

STOCK RETURN CO-MOVEMENT AND SYSTEMIC RISK IN THE TURKISH BANKING SYSTEM

Mahir Binici, Bülent Köksal, and Cüneyt Orman*

ABSTRACT This paper investigates the evolution of systemic risk in the Turkish banking sector over the past two decades using co-movement of banks' stock returns as a systemic risk indicator. In addition, we explore possible determinants of systemic risk, the knowledge of which can be a useful input into effective macroprudential policymaking. Results show that the correlations between bank stock returns almost doubled in 2000s in comparison to 1990s. The correlations decreased somewhat after 2002 and increased again after the 2007-2009 financial crisis. Main determinants of systemic risk appear to be the market share of bank pairs, the amount of non-performing loans, herding behavior of banks, and volatilities of macro variables including the exchange rate, US T-bills, EMBI+, VIX, and MSCI emerging markets index.

JEL C22, C58, G21, G32

Keywords Stock returns, Co-movement, Systemic risk, Turkish Banking System

ÖZ Bu çalışmada sistemik risk göstergesi olarak bankaların hisse senedi getirilerinin birlikte hareketi kullanılarak son yirmi yılda Türk bankacılık sektöründe sistemik riskin gelişimi incelenmiştir. Buna ek olarak, etkin makro ihtiyati politika geliştirmeye katkı sağlamak amacıyla sistemik riskin muhtemel belirleyicileri de araştırılmıştır. Bulgular banka hisse senedi getirileri arasındaki korelasyonların 1990'lara kıyasla 2000'li yıllarda neredeyse iki katına çıktığını göstermektedir. Korelasyonlar 2002 yılından sonra bir miktar azalmış, 2007-2009 finansal krizinden sonra ise tekrar artmıştır. Sistemik riskin ana belirleyicilerinin banka çiftlerinin pazar payları, takipteki kredilerin tutarı, bankaların sürü davranışı ve döviz kuru, ABD hazine bonusu, EMBI+, VIX ve MSCI gelişmekte olan piyasa endeksi gibi makro değişkenlerin oynaklıkları olduğu görülmektedir.

TÜRK BANKACILIK SİSTEMİNDE HİSSE SENETLERİNİN BİRLİKTE HAREKETİ VE SİSTEMİK RİSK

JEL C22, C58, G21, G32

Anahtar Kelimeler Hisse senedi getirisi, Birlikte hareket, Sistemik risk, Türk Bankacılık Sistemi

* **BİNİCİ:** Central Bank of the Republic of Turkey, Banking and Financial Institutions Department, Ulus, 06100 Ankara, Turkey, mahir.binici@tcmb.gov.tr ■ **KÖKSAL:** İpek University, Department of Economics, 06550 Çankaya, Ankara, Turkey, bkoksal@gmail.com ■ **ORMAN:** Central Bank of the Republic of Turkey, Communications and Foreign Relations Department, Ulus, 06100 Ankara, Turkey, cuneyt.orman@tcmb.gov.tr ■ The views expressed in this paper belong to the authors only and do not represent those of the Central Bank of the Republic of Turkey or its staff.

1. Introduction

The financial crisis of 2007-2009 has resulted in widespread failures of financial institutions and freezing up of capital markets, with significant effects on the real economy in both developed and emerging economies. It appears that a full recovery is still underway. The crisis has also demonstrated how interconnected financial institutions and markets are, both within and across countries, with a shock to one financial institution or market spreading rapidly to others, thereby threatening the stability of the whole system. The crisis therefore underscored the relevance of systemic risk, renewed the interest in its measurement, and urged a need for putting in place macroprudential policies to mitigate such risk in financial markets.

Recent research on systemic risk has addressed the issue from various angles which includes defining fine approaches to measure systemic contributions, building sound indicators for systemic risk potential, and identifying systemically important institutions. From policy making perspective, the design of macroprudential policies and regulation to mitigate systemic risk has also been at the center of the discussions by international organizations and financial authorities. For instance, Basel Committee on Bank Supervision (BCBS) and the Financial Stability Board (FSB) have identified global systemically important banks and are currently considering policy options to deal with such institutions. Similarly, the Dodd-Frank Act has also created an institutional structure to identify and oversee systemically important banks that could pose a threat to the US financial system.

From a theoretical perspective, as discussed in Acharya (2009) and Billio et al. (2010), there is a consensus that the likelihood of a major financial disruption depends on the degree of correlation among the assets of financial institutions. Additionally, the sensitivity of such assets to the changes in market prices, and domestic and external macroeconomic conditions, and their concentration on particular sectors or industries are possibly the other sources to which financial shocks could be related to.¹ Thus, several approaches have been proposed by the most recent studies to measure financial linkages and systemic risk contributions such as conditional value-at-risk (CoVaR) measure of Adrian and Brunnermeier (2011), marginal expected shortfall (MES) of Acharya et al. (2010), distressed insurance

¹ For further discussion and references, see Billio et al. (2010).

premium (DIP) of Huang et al. (2011) and systemic risk measure (SRISK) of Brownlees and Engle (2011).

The common approach in these studies is to document the impact of a firm's total loss on the financial system given that system is under distress. While the main focus, and hence the advantage of these approaches is to provide a quantitative measure of systemic risk exposure, they do not offer a historical perspective on how the systemic risk has evolved for the financial institutions under question. Thus, in this paper we follow the broad contagion/spillover literature which focuses on co-movement/correlation of various indicators of financial institutions and their implication for the systemic event of distress.

There is a vast literature on measuring and explaining stock return co-movement of both domestic and international financial institutions. The earlier studies on co-movement could be classified under the literature on contagion and spillover. For instance, Karolyi and Stulz (2002) and Dungey et al. (2005), among others, provide an extensive review of the earlier studies on contagion and stock return co-movement. Instead of reviewing this vast literature, we only provide a brief summary of the few papers that are most closely related to our study. Among those, De Nicolo and Kwast (2002) look at cross-correlations of weekly stock returns of a sample of large and complex banking organizations (LCBO) in the US over 1988-1999. To detect time variation in correlations, they estimate a bi-variate GARCH constant conditional correlation model introduced by Bollerslev (1990) with time trend in conditional variances and a correlation equation for each pair of 22 firms in their sample. Using a 52-week rolling window, they find a significant positive trend in stock return correlations, indicating an increase in systemic risk in the financial sector over the period of their analysis.²

Patro et al. (2012), in a closely related paper to ours, examine stock return correlations and default correlations among bank holding companies and investment banks as an indicator of systemic risk. Using daily stock returns data for the 22 largest banks in the US from 1988 to 2008, they find an increasing trend in the stock return correlations among banks, suggesting an increase in systemic risk. Disaggregating stock returns into systematic and idiosyncratic components, they also find that the increasing trend in correlations is largely driven by the increases in correlations between banks' idiosyncratic risks. They also show that this is true even though banks' individual risks have been declining during that period. They interpret these

² Longin and Solnik (1995) use the same model to study the correlation of monthly excess returns for seven major countries over the period 1960-90. Using an explicit model for the conditional correlation, they find increasing correlations between international markets over thirty years.

findings as a supportive evidence for the use of stock return correlations as a measure of systemic risk.

Following De Nicolo and Kwast (2002) and Patro et al. (2012), we calculate bi-variate correlations of bank equity returns on a rolling basis to evaluate how systemic risk has evolved in the Turkish banking system over 1990-2011. Then, we provide some evidence on the potential factors that drive the pattern of this evolution. The main contribution of this paper is therefore twofold: First, we use data from Turkish banking industry to provide some perspective on systemic risk by examining the relevance of stock return correlations as an indicator of systemic risk. We believe that extending previously tested models of advanced countries to a specific case of an emerging economy is worthwhile since the structure of the financial market and price dynamics could vary due to both differing domestic and external factors specific to emerging economies.

Second, we investigate to what extent various factors, including bank-specific, country-specific and external ones, account for the co-movement of bank stock returns, and hence explain systemic risk. It is important to emphasize that our analysis sheds light on the evolution of systemic risk in the Turkish banking industry using a long span of data that covers various systemic events driven completely by domestic policies, such as the crisis of 1994, 2000-2001, and by external shocks such as East Asian crisis, and the crisis following the US sub-prime market collapse.

Our results show that there has been an increase in inter-dependency in Turkish banking system over the past two decades, signaling an increase in the potential for a shock to become systemic. Our results also suggest that market share, in particular, is an important determinant of co-movement among bank stock returns. Furthermore, non-performing loans and herding behavior also seem to be important bank- and industry-specific determinants of inter-dependency.

We also find that both domestic and external factors play important role in driving bank inter-dependency. In particular, the exchange rate volatility as an indicator of domestic financial and economic conditions is a significant contributing factor to the return correlations. Similarly, the external market conditions as proxied by the volatilities of macro variables including US T-bills, EMBI+, VIX, and MSCI emerging markets index all have significant positive effects on domestic bank stock return correlations.

The remainder of this paper is as follows. Section 2 provides an overview of literature on co-movement/inter-dependency and its sources. Section 3 describes the dataset. Section 4 documents the co-movement of stock returns

and discusses the related models. Section 5 provides a discussion on the drivers of inter-dependency. Section 6 concludes the paper.

2. General Overview of Co-movement and Its Sources

In this study, we measure total inter-dependencies by stock return correlations, and use these correlations as indicators of systemic risk since an increase in stock return correlations possibly signal an increase in the potential for a shock to become systemic. In this context, stock return correlations are relevant because stock prices measure banks' overall performance by reflecting market participants' collective evaluation of future prospects of the firm and its interactions with other institutions. In other words, stock prices reflect investors' perception about a firm's future profitability, thus its potential income, debt and leverage structure, and interaction with the overall system. The forward looking information embedded in banks' stock prices and their movements gives policy makers some direction on determining how systemic risk evolves, and guides them to undertake proactive measures to contain such risk.

Among various measures of inter-dependency, asset and stock return correlations have been used as an indicator of systemic risk by Lo (2008), Acharya (2009), Goodhart and Wagner (2012), Patro et al. (2012), among others. Acharya (2009) theoretically shows that asset correlations are relevant in modeling systemic risk because banks prefer correlated investments which give rise to an inefficiently high correlation of asset returns, resulting in systemic or aggregate risk. On the other hand, Lo (2008) argues that given the complexity of the global financial system, it is necessary to consider a collection of measures, which should be designed to capture different aspects of risk exposure. Thus, among several measures including leverage, liquidity and concentration, he also proposes correlation as a quantitative measure of systemic risk to be followed so that the overall level of risk to the financial system is monitored and managed.

As a proposal for a pro-diversity regulation, Goodhart and Wagner (2012) argue that financial institutions should be subject to capital requirements that are conditioned on how correlated their overall activities are with the rest of the financial system. To measure such correlations, they suggest using correlation of share prices with a corresponding banking sector index, since, as they argue, share prices are forward-looking and their correlations have the appeal that they incorporate information in a timely manner.

Patro et al. (2012), as discussed above, is one of the recent studies that also use stock return correlations and default correlations among commercial and investment banks to address the evolution of systemic risk in the US banking system. They argue that the stock return correlation is a simple,

robust, forward-looking, and timely systemic risk indicator. In addition, compared to other potential systemic risk indicators, stock return correlations have the additional advantage that they are robust and not subject to model errors or data limitations.

While stock return correlations are now widely used in the literature as an indicator of systemic risk, the factors that drive such correlations have been not been addressed and empirically investigated to the same extent. De Nicolo and Kwast (2002) classify the sources of inter-dependencies among financial institutions as direct or indirect ones, and hypothesize that the size of financial institutions' total inter-dependencies with other financial institutions is the determinant of how a shock to an institution would propagate across the system to trigger a systemic crisis.

De Nicolo and Kwast (2002) argue that inter-firm on- and off-balance sheet exposures including exposures arising from inter-bank loans from overnight market or repo transactions and counter party credit exposure on derivative markets account for the direct inter-dependencies among financial institutions. As for the indirect measures, the inter-dependencies could arise from exposure to the same or similar assets such as loan concentrations to the same industry and highly correlated portfolios. The choice of industries by different banks which determines the correlation of banks' portfolio returns, and the concentration in the same industries is also the underlying factor that causes systemic risk in the model introduced by Acharya (2009). He argues that more complex patterns in inter-bank loans, derivatives and other transactions is what determines the joint failure of banks that propagates systemic risk.

Other factors potentially influencing inter-dependency and impacting systemic risk addressed in the literature include inter-bank lending as in Rochet and Tirole (1996), financial system consolidation as in De Nicolo and Kwast (2002) and VaR induced herding behavior in bank trading patterns as in Jorion (2007). As discussed in the next section, we include each of these factors in various specifications of our models in order to examine the extent to which they account for the correlation of stock returns. We believe that this is the main contribution of our paper to the extant literature on the linkages between co-movement and systemic risk.

3. Data

We use daily stock price data of the 17 banks listed on the Istanbul Stock Exchange (ISE). Table 1 lists the 17 banks included in our analysis that has commercial banks, participation banks, and investment banks. Thus, our analysis includes all ISE-listed banks which vary across business models, size, and ownership types. The sample size is different for each bank since

the date since when a particular share is traded on the ISE changes for each institution. However, the broad sample covers the period 01:1990-07:2011. The total assets of banks listed on the ISE and included in our sample account for approximately 76% of the Turkish banking system as of September 2011. Some of these banks, such as İş Bankası, Garanti, Halk, and Akbank, are among the largest and potentially the most interconnected ones, and hence are most likely to be the sources of significant events that might trigger systemic risk in the banking industry. However, as discussed in the IMF (2009) study on systemically important institutions, large balance sheets are not necessarily the only reason for systemic importance; rather the level of interconnectedness of an institution can also be an important factor contributing to the systemic importance of an institution.

Table 1. Banks' Asset Size and Market Share

Bank (Ticker) (Bank type)	Total Assets (Million TL)	% share of assets in ISE banks	% share of assets in banking sector
T. İş Bankası (ISCTR) (D)	160.005	17,59	13,35
T.Garanti Bankası (GARAN) (D)	148.644	16,34	12,40
Akbank (AKBNK) (D)	132.975	14,62	11,10
Yapı ve Kredi Bankası (YKBANK) (D)	106.369	11,69	8,88
T. Halk Bankası (HALKB) (D-S)	90.714	9,97	7,57
T. Vakıflar Bankası (VAKBN) (D-S)	89.255	9,81	7,45
Finans Bank (FINBN) (D)	47.354	5,21	3,95
Türk Ekonomi Bankası (TEBANK) (D)	40.008	4,40	3,34
Denizbank (DENIZ) (D)	37.421	4,11	3,12
Şekerbank (SKBNK) (D)	14.988	1,65	1,25
Bank Asya (ASYAB) (P)	13.241	1,46	1,10
T.Sinai Kalkınma Bankası (TSKB) (I)	9.184	1,01	0,77
Albaraka Türk (ALBRK) (P)	7.672	0,84	0,64
Alternatif Bank (ALNTF) (D)	6.192	0,68	0,52
Tekstil Bankası (TEKST) (D)	3.199	0,35	0,27
T. Kalkınma Bankası (KLNMA) (I)	2.557	0,28	0,21
<i>ISE listed bank total</i>	<i>909.777</i>		<i>75,91</i>
<i>Banking sector total</i>	<i>1.198.441</i>		

Note: Balance sheet data for commercial and investment banks are as of September 2011 and for participation banks are as of Sept. 2010. Disbank and later Fortis Bank is also included in our analysis, but due its merger with the TEBNK at the beginning of February 2011, its balance sheet data is not reported. For bank type, "D", "D-S", "I" and "P" stands for deposit banks, deposit-state owned banks, investment banks and participation banks, respectively.

Source: The Banks Association of Turkey and Participation Banks Association of Turkey.

We calculate banks' stock returns by using daily closing prices as $100 * (\log(p_t) - \log(p_{t-1}))$ which are adjusted for dividend payments and changes in capitalization. Table 2 reports the summary statistics and pairwise correlations of banks' daily equity returns. The table displays large heterogeneity in terms of sample size, volatility of stock returns, and correlation of stock returns both within and between bank-groups. For

instance, stock return correlations among large banks³ are notably larger, overall, than the correlation of their stock returns with those of smaller ones. Similarly, the correlations of returns between small banks are also smaller. This correlation pattern by itself suggests that the size of financial institutions is a factor that explains, to a large extent, the sources of inter-dependencies among them, which is in line with the view that financial consolidation is a driving factor of systemic risk as in De Nicolo and Kwast (2002).

Table 2. Basic Statistics and Correlation Matrix of Banks' Stock Returns

Bank	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
MEAN	0.16	0.00	0.04	0.04	0.12	0.18	0.17	0.19	0.05	0.09	0.07	0.10	0.07	0.10	0.18	0.03	0.20
STD	3.77	2.17	4.50	2.82	3.39	3.81	4.12	4.06	3.11	3.46	4.35	3.45	3.42	4.73	4.33	2.88	4.61
N	5223	1011	3992	1298	1702	5336	5088	5253	1048	3284	3649	2248	2844	4508	5441	1417	5488
(1) AKBNK	1.00																
(2) ALBRK	0.48	1.00															
(3) ALNTF	0.38	0.47	1.00														
(4) ASYAB	0.55	0.59	0.46	1.00													
(5) DENIZ	0.29	0.20	0.31	0.23	1.00												
(6) FINBN	0.37	0.23	0.43	0.24	0.42	1.00											
(7) FORTS	0.41	0.46	0.43	0.48	0.27	0.46	1.00										
(8) GARAN	0.50	0.50	0.44	0.60	0.29	0.46	0.46	1.00									
(9) HALKB	0.69	0.50	0.54	0.58	0.28	0.30	0.53	0.74	1.00								
(10) ISCTR	0.75	0.53	0.46	0.60	0.33	0.55	0.61	0.74	0.73	1.00							
(11) KLNMA	0.39	0.31	0.34	0.36	0.23	0.37	0.41	0.40	0.34	0.43	1.00						
(12) SKBNK	0.47	0.51	0.47	0.49	0.28	0.38	0.45	0.53	0.62	0.54	0.34	1.00					
(13) TEBNK	0.54	0.45	0.41	0.53	0.27	0.43	0.55	0.56	0.61	0.54	0.41	0.44	1.00				
(14) TEKST	0.34	0.45	0.41	0.51	0.32	0.38	0.43	0.37	0.56	0.46	0.34	0.46	0.39	1.00			
(15) TSKB	0.32	0.49	0.37	0.53	0.27	0.32	0.37	0.36	0.61	0.57	0.39	0.49	0.47	0.36	1.00		
(16) VAKBN	0.70	0.55	0.53	0.62	0.24	0.25	0.60	0.77	0.74	0.77	0.43	0.56	0.65	0.55	0.65	1.00	
(17) YKBNK	0.46	0.52	0.40	0.61	0.28	0.43	0.46	0.53	0.71	0.62	0.35	0.50	0.44	0.37	0.35	0.73	1.00

Besides the balance sheet size and market share effect, the intra-group correlations are also considerably higher. For instance, the correlations among the state owned banks (HALKB and VAKBN) and participation banks (ALBRK and ASYAB) are quite high. Similar portfolio allocation or concentration on similar assets due to their business models or policy-oriented decisions might be contributing to these co-movements among bank stock returns.

4. Evolution of Co-movement

To document the inter-dependency/co-movement among the banks included in our analysis, we first compute daily (Pearson) correlations for all stock pairs using a three-month rolling window throughout the sample

³ Large banks are ISCTR, GARAN, AKBNK, YKBNK, HALKB, and VAKBN whose share of assets among ISE listed banks are approximately 10% or higher.

period.⁴ We then calculate the mean and median of bi-variate correlations for each day by using at most 136 (=17:2 combination) observations.⁵ The number of observations for a specific date varies depending on the number of banks whose shares are traded on the ISE on that date. The unconditional correlation measures and their evolution over time would provide some indication regarding whether the banking industry has become more inter-connected, and thus the shocks during some of the major events such as the crisis of 1994, 2000-2001 and later during global financial crisis of 2008-2009 had the potential to become a systemic crisis.

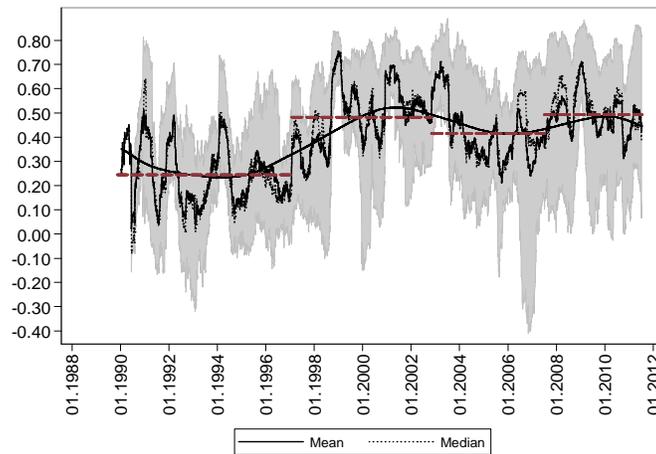
Figures 1 and 2 display the time series of inter-dependency among the banks measured by mean and median of daily stock return correlations as described above.⁶ The overall impression from these figures is that the banking industry has become more inter-connected, indicating that the potential of any major shock to the financial system to become a systemic crisis has increased overtime. In other words, the increase in correlation particularly after late 1990s is indicative of increase in exposure to common factors, which had introduced larger fragility in the banking system. Besides an upward trend in unconditional correlations, Figure 1 also displays large spikes during significant economic event including the crisis of 1994, 2000-2001 and later during international financial crisis of 2008-2009, particularly in the aftermath of the Lehman collapse. These results are consistent with the evidence in the literature that the volatility in equity prices may drive the return correlations.

⁴ Campbell et al. (2001) perform calculations with daily data using a one-year rolling window and with monthly data using a five-year rolling window. De Nicolo and Kwast (2002) use weekly data, and a 52-week rolling window.

⁵ As discussed by Forbes and Rigobon (2002), trends in correlations can depend on return volatility. To test whether our results are partly driven by trends in return volatility, we calculate daily pair-wise correlations between stock returns by estimating a bi-variate DCC-GARCH model introduced by Engle (2002) in which we control for changing volatility by including time trends in the variance equations. Results are similar. We do not report the complete results from the DCC model because the likelihoods of some models do not converge, which is typical in ARCH/GARCH type models.

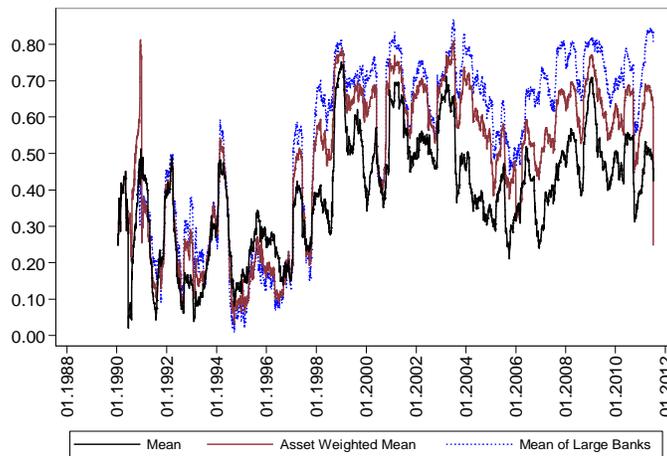
⁶ As an alternative approach, we also report principal component results using 90-day rolling windows. Since the principal components results are quantitatively similar to simple correlation, we report these results at Figure 1A in appendix.

Figure 1. Mean and Median of Bank Return Correlations



Note: Solid line is the lowest smoothed mean (bw=0.4). The area between 5th and 95th percentile of correlations is shaded in gray. Dashed lines show the means of subsamples separated by the following dates: 22/01/97, 03/11/02, and 01/07/07. Subsample means are statistically significantly different from each other.

Figure 2. Mean of Bank Return Correlations



The means of subsamples pre-97, 1997-late 2002, and mid 2007 and afterwards display significant variation, which likely has been the result of either major external shocks or domestic political events. We find that the

sub-sample means are statistically significantly different from each other,⁷ demonstrating a marked change and increase in correlation over these particular periods.

The considerable variation in stock return correlations over time and the increasing trend is more evident for the sub-sample of large banks, and particularly when the bivariate correlations are adjusted with asset size. Figure 2 shows that asset weighted mean of stock return correlation and the correlation of returns among large banks display further increase in recent years compared to the overall correlation index. This result suggests a size effect and is consistent with the results in Table 2.

To relate the trends discussed above to other stock market indicators, we regress daily bi-variate correlations to log of total daily bi-variate transaction volume, number of trades and market capitalization in different specifications. Results reported in Table 3 indicate that, market activity as measured by volume and number of trades, and size of the banks as measured by market capitalization positively affect the trend and co-movement of ISE listed banks' stock returns.

Table 3. Stock Return Correlations and Market Data-Volume, Transactions and Capitalization

	(1)	(2)	(3)	(4)	(5)
Trading Volume	0.0047 *** (0.0005)			0.0086 *** (0.0005)	
Number of Transactions		0.0215 *** (0.0008)			0.0207 *** (0.0008)
Market Capitalization			0.0218 *** (0.0014)	0.0298 *** (0.0014)	0.0200 *** (0.0013)
Observations	320471	320471	320471	320471	320471
R-squared	0.0136	0.0875	0.0430	0.0839	0.1233

Note: Dependent variable is pair-wise daily stock return correlations. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The co-movement of returns is also summarized by estimating three ‘‘market model’’ regressions as follows:

$$\text{Market Model 1: } r_{i,t} = \beta_0 + \beta_1 r_{ISEAll,t} + \varepsilon_t \quad (1)$$

$$\text{Market Model 2: } r_{i,t} = \beta_0 + \beta_1 r_{ISE100,t} + \varepsilon_t \quad (2)$$

$$\text{Two-Index Model: } r_{i,t} = \beta_0 + \beta_1 r_{ISEAll,t} + \beta_2 r_{XBankResid,t} + \varepsilon_t \quad (3)$$

⁷ To save space, we do not report the results from these mean comparison tests.

where $r_{i,t}$ is the compounded return for stock i on day t , $r_{ISEAll,t}$ is the compounded return of ISE-All index consisting of all ISE stocks, and $R_{XBankResid,t}$ series is constructed to be orthogonal to R_{ISEALL} as in De Nicolo and Kwast (2002).^{8,9} ISE-All index is available starting from January 1997. These regressions are estimated for each individual firm for each day using a three-month rolling window, and both market models and two-index model are corrected by using i.e. GARCH (1.1). We report several summary statistics obtained from estimating Equations 1 - 3 above to describe how the inter-dependency has evolved overtime. Figure 3 reports mean of R -squared statistics for Equations 1, and 3, Figure 4 reports mean and median of the market model beta from Equation 2 and finally Figure 5 displays median of $\hat{\beta}_1$ and $\hat{\beta}_2$ obtained from Equation 3.

Figure 3. Mean of R^2 Statistics for the Market Model Regressions

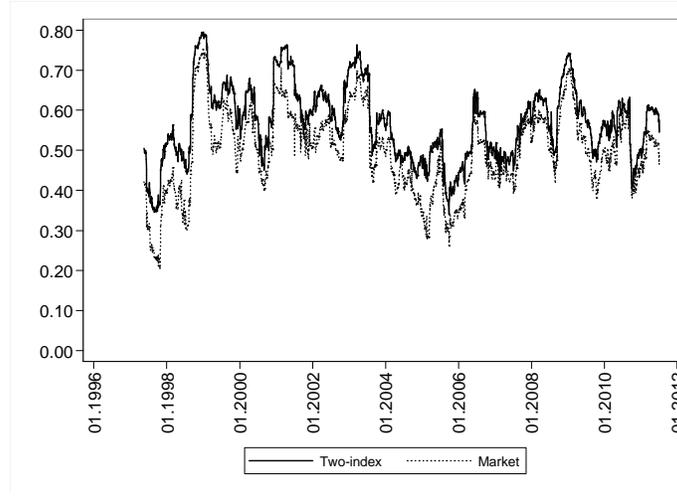


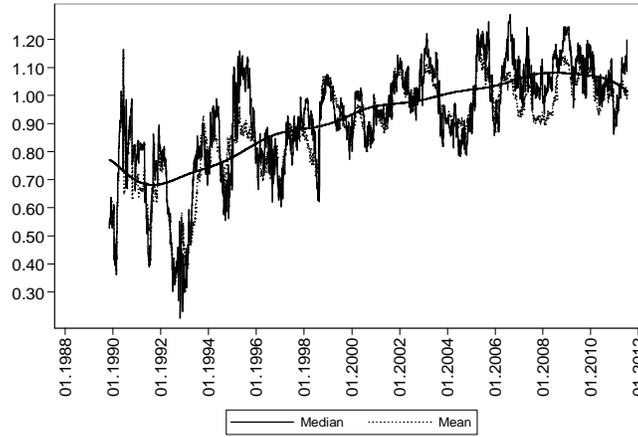
Figure 3 shows that the overall stock index and banking industry index explain a large part of the variation in individual equity returns. This indicates that to large extent the increase in return correlations are due to common factors rather than idiosyncratic components, which provides evidence on the prevalence of inter-dependency in the banking industry. This conjecture is also attested by a steady rise in, for instance, the market

⁸ We estimate Equation 2 in addition to Equation 1 because ISE100 Index has a much longer span than ISEAll Index.

⁹ $R_{XBankResid,t}$ is the residuals obtained from regressing the returns of an equally weighted banking index constructed by the authors on ISE-All index returns.

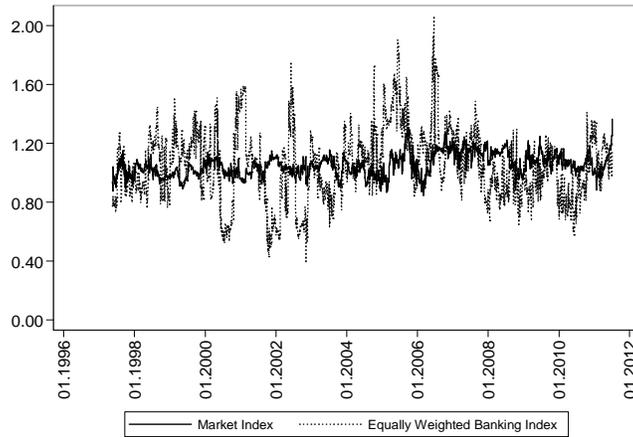
model beta as plotted in Figure 4. Finally, Figure 5 shows that much of the variation displayed in the previous figures is related to the shocks specific to the banking sector.¹⁰

Figure 4. Market Model Beta



Note: Solid line is the lowest smoothed median (bw=0.4).

Figure 5. Two-index Model Median Betas



Note: Solid and dashed lines are the medians of estimated values of β_1 and β_2 respectively, in Equation 3.

¹⁰ That is $\widehat{\beta}_2$ has a much larger variation than $\widehat{\beta}_1$ in Figure 5.

5. Drivers of Co-movement

The second step of our analysis in addressing the inter-dependency among banks is to formally investigate the extent to which stock return correlations could be explained by bank specific, domestic macroeconomic and external factors.^{11,12} The selection of factors in each category is based on previous empirical and theoretical studies. For instance, to proxy for financial system consolidation as an underlying factor that explains systemic risk and inter-dependency in De Nicolo and Kwast (2002), we use the ratio of each pair of banks' total assets to total assets of the banks listed on the ISE. Furthermore, size, interconnectedness, and substitutability are measures also used by IMF/BIS/FSB (2009) to identify the systemic importance of a financial institution. A similar approach is adopted in Thomson (2009), where he also suggests using size and other inter-dependency measures to determine the systemic importance of a bank. In addition, interbank lending, such as bank loans and repo transactions, and its implications for systemic risk is addressed in Rochet and Tirole (1996). Hence, the balance sheet items that we consider in our models to explain the correlation of stock returns, which are our measure of systemic risk, in a sense to capture various facets of previous studies in a more formal way.

An additional industry-specific factor that also contributes to systemic risk is potential herd behavior in bank lending. Therefore, to account for herd behavior, we use the herding index constructed by Binici and Unalmis (2012) who apply Lakonishok et al. (1992) herding measures to Turkish banking data. They utilize bank level loan data for the period 2002-2011 at monthly frequency. Herd behavior in the loan market is investigated by looking at the major types of loans including consumer loans, credit cards, and corporate loans.

Bank inter-dependency and systemic risk potential could also stem from common factors that are domestic and external market-specific rather than bank- or industry-specific ones. For instance, empirical evidence suggests that markets are highly correlated in periods of high volatility and in some

¹¹As discussed in previous literature, the correlated trading activities of noise traders and rational arbitrageurs as in Shiller (1984) and Shleifer and Summer (1990), and the natural "habitat" argument in Barberis et al. (2005) are different views on the market sentiment that explain the stock return co-movements. Rather than addressing the alternative behavioral finance view on the correlated trading of retail investors, our focus is on the role of innovations in fundamentals and bank-level factors and their linkages with the correlation of returns. For a more detailed discussion on the theoretical effects of investor sentiment on stocks, see Baker and Wurgler (2007).

¹²Related to the points addressed above, we do not address potential demand-side explanations including investors sentiments (e.g. Baker and Wurgler, 2006; Barberis et al. 2005), and investors' incentives to trade individual securities or correlated trading behavior of institutional investors (Karolyi et al., 2011) as drivers of the stock return co-movement. We leave this for future research that combines both supply- and demand-side views of co-movement.

periods of the business cycle which are characterized by, among the others, high level of interest rates (Longin and Solnik, 1995). Compared to bank- or industry- specific factors, as discussed in Borio (2003), macroeconomic or domestic factors could be the main drivers of co-movement. Thus, Borio (2003: 6) states that “But the significance of such instances (*bank failures that result from idiosyncratic factors*) pales in comparison with that of the cases where systemic risk arises primarily through common exposures to macroeconomic risk factors across institutions. It is this type of financial distress that carries the more significant and longer-lasting real costs. And it is this type that underlies most of the major crises experienced around the globe.”

Another source of the common exposure of national banks’ stock returns could be the regional or international shocks that trigger major economic events such as the Lehman collapse in September 2008. In an economy that is more integrated with international financial markets, national firms are more exposed to external factors. As such, the stock price behavior may reflect the behavior of an internationally diversified portfolio and international correlations of equity markets are expected to be higher (Longin and Solnik, 1995). Therefore, besides the domestic and bank-specific factors, we also consider global factors that affect the co-movement of banks’ stock returns. To this end, we incorporate the volatilities of US stock and bond returns to proxy for global financial factors in our models. From a slightly different perspective, Bae et al. (2003) also find that interest rates, exchange rates, and stock market volatility have predictive power about whether contagion is likely to occur.¹³ Additionally, we consider subgroup factors such as EMBI+ and MSCI indices for bond and capital markets as indicators for emerging economies that could capture the decoupling conjecture, if there is any.

To summarize, we estimate different versions of the following model:

$$C_{ijt} = \alpha + X'_{ijt}\beta + Y'_t\phi + Z'_t\lambda + \varepsilon_{ijt} \quad (4)$$

where C is the pair-wise correlation between bank i and j at time t , X is pair-wise bank specific factors, Y is domestic/macro-economic factors (including the herding series), and Z is external/international factors that are common to all bank pairs. Bank related factors are calculated for each bank pair and include market share, repo transactions, total loans and non-performing

loans, which are defined monthly as $(X_i + X_j) / \sum_{k=1}^{17} X_k$. For example,

¹³ For a more detailed discussion of the literature on stock market co-movement, see Beine et al. (2010) and references therein.

market share of a bank pair for a given month equals the sum of total assets of these two banks divided by the total assets of the banks listed on the ISE for that month. Domestic/macroeconomic factors include exchange rate volatility and external/international factors include the volatility of bond returns, EMBI+ and MSCI, and VIX.

We estimate Model 4 by including all balance sheet factors in each specification while we add domestic and external factor volatilities in each specification individually due to possible multicollinearity between these indicators. The model is estimated using pooled ordinary least squares (OLS) and standard errors are adjusted for possible heteroskedasticity and autocorrelation. The time frequency of Model 4 is monthly, and the monthly data for domestic and external volatility indicators are the standard deviation of daily series. The bank balance sheet data are monthly data.¹⁴

Table 4 reports results from estimating Equation 4. The bank specific factors that include market share, total loan, non-performing loan, and repo transactions are all the share of bank pair in the total banking industry. Thus, we test, for instance, whether the market share of bank pairs explains the correlation between their equity returns, which is indirectly testing the bank consolidation as a driving factor of inter-dependency as in De Nicolo and Kwast (2002). In all specifications, market share is a significantly positive determinant of bank inter-dependency and is consistent with the results of bank group analysis reported in Table 2.

Among the other bank-specific factors, the total loan of bank pairs are not consistently significant, but when it is, it is negative; implying that share in bank loans is negatively associated with bank inter-dependency. However, the direction of the relationship between loans and return correlation is not well addressed in the literature. This relationship is expected to be positive if loans are concentrated in particular industries or if the allocation of loans is the outcome of some herd behavior, which in turn increases the potential for aggregate risk. A highly correlated portfolio allocation will be reflected in stock prices if market participants are able to evaluate the future prospects of these investments and their potential to be non-performing.

On the other hand, an increase in the aggregate loan volume could be driven by the business cycle, where during upturns banks tend to increase their lending since the expected default is lower and expected return from such investment is higher. The business cycle upturns are also the periods during which banking system fragility or the likelihood of distress is lower.

¹⁴ The same models are estimated using annual data using monthly average of balance sheet items, and standard deviation of daily data for volatility indicators. The average of monthly series is used to avoid possible cyclical changes that may introduce bias in the parameter estimates. Overall results are quantitatively similar; therefore we provide results using monthly data only to save space.

However, upturn cycles that overlap with credit-intensive booms tends to be followed by deeper recessions, which also coincides with systemic crises.¹⁵ Therefore, the association between return correlation and loan volume could be negative under the pro-cyclical leverage and credit growth. In this case, the results shown in Table 4 are supportive of the business cycle argument, even though a more elaborate theoretical framework and econometric test is warranted.

The other bank-specific factors we consider are non-performing loans and total volume of repo transactions. Our results show that while the former has a positive and significant effect on bank-interdependency, the latter is insignificant. Finally, to test the herding behavior and bank interdependency relationship, we use the index developed in Binici and Unalmis (2012) which applies Lakonishok et al. (1992)'s herding measures to Turkish banking sector data. Consistent with theoretical predictions, in most specifications in Table 4, herd behavior in bank loan market increases bank inter-dependency and hence the potential for systemic risk. Moreover, the coefficient of the herding index interacted with large bank dummies indicates that the relationship is stronger for the large banks than the small ones, thereby providing evidence on the systemic importance of large banks.^{16,17}

Besides the bank and industry-specific drivers, domestic and external indicators are also considered in Table 4. As discussed above, these indicators are included in various model specifications one at a time in order to avoid possible multicollinearity among the variables. As a domestic driver of equity return correlation, we prefer using exchange rate (FX) volatility, which to a large extent reflects the macro and financial condition of the economy. The FX volatility could be a major source of risk exposure if the banking system has foreign exchange mismatch between assets and liabilities. In particular, if the mismatch is not perfectly hedged, and the banking sector has short position, for instance, the depreciation of domestic currency results in losses in the banking sector. FX volatility seems to have a positive and significant effect on return correlations indicating that exchange rate movement captures the periods of distress during which bank-interdependency is higher.

¹⁵ For a long-term perspective of the relationship between leverage, business cycles, and crises in advanced economies, see Jorda et al. (2011).

¹⁶ Note that the herd measure used in this study is an index for the entire banking industry and not only for ISE listed banks. Therefore, the index is common to all banks and hence can be viewed as an industry-specific factor that affects all pair-wise bank returns.

¹⁷ Data on repo transaction and herding index is only available after 2002, which is why the sample size is limited in specification (7) and afterwards in Table 4.

As for external drivers of equity return correlation, we consider the US T-bill volatility and the volatility of S&P-500 as measured by VIX. Both indicators have positive and significant effects on return correlation, which reflects the importance of integration of domestic financial markets with the rest of the world and internationally diversifiable portfolios.¹⁸ Similar results are obtained when the country group indicators for bond and equity volatilities, EMBI+ and MSCI, are included in the models. These results also suggest that the inter-dependency among banks is also subject to common exposure of risk to the emerging economies besides the global factors.

6. Conclusion

This paper uses correlation of bank equity returns to evaluate how systemic risk has evolved in the Turkish banking system over 1990-2011. We use daily stock price data of 17 banks listed in Istanbul Stock Exchange (ISE), which includes commercial banks, participation banks, and investment banks, and accounts for approximately 76% of all banking system assets.

Looking at the pair-wise bank return correlations, we have documented that inter-dependency has increased in the Turkish banking system over the period of our analysis. We interpret this observed increase in the correlation among stock returns as signaling an increase in the potential for a shock to become systemic. The factor model estimation results also show an increase in return correlations, which are in part driven by an increase in exposures to common factors, while the degree of inter-dependencies among financial institutions is the source of risk to be systemic once it materializes.

In addition, we have investigated to what extent various factors, including bank-specific, country-specific, and external-specific ones, account for the co-movement of bank stock returns, and hence explain systemic risk. We find that market share, in particular, is an important determinant of co-movement among bank stock returns. Furthermore, total loans, non-performing loans, and herding behavior also seem to be important bank- and industry-specific determinants of inter-dependency.

On the other hand, both domestic and external factors seem to play important roles in driving bank inter-dependency. In particular, exchange rate volatility as an indicator of domestic financial and economic conditions is a significant contributing factor to the return correlations. Similarly, external market conditions as proxied by the US Treasury bill volatility,

¹⁸ For discussion on the impact of trade and financial integration on stock market co-movement for the case of European countries, see Wälti (2011).

equity market volatility, and indicators for volatility of emerging economies, such as EMBI+, all have significant positive effects on domestic bank stock return correlations.

Measured by the co-movement of stock return correlation, this simple and timely indicator proposed here could be used as a tool to monitor for a better management of the systemic risk, as a complementary tool to other measures. In terms of policy implications, the discussion on the co-movement is in line with the debate on the systematically important financial institutions (SIFI) as correlation is one of the components to identify such institutions, and to impose capital surcharges on them. Therefore, as discussed in Goodhart and Wagner (2012), these financial institutions could be subjected to additional capital requirements that are conditioned on how correlated their overall activities are with the rest of the financial system.

An increase in the co-movement of stock returns might be indicative of systemic risk, however, it does not necessarily measure each institution's contribution to systemic risk. Thus, future studies can also investigate how the episodes of high co-movement of stock returns are correlated with the systemic risk measures of Acharya et al. (2010), Brownlees and Engle (2011), and Adrian and Brunnermeier (2011), each of which offers a different approach to measuring contributions to systemic risk.

References

- Acharya, V., 2009. "A Theory of Systemic Risk and Design of Prudential Bank Regulation" *Journal of Financial Stability*, 5(3), 224–255.
- Acharya V.V., Pedersen L.H, Philippon, T. and Richardson, M., 2010. "Measuring Systemic Risk" *Working Paper 1002*, Federal Reserve Bank of Cleveland.
- Adrian, T. and Brunnermeier, M.K., 2011. "CoVaR" *NBER Working Papers* 17454.
- Bae, K.-H., Karolyi, G.A. and Stulz, R.M., 2003. "A New Approach to Measuring Financial Contagion" *The Review of Financial Studies* 16 (3), 717–763.
- Baker, M. and Wurgler, J., 2006. "Investor Sentiment and the Cross-section of Stock Returns" *Journal of Finance* 61, 1645-1680.
- Baker M. P. and Wurgler, J., 2007, "Investor Sentiment in the Stock Market" *Journal of Economic Perspectives*, 21(2), 129-151.
- Barberis, N., Shleifer, A. and Wurgler, J., 2005. "Comovement" *Journal of Financial Economics*, 75, 283–317.
- Beine, M., Cosma, A. and Vermeulen, R., 2010. "The Dark Side of Global Integration: Increasing Tail Dependence" *Journal of Banking & Finance*, 34(1), 184-192.
- Billio, M., Getmansky, M., Lo, A. W. and Pelizzon, L., 2010. "Econometric Measures of Systemic Risk in the Finance and Insurance Sectors" *NBER Working Paper* No. 16223
- Binici, M. and Unalmis, I., 2012. "Is There Herd Behavior in the Turkish Banking System?" Unpublished manuscript.
- Bollerslev, T., 1990. "Modeling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized Approach" *Review of Economics and Statistics*, 72 (3), 498–505.

- Borio, C., 2003. “Towards a Macroprudential Framework for Financial Supervision and Regulation” *BIS Working Papers*, No 128.
- Brownlees, C.T. and Engle, R.F., 2011. “Volatility, Correlation and Tails for Systemic Risk Measurement” SSRN: <http://ssrn.com/abstract=1611229>.
- Campbell, J.Y., Lettau, M., Malkiel, B.G. and Xu, Y., 2001. “Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk” *Journal of Finance*, 56 (1), 1–43.
- De Nicolo, G. and Kwast, M.L., 2002. “Systemic Risk and Financial Consolidation: Are They Related?” *Journal of Banking & Finance*, 26, 861–880.
- Dungey, M., Fry, R., Gonzalez-Hermosillo, B. and Martin, V., 2005. “Empirical Modeling of Contagion: a Review of Methodologies” *Quantitative Finance*, 5(1), 9–24.
- Engle, R., 2002. “Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models” *Journal of Business & Economic Statistics*, American Statistical Association, 20(3), 339–50.
- Forbes, K. J. and Rigobon, R., 2002. “No Contagion, Only Interdependence: Measuring Stock Market Comovements” *The Journal of Finance*, 57, 2223–2261.
- Goodhart, C. A.E. and Wagner, W., 2012. “Regulators Should Encourage More Diversity in the Financial System” *VoxEU.org*, 12 April.
- Huang, X., Zhou, H., and Zhu, H., 2011, “Systemic Risk Contribution” *Finance and Economics Discussion Series 2011-08*, Board of Governors of the Federal Reserve System.
- IMF/BIS/FSB, 2009. “Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations” *Report to the G-20 Finance Ministers and Central Bank Governors*, October.
- International Monetary Fund, 2009. “Systemically Important Institutions, Markets and Instruments” (October 2009), Washington, DC.
- Jordà, Ò., Schularick, M. and Taylor, A. M., 2011. “When Credit Bites Back: Leverage, Business Cycles, and Crises” *NBER Working Papers*, No: 17621.
- Jorion, P., 2007. “Bank Trading Risk and Systemic Risk” in *The Risks of Financial Institutions*, pages 29–58, NBER.
- Karolyi G. A. and Stulz, R.M., 2002. “Are Financial Assets Priced Locally or Globally?” *NBER Working Papers* 8994.
- Karolyi, G. A., Leeb, K-H. and van Dijk, M. A., 2011. “Understanding Commonality in Liquidity Around the World” *Journal of Financial Economics*, forthcoming.
- Lakonishok, J., Shleifer, A. and Vishny, R.V., 1992. “The Impact of Institutional Trading on Stock Prices” *Journal of Financial Economics*, 32, 23–43.
- Longin, F. and Solnik, B., 1995. “Is the Correlation in International Equity Returns Constant: 1960–1990?” *Journal of International Money and Finance*, 14 (1), 3–26.
- Lo, A.W., 2008. “Hedge Funds, Systemic Risk, and the Financial Crisis of 2007–2008: Written Testimony for the House Oversight Committee Hearing on Hedge Funds” *MIT Working Paper*.
- Patro, D. K., Qi, M. and Sun, X., 2012. “A Simple Indicator of Systemic Risk” *Journal of Financial Stability*, doi:10.1016/j.jfs.2012.03.002.
- Rochet, J.C. and Tirole, J., 1996. “Interbank Lending and Systemic Risk” *Journal of Money, Credit and Banking* 28, 733–762.
- Shiller, R.J., 1984. “Stock Prices and Social Dynamics” *Brookings Papers on Economic Activity* 2, 457–510.

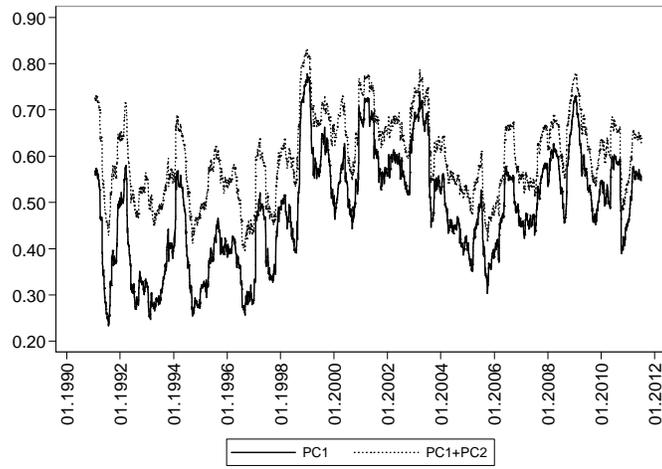
- Shleifer, A. and Summers, L. H., 1990. “The Noise Trader Approach to Finance” *Journal of Economic Perspectives* 4, 19–33.
- Thomson, J.B., 2009. “On Systemically Important Financial Institutions and Progressive Systemic Mitigation” Federal Reserve Bank of Cleveland Policy Discussion Paper No. 27.
- Wälti, S., 2011. “Stock Market Synchronization and Monetary Integration” *Journal of International Money and Finance*, 30(1), 96-110.

Table 4. Determinants of Banks' Stock Return Comovement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Share	0.0109*** (0.0039)	0.0091** (0.0039)	0.0171*** (0.0041)	0.0075** (0.0037)	0.0116*** (0.0040)	0.0092** (0.0039)	0.0126** (0.0059)	0.0105* (0.0059)	0.0154** (0.0061)	0.0058 (0.0057)	0.0150** (0.0063)	0.0092 (0.0060)
Total Loans	0.0012 (0.0028)	0.0033 (0.0028)	-0.0042 (0.0031)	0.0042 (0.0027)	0.0017 (0.0028)	0.0038 (0.0028)	-0.0121** (0.0048)	-0.0108** (0.0048)	-0.0162*** (0.0050)	-0.0045 (0.0047)	-0.0161*** (0.0049)	-0.0091* (0.0048)
Non-performing Loans	0.0041*** (0.0011)	0.0032*** (0.0011)	0.0029** (0.0013)	0.0025** (0.0011)	0.0037*** (0.0012)	0.0032*** (0.0011)	0.0046** (0.0022)	0.0041* (0.0021)	0.0055** (0.0022)	0.0035 (0.0022)	0.0049** (0.0022)	0.0038* (0.0022)
Repo Transaction Volume							-0.0006 (0.0007)	-0.0005 (0.0007)	-0.0006 (0.0008)	-0.0004 (0.0007)	-0.0007 (0.0008)	-0.0006 (0.0007)
Herding Index							0.1086*** (0.0412)	-0.0434 (0.0405)	0.0226 (0.0407)	0.1700*** (0.0410)	0.0413 (0.0412)	0.1154*** (0.0417)
Herding Index*Large Banks							0.1881*** (0.0643)	0.1816*** (0.0658)	0.1937*** (0.0673)	0.1906*** (0.0652)	0.1835*** (0.0640)	0.1822*** (0.0643)
Exchange Rate Volatility	0.0552*** (0.0037)						0.1218*** (0.0042)					
U.S. T-Bill Volatility		0.0019*** (0.0001)						0.0020*** (0.0001)				
EMBI+ Volatility			0.0912*** (0.0069)						0.1535*** (0.0062)			
MSCI Volatility				0.1083*** (0.0033)						0.1044*** (0.0032)		
VIX					0.0014*** (0.0001)						0.0018*** (0.0001)	
VIX Volatility						0.0198*** (0.0009)						0.0232*** (0.0009)
Observations	16,107	16,107	15,430	16,107	16,106	16,107	10,137	10,137	10,137	10,137	10,137	10,137

Notes: Dependent variable is pair-wise stock return correlations. Panel data models are estimated by pooled OLS. The frequency of data is monthly. All volatility indicators are standard deviations of daily data for each month. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A1. Principal Components of Stock Returns



Note: PC1 indicates first principal component, PC1+PC2 indicates cumulative first and second principal components of stock returns. Principal components are calculated using 90-day rolling windows.