rho)\alpha\left[n'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2 {\delta_I}^2 + m'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2 {\delta_O}^2\right]\right\}}{\partial \delta_O}$$

$$= 2(1-\rho)\alpha m'\left(\frac{1}{\bar{n}+\bar{m}}\right)^2 \delta_O \geq 0$$

Based on these results, we can derivative

$$\frac{\partial Var[r_p]}{\partial \delta_O} = \sum_{i=1}^n \omega_i^2 \frac{\partial Var[r_i]}{\partial \delta_O} + \sum_{\substack{i=1 \\ i \neq j}}^n \sum_{j=1}^n \omega_i \omega_j \frac{\partial Cov(r_i, r_j)}{\partial \delta_O} \geq 0 \qquad (C6)$$

(2) The partial derivative of the average correlation of the portfolio with respect to strength of outer connection is:

$$\frac{\partial \bar{\rho}}{\partial \delta_O} = \frac{2}{n(n-1)}\left[\frac{n_1(n_1-1)}{2}\frac{\partial \rho}{\partial \delta_O} + n_2\bar{n}\frac{\partial \rho_1'}{\partial \delta_O} + n_2(n_1-\bar{n})\frac{\partial \rho_2'}{\partial \delta_O} + \frac{n_1(n_1-1)}{2}\frac{\partial \rho''}{\partial \delta_O}\right] \begin{matrix} < \\ =0 \\ > \end{matrix}$$

$$(C7)$$

The average correlation of the portfolio is defined as:

$$\bar{\rho} = \frac{1}{w} \sum_{i}^{n} \sum_{j>i} Corr(r_i, r_j)$$

where w is the number of sector pairs with the portfolio.

$$\bar{\rho} = \frac{2}{n(n-1)} \left[\frac{n_1(n_1-1)}{2} \rho + n_2 \bar{n} \rho_1' + n_2(n_1 - \bar{n}) \rho_2' + \frac{n_1(n_1-1)}{2} \rho'' \right]$$