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ABSTRACT

This paper investigates the evolution of systemic risk in the Turkish banking sector over the past two decades using comovement 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 as a result of 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, U.S. T-bills, EMBI+, VIX, and MSCI emerging markets index.

Key Words: Stock returns, comovement, systemic risk, banking.
JEL Classification: C22; C58; G21; G32

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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 closely-knit and 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 U.S. 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 premium (DIP) of Huang et al. (2011) and systemic risk measure (SRISK) of Brownlees and Engle (2011).

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

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 comovement/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 comovement of both domestic and international financial institutions. The earlier studies on comovement 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 comovement. 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 U.S. 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 U.S. 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 findings as support for the use of stock return correlations as a measure of systemic risk.

[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.

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 U.S. 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 comovement 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 an 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 U.S. 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 comovement/inter-dependency and its sources. Section 3 describes the dataset. Section 4 documents the comovement 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 Comovement 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 U.S. 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 comovement 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 percent of the Turkish banking system as of September 2011. Some of these banks, such as Iş 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.

[Insert Table 1]

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 pair-wise 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 banks[3] 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).

[Insert Table 2]

Besides the balance sheet size and market share effect, the inter-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 comovements among bank stock returns.

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

4. Evolution of Comovements

To document the inter-dependency/comovement 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 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 whether 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. 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.

[Insert Figures 1, 2]

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. The sub-sample means are found to be significantly different from

[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.

each other, 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.

[Insert Table 3]

The comovement of returns is also summarized by estimating three ''market model'' regressions as follows:

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

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

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

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).[6],[7] 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. 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

[6] We estimate equation (2) in addition to equation (1) because ISE100 Index has a much longer span than ISEAll Index.

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

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).

[Insert Figure 3]

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 is 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 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.[8]

[Insert Figures 4, 5]

5. Drivers of Comovement

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. 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 is 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 Lakonishock et al. (1992) herding

[8] That is $\widehat{\beta_2}$ has a much larger variation than $\widehat{\beta_1}$ in Figure 5.

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 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 comovement. Thus, Borio (2003) 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." (pg. 6).

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 comovement of banks' stock returns. To this end, we incorporate the volatilities of U.S. 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.[9] Additionally, we consider sub-group factors such as EMBI+ and MSCI indices for bond and capital markets as indicators for emerging economies that could capture the de-coupling conjecture, if there is any.

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

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

[9] For a more detailed discussion of the literature on stock market comovement, see Beine et al. (2010) and references therein.

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/macroeconomic 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 $\left(X_i + X_j\right) / \sum_{k=1}^{17} X_k$. For example, 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 while including balance sheet factors in all specifications and add domestic and external factor volatilities in each specification 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.[10]

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

[10] 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 daily 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.

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. However, upturn cycles that overlap with credit-intensive booms tends to be followed by deeper recessions, which also coincides with systemic crises.[11] 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 inter-dependency relationship, we use the index developed in Binici and Unalmis (2012) which adapts the Lakonishock et al. (1992) 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. [12,13]

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 a given

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

[12] 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.

[13] 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.

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, 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.

As for external drivers of equity return correlation, we consider the U.S. 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.[14] 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 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 account for approximately 76 percent 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

[14] For discussion on the impact of trade and financial integration on stock market comovement for the case of European countries, see Wälti (2011).

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

As for future research, one could explore alternative approaches widely used in the literature to extract the unspecified factors affecting stock comovement using, for instance, principal component analysis (PCA) and factor analysis as in Hawkesby et al. (2007). This analysis could be extended so as to disentangle the contributions to variance of stock returns and hence shed light on the relative importance of common, regional, and idiosyncratic factors. In addition, although an increase in the co-movement of stock returns might be indicative of systemic risk, it does not necessarily measure systemic risk or each institution's contribution to such risk. Thus, future studies can also investigate how the episodes of high comovement 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.

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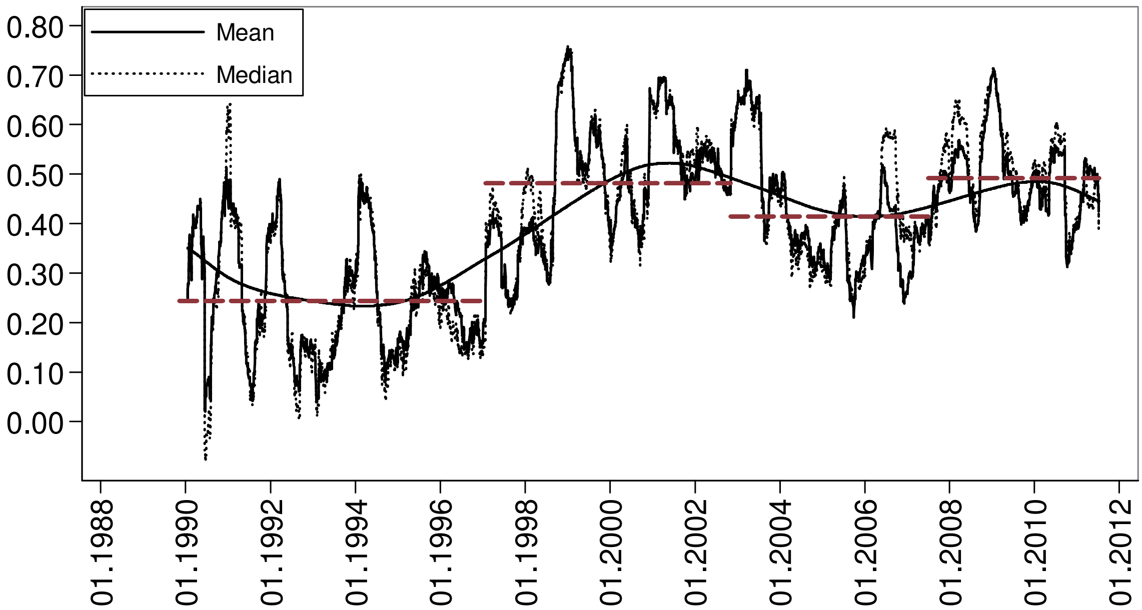
Figure 1. Mean and median of bank return correlations.



Note. Solid line is the lowess smoothed mean (bw=0.4). Dashed lines show the means of subsamples separated by the following dates: 22/01/97, 03/11/02, 01/07/07. Subsample means are significantly different from each other.

Figure 2. Mean of bank return correlations.

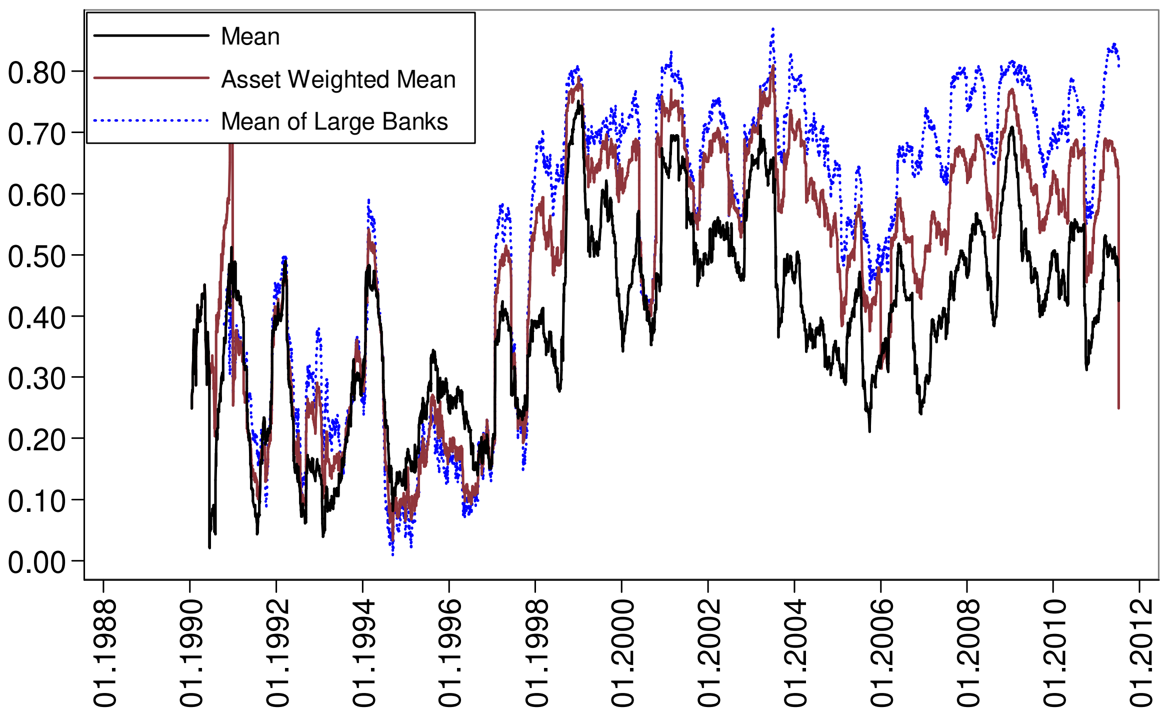


Figure 3. Mean of R^2 statistics for the market model regressions

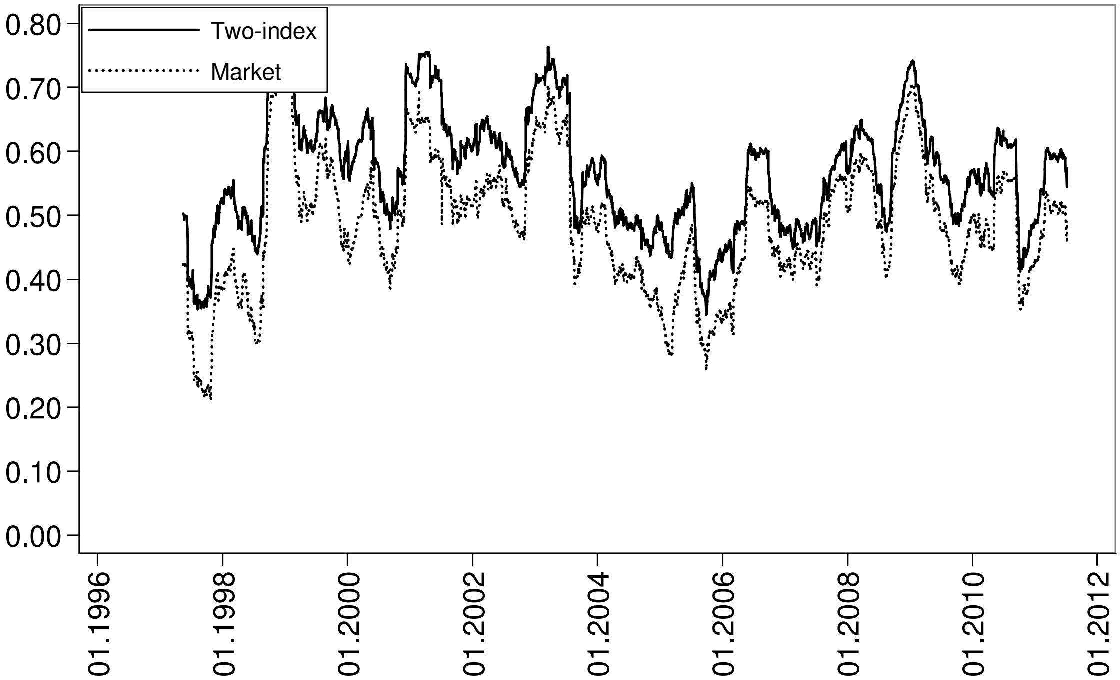
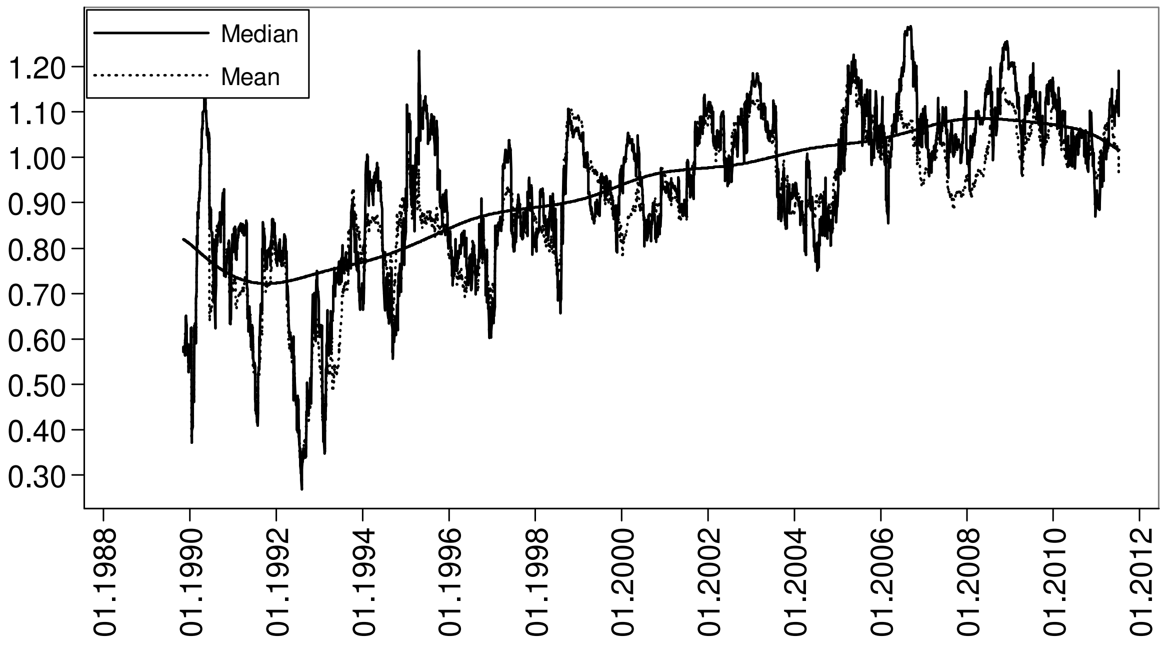
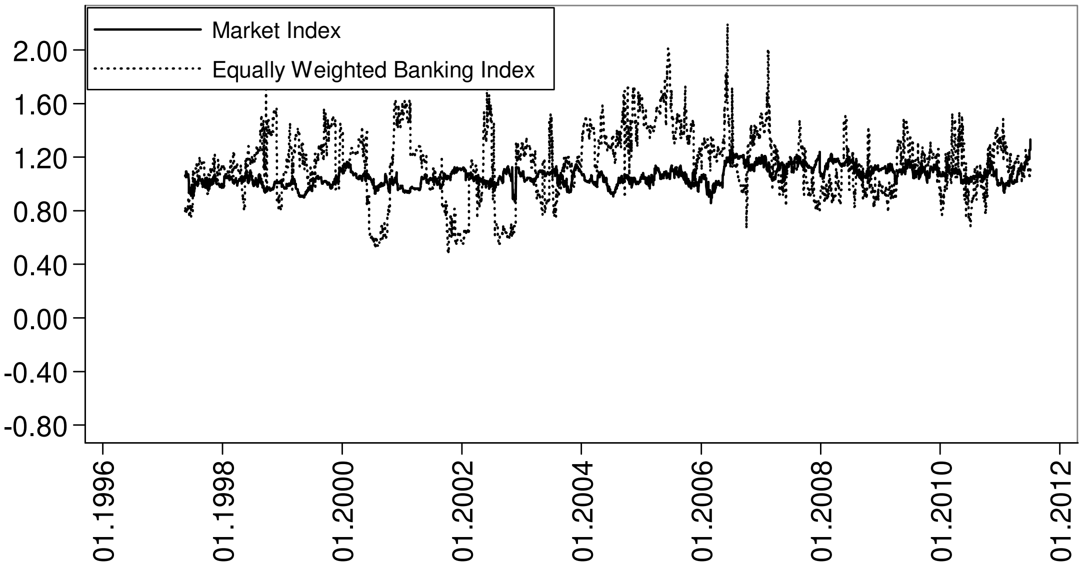


Figure 4. Market model beta.



Note. Solid line is the lowess 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).

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 (YKBNK) (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 (TEBNK) (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.Sınai 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
ISE listed bank total	*909.777*		*75,91*
Banking sector total	*1.198.441*		

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" stads 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.

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

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

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Trading Volume	0.0047***			0.0086***	
	(0.0005)			(0.0005)	
Number of Transactions		0.0215***			0.0207***
		(0.0008)			(0.0008)
Market Capitalization			0.0218***	0.0298***	0.0200***
			(0.0014)	(0.0014)	(0.0013)
Observations	320,471	320,471	320,471	320,471	320,471
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.

Table 4: Determinants of Banks' Stock Return Comovement

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