SECTORAL CREDIT RISK IN THE EURO AREA*

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ABSTRACT

This article outlines a method to compute market-based corporate default risk indicators at sectoral level and evaluates systemic and idiosyncratic determinants of default risk. This approach takes into account observed and unobserved common factors and the presence of different degrees of cross-section dependence in the form of economic proximity. The results contribute to the financial stability literature with a contingent claims approach to a sector-based analysis with a less dominant macro focus while being compatible with existing stress-testing methodologies in the literature. A disaggregated analysis of the different corporate and financial sectors allows for a more detailed assessment of specificities in terms of sectoral risk profile, *i.e.* heterogeneity of business models, risk exposures and interaction with the rest of the macro environment.

1. Introduction

Financial stability analysis has embarked on a growing research agenda. One of these new areas of research addresses the credit risk interactions between the financial system and the rest of the economic agents and sectors. Most of the emerging literature on this topic has focused on the analysis of risk in financial sector or the non-financial corporate sector in terms of their sensitivity to shocks generated in the macroeconomic environment or the financial markets.

Although the general economic conditions are a very important and arguably the most relevant factor explaining credit risk at sectoral level, little attention has been given so far to the risk interactions across corporate sectors due to the many and complex relationships that take place among them. In turn, these linkages matter significantly in both the direction and intensities of the macro-financial shocks and they also constitute channels of direct risk shocks across sectors.

Understanding the nature of these risk determinants and channels of risk transmission is therefore of great relevance for policy and crisis management. This article takes a step to address this question. In the following section, it reviews a method to compute a forward-looking credit risk indicator, the Portfolio Distance-to-Default (PDD), at sectoral level for corporate sectors based in the euro area using firm level information from company statements and sector level data from equity and option markets. These indicators inform about market expectations as regards aggregate sector profitability, capitalization and asset volatility, which constitute the main drivers of corporate default risk.

Then, the article highlights the ability of the PDD series to detect sector-wide stress and analyse their dynamics since the introduction of the euro. Finally, an econometric model is set up in order to reassess

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the common findings in the literature as regards sectoral sensitivity to macro-financial shocks and to shed some light to the role that the cross-sectional dependence plays in these credit risk relationships.

The results of this analysis make a strong argument for a sector-level analysis to monitor systemic risk and the spillover of corporate default risk, that highlights sectoral heterogeneity. From a financial stability perspective, these findings call attention to the inclusion of these relationships for stress testing exercises of the financial system, as a natural extension of what is happening with the inclusion of the government sector.

2. A Sectoral Risk Measure for the Financial and Corporate Sectors

Sectoral analysis of risk entails two practical and largely subjective choices. The first concerns the corporate default risk measure and the second is the definition of sectors included in the analysis.

As for the choice of the corporate default risk measure, this article analyses Portfolio Distance-to-Default series (PDD). PDD is an extension of the Distance-to-Default (DD) modeling. DD is a market-based indicator of default risk with extensive applications in quantitative modeling and stress testing. It is based on the Black-Scholes-Merton model of option pricing and it measures the standardized distance between the market value of assets and a default barrier defined by a given liabilities structure,[1] under the assumption that firm equity is a call option on the assets in the event of default. A decrease in DD reflects a deteriorating risk profile, as a result of the combination of lower expected profitability, weakening capitalization and increasing asset volatility. At aggregate corporate sector-level, DD signals the probability of generalized distress or joint failure and its dynamics contains valuable informational signals of market valuation of distress.

For a given choice of sectoral classification, the analysis of an entire corporate sector turns into the analysis of a portfolio of companies that need to be aggregated together into a single, tractable and highly representative metrics. Most studies apply an ex-post aggregation of individual DD series via weighted or simple averages or medians. This approach highlights the overall risk outlook in the sector and captures the intensity of distress but it tends to overemphasize the large companies in the portfolio and it may largely neglect interdependencies among constituents. In contrast, the use of PDD treats the set of companies by sector as a single and large entity via the ex-ante aggregation of balance sheet and equity-based data and the use of portfolio volatility before calibrating the PDD.

PDD series have complementary informational properties with respect to average DD and enhances them in several ways when they include market expectations via index option implied volatilities. First, PDD series do not only detect overall risk in the sector and distress intensity but they have the ability to capture market expectations of interdependences among the portfolio constituents without assuming the correlation structure. In particular, in periods of low market volatility, PDD is considered the upper bound of joint distance to distress (the lower bound in terms of joint probabilities of distress) and exceeds the average company DD. In times of high market volatility, there is a generalized increase in (expected) returns covariance within a given sector, even if the company fundamentals of portfolio may be solid. As a result, the PDD series tend to decrease sharply and converge with the average DD for as long as the state of high volatility persists.

The forward-looking properties embedded in option implied volatilities add three additional features. First, for a given state of market volatility, options react very quickly but for a short period to market news. Second, as option implied volatilities are shown to be good predictors of realized market volatility, the PDD are endowed with early turning points nearing systemic crisis events and record breaks before

1 See Gray and Malone (2008), for an extensive discussion about the DD technicalities and modeling assumptions. Echeverría *et al*. (2006, 2009), and Saldías (2010), provide an overview of the differences between methods to aggregate DD series into sectoral measures.

most other risk indicators. Finally, PDD incorporate information content from index implied volatilities about tail events in episodes of crisis.

The second empirical question is the selection of sectors of analysis. In this article, the sample selection is based on the Industry Classification Benchmark (ICB) at Supersector level,[2] which is a method that aggregates companies according to their main sources of revenue and thus ensures a large degree of homogeneity in business models and sectoral characteristics in each portfolio.

Accordingly, the PDD series are computed for 12 of the 19 Supersectors that constitute the core of the EURO STOXX Index. These sectors comprise the financial sector, – Banks and Insurance – and 10 Supersectors from the non-financial corporate sector. These measures aggregate information of over 250 companies in the reference index between December 2001 and October 2009.

These 12 Supersectors are the most relevant corporate sectors by different measures of size such as assets, market value, employment and geographical diversification of corporate activities. This sector selection also ensures the best informative quality of their PDD and is based on two criteria, namely the stock market capitalization of their corresponding Supersector STOXX Indices and availability and high liquidity of their associated Eurex Index options quotes. A brief summary is presented in Table 1.

Table 1

SAMPLE

	Supersector ICB	Industry ICB	Portfolio Size
1	Banks	Financials	40
2	Telecommunications	Telecommunications	17
3	Oil & Gas	Oil & Gas	19
4	Insurance	Financials	17
5	Technology	Technology	21
6	Automobiles & Parts	Consumer Goods	13
7	Utilities	Utilities	22
8	Industrial Goods & Services	Industrials	56
9	Chemicals	Basic Materials	14
10	Food & Beverage	Consumer Goods	13
11	Media	Consumer Services	25
12	Health Care	Health Care	17
			274

Source: Industrial Classification Benchmark.

3. Preliminary Analysis and a primer on Sectoral Cross-section Dependence

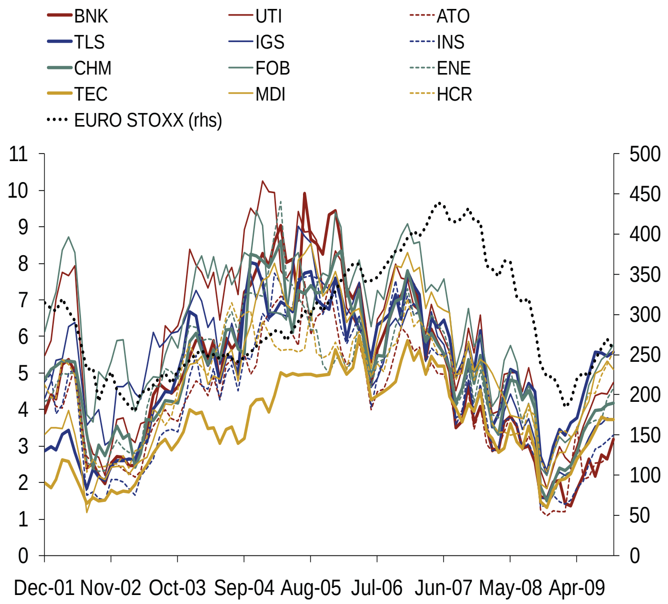
3.1. PDD series dynamics

The resulting 12 PDD series are displayed in Chart 1 together with the EURO STOXX index. As market-based indicators, PDD move along with the benchmark stock index but they anticipate turning points along the entire period due to the information embedded via index option implied volatilities. As an

2 Even though Industries, Supersectors and Sectors are clearly differentiated as ICB Categories, the use of these terms in this paper will uniquely refer to Supersectors.

Chart 1

PORTFOLIO DISTANCE-TO-DEFAULT SERIES | MONTHLY VALUES



Sources: Thomson Reuters and author's calculations.

example, the PDD series start to recover from the dot-com bubble before the end of 2002, while the EURO STOXX index does it at least one quarter later. Similarly, the PDD reach their bottom from the subprime crisis at the end of 2008 while the reference equity index only starts to pick up after the end of the first quarter of 2009.

The PDD series do not show a linear trend but they suggest a high degree of comovement along the whole time span. In addition, the correlation coefficients among them for the time span of analysis are very high both in levels (0.84) and in first differences (0.60) and statistically significant.

Charts 2 and 3 show the median and quartile regions of sectoral bilateral correlation coefficients across sectors using 24-month moving windows of PDD series levels and first differences in order to illustrate the changing pattern of cross-section sectoral risk correlation over time.

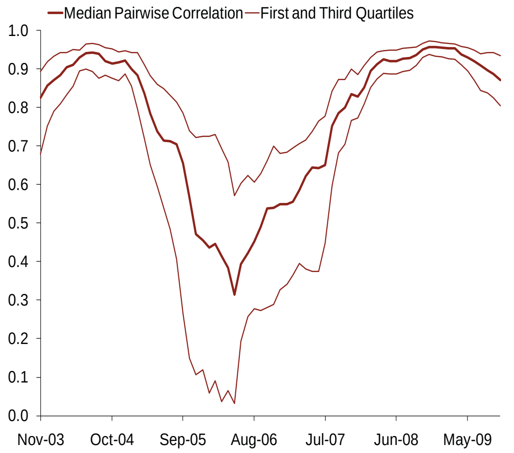
Median correlation is high over the entire sample. However, there is greater dispersion in tranquil times where sectoral-specific drivers of sector risk dominate. Median correlation increases and its dispersion across sectors narrows significantly in episodes of higher stress in financial markets, *e.g.* in the aftermath of the dot-com bubble burst in 2002; after the subprime crisis start in August 2007; and especially in the third quarter of 2008, after Lehman Brothers' collapse. At the end of the sample, median risk correlation across sectors remains high, but there is greater dispersion suggesting a moderation in the role of sector-wide risk drivers prior to the European sovereign debt crisis.

This overall high correlation pattern points out to a high degree of cross-section dependence (CD) across the sectors in sample. The reported correlation coefficients are good preliminary approximations but more robust results confirm the graphical inspection of the series if cross-section dependence tests are applied. Indeed, the Pesaran (CD_P) and Lagrange Multiplier (CD_{LM}) cross-section dependence tests applied to the series displayed in the Charts 2 and 3 show very high values that confirm the existence of high CD in the PDD series.[3]

3 CD_P=66.7 and CD_{LM}=4486.4 for the series in levels and CD_P=46.9 and CD_{LM}=2245.4 for the series in differences. These results lead reject the null hypothesis of no CD. These results are robust after controlling for serial correlation in the series.

Chart 2

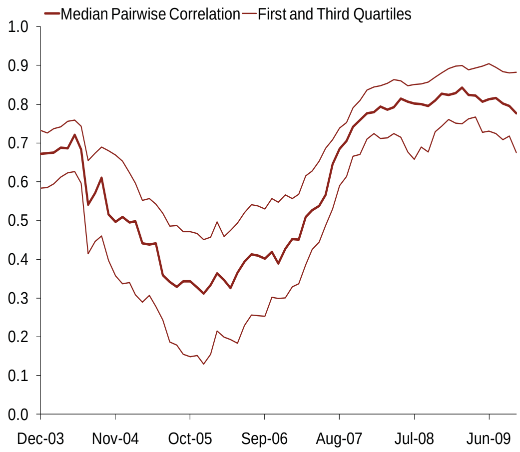
SECTORAL PDD SERIES PAIRWISE CORRELATION – LEVELS



Source: Author's calculations.

Chart 3

SECTORAL PDD SERIES PAIRWISE CORRELATION – FIRST DIFFERENCES



Source: Author's calculations.

3.2. Cross-section Dependence and Corporate Credit Risk

The CD tests highlight the strong interrelations of corporate default risk across the Supersectors in the sample. There are several factors driving the common behavior of sectoral risk and they may be both observable and unobservable in nature. The general economic conditions are naturally strong candidates as observable common factors. In addition, as PDD are market-based indicators, financial markets are also a strong common source of cross-section dependence among sectors. As a result, most literature on corporate default risk evaluates these effects. Very comprehensive studies in this area can be found in Alves (2005), Bernoth and Pick (2011), Carling *et al*. (2007), Castrén *et al*. (2009a, 2009b, 2010) and other references cited in Saldías (2011).

Additionally, strong comovement and high and time-varying correlation in PDD series is likely to be caused by risk diffusion across sectors as a result of different degrees of economic proximity. As in other economic groups, sectoral characteristics are interrelated and non independent to those of their closest peers but this cross-sectoral dependence is heterogeneous as their intensities change over time. These sources of default risk determinants and channels are often neglected in the literature but do play a relevant role.

In particular, similarity of business lines is a first source of this form of economic proximity and it includes inter alia a common customer or inputs channels and competition relationships. Financial linkages create another source of shock spillovers. They take place predominantly, yet not exclusively between the financial sector and the non-financial corporate via credit relationships and corporate governance linkages. Among non-financial companies, trade credit chains and counterparty risk relationships in securities markets do play a role in this sense. Finally, there are other several and relevant complementarity relationships across sectors that produce common risk movements. They can take place through technological linkages or collateral channels of risk through the securities channel.

4. Econometric Model

In order to assess the relevance and intensity of these relationships at sectoral level, the analysis of sectoral risk determinants and transmission is conducted using a dynamic panel, where the dependent variables are the PDD series. The risk determinants comprise three sets of variables.

The first set of regressors are observed common factors that capture common macroeconomic and systemic market shocks. In line with the literature, they are assumed to be exogenous and include the annual rate of change of the Industrial Production Index (ΔPI_t) and the Harmonised Index of Consumer Prices (ΔCP_t) in the euro area, in order to capture the effect of demand shocks. Brent Oil (1-Month Forward Contract) prices changes denominated in euro (ΔOIL_t) detect supply shocks. The short-term benchmark interest rate is also included using the 3-Month Euribor Rate ($R3M_t$), which also reflects developments in the money market affecting the financial sector and serves as a proxy for corporate debt yields and borrowing costs. They also are linked to corporate asset return growth. Finally, the Chicago Board Options Exchange Volatility Index (VIX_t) is included to gauge global equity market sentiment. The VIX index tends to be low when markets are on an upward trend and tends to increase with market pessimism, therefore its relationship with PDD series is expected to be negative.

The second set of regressors are sector-specific regressors and it includes the first lag of PDD in order to capture credit risk persistence ($PDD_{i,t-1}$) and the effect of the PDD inputs, *i.e.* market-implied assets' returns and volatility and aggregated leverage. The model also includes the direct risk spill-overs from "neighboring sectors"[4] and two other sector-specific variables related to the performance of each Supersector, namely the annual rate of change of the Price-Earnings Ratio, ($\Delta PE_{i,t}$), and the annual rate of change in Dividend Yields, ($\Delta DY_{i,t}$).

The general model specification is the following:

$$PDD_{i,t} = \alpha_i d_t + \beta_i X_t + u_{i,t} \tag{1}$$

where $PDD_{i,t}$ is vector of PDD series of sector i at time t. The vector d_t includes the intercepts and a set of observed common factors that capture common macroeconomic and systemic market shocks. $X_{i,t}$ group the sector-specific regressors. All coefficients are allowed to be heterogeneous across sectors and all remaining factors omitted are captured in the error term ut although the effect of unobserved common regressors is captured in the estimation. The CCE Mean Group estimator can be computed by OLS applied to sector-individual regressions where the observed regressors are augmented with cross-sectional averages of the dependent variable and the individual-specific regressors.[5]

5. Results and Discussion

The results from estimation of Equation (1) are reported in Table 2. The first three columns are estimates of naïve OLS Mean Group (MG) models that neglect cross-section dependence (CD) induced by unobserved common factors. The last three columns are Common Correlated Effects (CCE) estimates of these same specifications, hence more consistent given the CD in the data.

4 Credit spill-overs from sector i's neighboring sectors $\left(\overline{PDD}_{i,t}^{n}\right)$ is defined as the simple average of the n PDD series of the sectors that are assumed to be sector I's neighbors. The definition of neighbors relies on similarity of business lines embedded in the ICB methodology and covers important and overlapping dimensions of sectoral interdependencies, namely: balance-sheet exposures, financial linkages, common accounting practices, technological linkages, etc. Supersectors are first assumed to be neighbors if they belong to the same Industry, an upper level of aggregation to Supersectors in the ICB methodology structure. For instance, the Industry of Consumer Goods links the Supersectors of Automobiles & Parts and Foods & Beverages while Banks and Insurance Supesectors are bundled together as Financials. The second proximity relies on the most frequent company reclassifications across Supersectors within or outside a given Industry during the time span used in the paper. Examples of this were frequent in supersectors such as Industrial Goods & Services, Oil & Gas and Utilities, which do not belong to the same ICB Industries. For more discussion on this approach, refer to Saldías (2011).

5 For the correct model specification, panel unit root tests were conducted on the PDD series and the sector specific regressors. The results of $CIPS$ tests showed that they are stationary after controlling for CD, which means that these series are a combination of non-stationary common factors and stationary idiosyncratic components. These results mean that there is long-run equilibrium in sectoral risk, with temporary deviations caused by the macro-financial environment, sector-specific shocks and the cross-sectoral dynamics. Individual ADF tests were run for the exogenous macro-financial variables and they were differentiated when required to enter the econometric model.

The first three models are strongly consistent with the previous findings in the literature. In general, the results find high aggregate statistical significance of macro-financial variables (VIX, money market rates and consumer prices inflation). A closer look, although not reported here, does show heterogeneous signs across-sectors. The inclusion of persistence in the model and neighboring effects increases the explanatory power of the estimation. However, the CD tests on the residuals of these equations show that CD is still strong and therefore there is a potential bias in these results.

When the CD is controlled for in the model, the CCE estimates show interesting results. First, there is a loss of aggregate significance of macro-financial variables and only sector-specific regressors do exert statistically significant effects in aggregate terms. This result has been previously detected Sorge and Virolainen (2006) and can be interpreted as a consequence of the market-based nature of the PDD series, as they are less responsive to macroeconomic variables due to non-linearities in their interaction and as they are smoothed from business cycle volatility by construction. The role of the general economic environment hence becomes more indirect way, via market news already embedded in the PDD inputs and/or through cross-dynamics transmitting risk across industries.

The model CCE estimates also shows that risk persistence dominates, which emphasizes the effect of market-implied assets› returns and volatility and aggregated leverage in aggregate sectoral credit risk. In addition, the sectoral performance, as measured by dividend yields growth, is a relevant risk driver, where the associated negative sign highlights the negative relationship between risk taking and aggressive dividend policies (Acharya *el at*., 2011).

The role of the neighboring sectors at aggregate level seems non-significant. However, individual results at sectoral level show additional insights about this. Based on the last column in Table 2, Table 3 reports the individual results of the most comprehensive CCE model estimates in order to illustrate the heterogeneity of risk determinants across sectors. In particular, macroeconomic variables do matter for some sectors directly and with different signs and intensities. In addition, risk persistence is also diverse across sectors while the neighboring risk-spill-over effects show alternate signs.

Finally, it is worth mentioning that the results based on the CCE estimates are unbiased, as the model checking based on CD tests applied to the residuals show that CD is no longer present. The implication of this difference is very relevant for policy analysis, as any policy recommendation based on models that neglect the role of CD in the risk determinants and interrelations is dangerously misleading.

6. Conclusions

This paper laid out a framework to model and analyze risk in the corporate sector that takes into account their strong sectoral linkages and comovement. First part, the article outlined a methodology to compute comprehensive forward-looking risk indicators at sector-level based on Contingent Claims Analysis with information from balance sheets, equity markets and, more importantly, index option prices. The rest of article reviewed the properties of the resulting Portfolio Distance-to-Default series and evaluated the determinants of corporate default risk with an econometric model that incorporates the cross-section dependence of the PDD series.

Controlling for cross-section dependence among the PDD series, the first result of this analysis shows that sectoral risk comprises a stationary idiosyncratic component and a non-stationary common factor. This result provides empirical support to the notion that aggregate sectoral risk evolves to a long-run equilibrium, with temporary deviations caused by the macro-financial environment, sector-specific shocks and the cross-sectoral dynamics.

Results of the econometric model estimation using the Common Correlated Effects (CCE) method find evidence supporting a more relevant role of sector-specific variables as sectoral risk determinants in the corporate sector overall at the expense of the impact from macro-financial variables. The sector-specific drivers include risk persistence, measures of overall sectoral performance and also direct risk spill-overs

Table 2

ECONOMETRIC RESULTS

Variable $PDD_{i,t}$	MG [1]	MG [2]	MG [3]	CCEMG [4]	CCEMG [5]	CCEMG [6]
$Intercept$	0.481**	0.612**	0.402**	-0.058	0.033	-0.008
ΔVIX_t	-0.083**	-0.081**	-0.082**	0.000	-0.001	0.000
$\Delta R3M_t$	0.670**	0.617**	0.614**	-0.010	0.004	-0.004
ΔOIL_t	-0.004	-0.003	-0.005	0.000	0.000	0.000
ΔPI_t	0.000	0.001	-0.003	0.000	0.002	0.000
ΔCP_t	-0.025**	-0.021	0.002	0.011	-0.004	0.003
$\Delta DY_{i,t}$		0.000	0.000		-0.002**	-0.002*
$\Delta PE_{i,t}$		0.002	0.002*		0.001	0.000
$PDD_{i,t-1}$	0.921**	0.897**	0.798**	0.740**	0.672**	0.591**
$\overline{PDD}^n_{i,t-1}$			0.123**			0.013
$Observations$	1128	1072	1072	1128	1072	1072
$\bar{\rho}$	0.424	0.431	0.434	-0.082	-0.081	-0.077
CD_P	33.4	33.2	33.4	-6.5	-6.3	-5.9
CD_{LM}	1207	1202	1208	176.7	195	175.4
$IPS\ W_t\text{-}stat$	-31.724	-31.306	-31.486	-31.197	-31.59	-31.127
$CIPS\text{-}stat$	-6.19	-6.19	-6.19	-6.19	-6.19	-6.19

Source: Author's calculations.

Note: Definitions: ΔVIX_t are changes in the Chicago Board Options Exchange Volatility Index; $\Delta R3M_t$ is the 3-Month Euribor Rate (in first differences); ΔOIL_t are Brent Oil (1-Month Forward Contract in euro) price changes. $\Delta PE_{i,t}$ annual rate of change of the Price-Earnings Ratio; $\Delta DY_{i,t}$ is the annual rate of change in Dividend Yields, $PDD_{i,t-1}$ is the lag of the dependent variable; $\overline{PDD}^n_{i,t}$ measures the direct risk spill-overs from "neighboring sectors". $\bar{\rho}$, CD_P, CD_{LM} are test statistics of cross-section dependence and the IPS and $CIPS$ stats are statistics of panel unit root tests applied to the residuals. See Saldías (2011) for more details.

from risk in related sectors. The macroeconomic and financial common variables are found to play a less direct role. This empirical finding challenges much of the literature that focuses mainly on macroeconomic risk drivers and tends to ignore sector-specific characteristics and specially interactions either explicitly or implicitly through an aggregate analysis of the whole corporate sector.

This study also provides empirical evidence of the high degree of heterogeneity as concerns the relevance and responsiveness to the risk drivers used in the model, both in macro-terms as in sector-specific terms. These results show that a macro-only focus of the analysis of financial stability would be misleading for policy if cross-section dependence and sectoral heterogeneity are ignored. These results make a case for a more disaggregated analysis of risk across sectors without neglecting the inherent interactions that take place among them.

Table 3

ECONOMETRIC RESULTS: HETEROGENEITY												
	Supersector ICB											
$PDD_{i,t}$	BNK	TLS	ENE	INS	TEC	ATO	UTI	IGS	CHM	FOB	MDI	HCR
$Intercept$	-1.280**	0.600**	0.386	-0.393	-0.098	-0.698**	-0.234	0.384	-0.292	0.697	-0.341	1.175**
ΔVIX_t	0.004	0.013	-0.001	0.003	-0.014	-0.021	-0.008	0.026**	-0.008	0.001	-0.001	0.005
$\Delta R3M_t$	-0.362	0.248	-0.030	-0.010	0.105	0.318	0.331	-0.270	0.314	-0.151	-0.550**	0.007
ΔOIL_t	-0.012	0.006	0.022*	-0.015*	0.009	-0.008	-0.011	0.009	0.019	-0.016	-0.006	0.000
ΔPI_t	0.005	-0.008	0.018	0.014	-0.005	-0.012	-0.010	-0.002	-0.006	-0.006	-0.006	-0.006
ΔCP_t	-0.016	-0.038	-0.069	0.015	-0.017	0.132	0.080	-0.047	0.029	0.112	-0.001	-0.140
$\Delta DY_{i,t}$	0.001	0.002**		-0.003	-0.001	-0.002	-0.004	-0.005	-0.003	0.000	0.003**	-0.005
$\Delta PE_{i,t}$	0.001	0.001		0.000	0.000	0.000	-0.008	0.001	0.000	0.011**	0.000	0.000
$PDD_{i,t\text{-}1}$	0.420**	0.555**	0.796**	0.646**	0.846**	0.299**	0.761**	0.334	0.370**	0.688**	0.784**	0.591**
$\overline{PDD}^n_{i,t-1}$	0.034	0.168	0.121*	0.046	0.160	-0.045	0.029	-0.838*	0.020	0.057	0.433**	-0.039

Source: Author's calculations.

Nota: Definitions: ΔVIX_t are changes in the Chicago Board Options Exchange Volatility Index; $\Delta R3M_t$ is the 3-Month Euribor Rate (in first differences); ΔOIL_t are Brent Oil (1-Month Forward Contract in euro) price changes. $\Delta PE_{i,t}$ annual rate of change of the Price-Earnings Ratio; $\Delta DY_{i,t}$ is the annual rate of change in Dividend Yields, $PDD_{i,t\text{-}1}$ is the lag of the dependent variable; $\overline{PDD}^n_{i,t}$ measures the direct risk spill-overs from "neighboring sectors. See Saldías (2011) for more details.

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