CHAPTER 7

Short-Term Drivers of Sovereign CDS Spreads

Marcelo Yoshio Takami

7.1 Introduction

Given the size of the sovereign credit default swaps (CDS) market (currently at $1.6 trillion) and the valuable information it reveals about market expectations on the probability of default, there is great need for gaining understanding the determinants of CDS spreads (Alsakka and Gwilym 2010). CDS contracts are particularly useful for a wide range of investors, either for hedging existing exposures or for speculators who wish to take positions without the need to maintain the reference obligation on their

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M. Y. Takami (✉)
Corporate Risk and Benchmarks Department,
Banco Central do, Brasília, Brazil
e-mail: marcelo.takami@bcb.gov.br

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books. This is one reason why the market of sovereign CDS is, in some cases, more liquid than the underlying sovereign bond market itself.[1] Moreover, CDS spreads may be monitored for gauging the market perception of the debt sustainability of specific governments, as they provide more timely and, arguably, within periods of crisis, more accurate, distress assessment than rating agencies, as conveyed by long-term ratings. Timely measures of credit risk are important, for example, to central banks concerned with the risk of their foreign reserves portfolios.

To account for model uncertainty, I fit all possible linear models using the chosen independent variables (which include both global and local factors), and choose the model specification with the best fit for 35 developed and emerging economies' sovereign CDS spreads (please see Table 7.1 for the full list). Identifying the best model separately for each country might prove useful for risk assessment and, eventually, for forecasting purposes. This procedure also allows us to gain insights about the relative importance of each of the factors considered. The most important result I find is that the S&P 500 index is contemporaneously negatively related to the CDS spreads for most of the countries. Further, the coefficients of the S&P 500 are higher for emerging markets than they are for advanced economies. I also conduct multiple robustness checks, all of which confirm the main result of this chapter.

It must be stressed that the proposed framework is not necessarily meant to either predict crises or enhance financial investment efficiency; however, it might prove useful for supporting short-term sovereign risk assessment. This chapter is closely related to Westerlund and Thuraisamy (2016) and Longstaff et al. (2011), but differs from these studies in the following aspects: (1) focus on the short-term relationship between spreads and drivers, and (2) comparing the drivers of CDS spreads in developed and emerging economies.

This chapter is organized as follows: Sect. 7.2 revises the related literature; Sect. 7.3 presents a short description of the CDS market; Sect. 7.4 describes the data; Sect. 7.5 provides the empirical strategy, the results, and the robustness assessment; and finally Sect. 7.6 concludes this chapter.

Table 7.1 Classification of sovereigns according to investment class

Investment class	*Countries*	*Rating*
SDR (Special Drawing Right) basket	Germany	Aaa
	France	Aa2
	Italy	Baa2
	Spain	Baa2
	Belgium	Aa3
	Netherlands	Aaa
	Austria	Aa1
	Portugal	Ba1
	Ireland	A3
	Finland	Aa1
	Japan	A1
Other G20 countries	Australia	Aaa
	China[2]	Aa3
	Korea	Aa2
	Turkey	Ba1
	Indonesia	Baa3
	Russia	Ba1
	South Africa	Baa2
	Brazil	Ba2
	Mexico	A3
Other highly rated countries	Denmark	Aaa
	Sweden	Aaa
	New Zealand	Aaa
	Hong Kong	Aa1
	Chile	Aa3
Other emerging markets	Israel	A1
	Poland	A2
	Czech Republic	A1
	Hungary	Ba1
	Peru	A3
	Slovakia	A2
	Philippines	Baa2
	Malaysia	A3
	Thailand	Baa1
	Colombia	Baa2

Source: Moody's, Sep/2016

7.2 Related Literature

In the spirit of Westerlund and Thuraisamy (2016), I test many models with different combinations of multiple drivers, instead of solely testing a specific model, for each sovereign. Applying a bootstrap-based panel predictability test, Westerlund and Thuraisamy (2016) find that the global drivers are the best predictors. In line with this analysis, I find that the S&P 500 is statistically significant across the board.

This chapter's results are also closely in line with Longstaff et al. (2011), who find that sovereign credit spreads are primarily driven by global macroeconomic forces and that the risk premium represents about a third of the credit spread.[3] Sixty-four per cent of the variations in sovereign credit spreads are accounted for by a single principal component which primarily loads on USA stock, high-yield markets and volatility risk premium (proxied by the VIX index). Instead of using principal components, this chapter tries to find the subsets of explanatory variables that can best explain short-term CDS spreads for each of the countries considered.

While this chapter focuses on the short-term determinants of sovereign risk, Remolona et al. (2008) are concerned with pricing mechanisms for sovereign risk and propose a framework for distinguishing market-assessed sovereign risk from its risk premia. They use a dynamic panel data model with a sample covering 16 emerging countries' sovereign CDS spreads. In contrast, I believe that this chapter provides a more comprehensive understanding of the determinants of credit risk, since this chapter's sample covers not only emerging countries but also advanced economies, summing up to 35 countries.

7.3 Description of the CDS Market

The sovereign CDS market grew from \$0.17 trillion (in terms of notional amounts outstanding) in December 2004 to almost \$2 trillion in December 2015.[4] During the same period, the credit derivatives market increased from \$6 trillion to \$15 trillion. Fig. 7.1 shows that positions in sovereign contracts have become an increasing part of the CDS market since December 2004, while total notional amount outstanding in the credit derivatives market as a whole has been declining markedly since 2007.[5]

CDS spreads indicate the cost of buying protection against the default of a reference entity. The protection buyer pays a premium or spread on a periodic basis and in exchange, upon the occurrence of a credit event (defined within the terms of a CDS contract), has the right to sell the

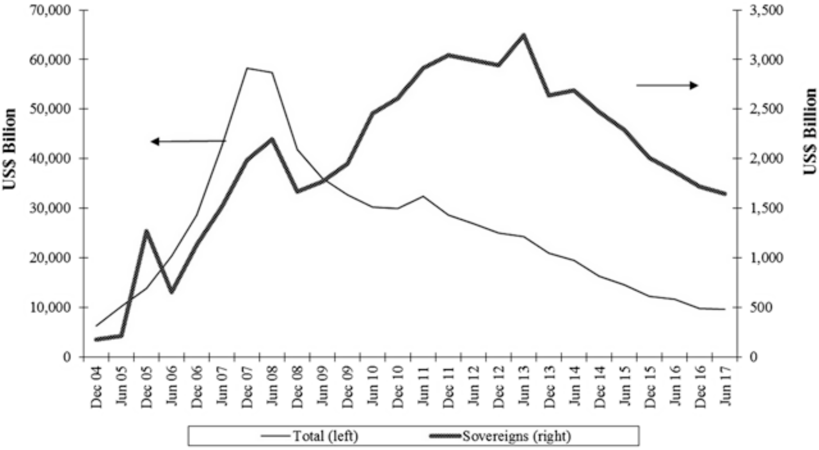

Fig. 7.1 Notional amount of CDS contracts outstanding: total versus sovereigns

bond to the protection seller at face value. CDS contracts are generally considered by market participants to be efficient and liquid instruments to mitigate credit risk. Further, they enable credit providers to diversify exposure and expand lending capacity. The protection seller, on the other hand, can take credit exposure over a customized term and earn the premium without having to fund the position. The spread is related to the expected loss of the bond: the higher the expected loss, the higher the spread. Since trades by market participants are more frequent than ratings (re)assessments by ratings agencies, CDS spreads are a more timely, though not necessarily a more accurate, way of gauging the market perception of credit conditions of specific entities.

Triggers for sovereign CDS contracts may be a failure-to-pay, a moratorium, or a restructuring. A failure-to-pay occurs when a government fails to pay part of its obligations in an amount at least as large as the payment requirement after any applicable grace period. A moratorium occurs when an authorized officer of the reference entity disclaims, repudiates, rejects, or challenges the validity of one or more obligations. A moratorium that lasts a pre-defined time period triggers a failure-to-pay event or a restructuring. Restructuring occurs when there is a reduction, postponement, or deferral of the obligation to pay the principal; when there is a change in priority ranking causing subordination to another obligation; or when there is a change in currency or composition of interest or principal payments to any currency which is not a permitted currency.

Upon default, there are two types of settlement: physical or cash. Both of them cause the termination of the contract. In the case of the physical settlement, the protection buyer delivers to the protection seller one of a list of bonds with equivalent seniority rights and the protection seller pays to the protection buyer the face value of the debt. In the case of cash settlement, the protection seller pays to the protection buyer the difference between the face value of the debt and its current market value.

7.4 DATA

The dependent variable for each of the 35 investment-class markets listed in Table 7.1 is the change in its five-year CDS spreads, with the reference obligation being a deliverable senior dollar-denominated external debt of the sovereign. Table 7.2 shows descriptive statistics for the sovereign CDS spreads of the 35 selected countries.

I select the set of global and local explanatory variables that could potentially be used by investors and risk-managers who take short-term views on sovereign risk. The focus of this chapter is on establishing statistical relationships, and not on identifying the economic content of the variables considered. The slope, for example, not only provides an indirect indication of future tax revenues, as they are related to growth prospects through the business cycle, but also captures the risk premia embedded in long-term yields. Alternatively, it could convey information about the state of the economy with respect to growth prospects, risk aversion, banking system vulnerability, and business cycle. In this chapter, I do not take a stand on which of these interpretations matters more for the results.

In the following, I use $sp500$, vix, $Slope$, and oil, respectively, to refer to the S&P 500 index, VIX index, USA slope factor, and Brent oil price index. The local factors that I consider as presumably providing information on specific aspects related to debt sustainability or overall risk premium are the local stock index level ($stock_i$), exchange rate (xr_i), local two-year yield ($localTY_i$), local slope factor ($localSlope_i$), and the average of banks' CDS spreads (when available) of the banking system of the corresponding jurisdiction ($bank_i$). Given the reasonable assumption of persistence of CDS spreads, I include the lagged dependent variable in the regression. The description of the variables, the economic reasoning behind their inclusion, and data sources are described in detail in Table 7.3.

Table 7.2 Descriptive statistics for CDS spreads

	Mean	*Standard deviation*	*Minimum*	*Median*	*Maximum*	*# obs*
Germany	38.6	26.1	12.2	28.2	112.4	317
France	81.1	53.1	25.4	67.2	241.3	317
Finland	34.2	18.0	18.1	26.9	87.4	317
Netherlands	47.7	29.8	15.5	40.5	130.1	317
Austria	64.0	51.3	21.2	39.2	228.2	317
Belgium	107.0	83.0	31.8	62.2	381.6	317
Slovakia	100.0	70.2	38.2	81.3	315.0	317
Spain	222.0	136.0	58.6	217.7	613.1	317
Italy	222.1	126.9	85.3	173.1	566.6	317
Ireland	285.5	274.9	40.3	145.7	1207.3	317
Portugal	468.2	347.4	119.3	350.4	1615.0	317
Denmark	43.5	35.8	14.1	26.8	152.4	317
Sweden	27.4	16.4	13.1	20.6	80.8	317
Poland	116.2	61.1	53.7	87.6	318.8	317
Czech Rep.	74.0	33.2	38.5	59.7	189.8	317
Hungary	286.0	134.3	117.6	271.1	699.2	317
Turkey	204.3	49.5	112.9	200.6	327.7	317
Russia	227.5	94.8	120.3	198.8	615.5	317
Australia	48.7	15.4	28.2	45.0	103.5	317
New Zealand	52.5	20.1	27.7	45.6	117.8	317
Japan	67.7	26.9	32.5	63.4	152.0	317
Hong Kong	52.7	13.8	35.6	47.5	103.8	317
Korea	83.5	32.0	46.3	69.9	214.2	317
China	95.0	24.4	54.5	89.5	191.6	317
Philippines	121.4	30.5	79.9	113.5	255.1	317
Indonesia	174.8	37.5	121.6	165.0	296.9	317
Thailand	121.9	26.7	81.7	118.4	237.5	317
Malaysia	114.6	35.4	66.7	106.9	232.4	317
South Africa	190.8	55.1	109.6	180.6	376.3	317
Israel	115.9	39.3	64.7	114.7	209.0	317
Brazil	191.9	100.2	94.2	155.9	498.6	317
Mexico	120.2	30.3	66.1	114.8	221.1	317
Peru	131.5	30.1	77.6	129.6	221.6	317
Chile	90.7	21.1	57.5	84.9	156.8	317
Colombia	138.1	47.8	75.5	123.6	312.7	317

Source: Capital IQ

To avoid potential problems of non-stationarity of the variables in our study, I analyse the first differences of all the variables at the weekly frequency from July 2005 to July 2016. I perform the analysis at the weekly frequency to get a sufficient sample size. This, however, has the drawback of making it infeasible to use other macroeconomic sovereign credit-related

Table 7.3 Description of explanatory variables

Variable acronym	*Description and economic reasoning*	*Expected sign*	*Source*
$spread_i$	The CDS spread referencing country *i*'s debt stands as the last daily prices of a five-year senior dollar-denominated CDS contract. This is the dependent variable in the estimation; its lag is also included as an eligible explanatory variable in the estimation	Negative/ positive	Capital IQ
*sp*500	The Standard & Poor's 500 Index is typically a gauge of the general state of the global economy	Negative	Bloomberg ticker: SPX
vix	VIX is a measure of market's expectation of stock market volatility. The positive variation of this index is associated with higher uncertainty and risk aversion among investors	Positive	Bloomberg ticker: VIX
Slope	The slope factor is set as the 10-Year USA Treasury Constant Maturity interest rates minus the three-month USA Treasury Constant Maturity interest rates. It presumably provides prospective information on the business cycle of the global economy. The slope factor is influenced positively by economic growth and by inflationary expectations; it is influenced negatively by risk aversion	Negative	Bloomberg tickers: H15T10Y and H15T3M
oil	The oil price is the last quoted price of the day of the London Brent Crude Oil Index. In general, increasing oil prices reflect both the surging of global economic activity or the impact of production shortfalls. As for the demand side, when the pace of economic expansion picks up, so is the global demand for energy expected to increase. Changes in oil prices might thus be deemed as a competing indicator of the state of the global economy as well as changes in S&P 500 or VIX indices	Negative	Bloomberg
$stock_i$	The local stock exchange index is expected to rise or remain stable when companies and the economy in general show positive prospects in terms of stability and growth. It is expected to decrease in periods of crisis. Then, it is an indicator generally used to gauge the overall economic health	Negative	Bloomberg

xr_i	The exchange rates are expressed in units of local currency per USA dollar. Arguably, currency devaluation might lead to additional charges for dollar-denominated indebted countries and for countries with negative balance of trade and highly dependent on import of manufactured products. On the other hand, as an indicator of relative international price competitiveness, currency devaluation might bring benefits derived from the international trade	Positive/ negative	Bloomberg
$localTY_i$	The two-year local government bond yield refers to the local currency denominated fixed rate government debt. All bond prices are mid-rates and are taken at the close of business in the local office for all markets. In general, high two-year yields are related to negative growth prospects in the near future. Moreover, high yields signal that the country might be struggling to attract investors to fund its expenses	Positive	Bloomberg
$localSlope_i$	The local slope factor is the difference between the interest rates on ten-year and two-year local government bonds. It is due to provide prospective information on the business cycle of the local economy. When the slope decreases or becomes negative, it indicates a slowdown in economic activity in the foreseeable future. On the other hand, higher slopes suggest expectations of increasing economic growth	Negative	Bloomberg
$bank_{i,\,t}$	Average of CDS spreads of banks comprising the banking system of a country *i*: the spreads stand as the last daily prices of a five-year senior CDS contract. The increasing deterioration of the banking system risk perception might be expected to spill over into the sovereign risk as long as its contingent liability becomes an ever growing part of the total government debt	Positive	Datastream

factors, such as deficit/GDP, debt/GDP ratios, or foreign reserves, as explanatory variables. These variables are available at best at a monthly frequency. I test as many as possible econometric models for a time period encompassing the period July 2005 to October 2012. The last 45 months (from November 2012 to July 2016) are set apart for calculating out-of-sample goodness-of-fit statistics.

7.5 Empirical Strategy and Results

First, in order to mitigate potential multicollinearity issues, I orthogonalized the variables most usually associated to the general economic conditions (*vix*, *oil*, and *stock*) to the S&P 500.

I begin the empirical analysis by attempting to narrow down the set of variables that could be included in the regressions, by means of the Granger-causality test (Granger 1969). This step is useful to reduce the computational time required for the analysis. I limit the set of eligible local explanatory variables to only endogenous and weakly exogenous ones, as given by the Granger-causality test. I narrow the set of variables because when estimating models with contemporaneous independent variables, a primary concern is the endogeneity of the regressors. For example, while weekly changes in the exchange rate may anticipate changes in CDS spreads, it could also be argued that currency changes might arise as a consequence of changes in CDS spreads. When associated with a negative outlook of government debt sustainability, increases in CDS spreads might lead currency depreciation as net capital outflows ensue. In order to mitigate such endogeneity issues, I run Generalized Method of Moments (GMM) estimations with instrumental variables for the endogenous variables. When the variable is set as exogenous *a priori* (this is the case for the global variables and the lagged dependent variable), I simply use it as instrument for itself; for the endogenous ones, I use their first lags as instruments. Non-exogenous and non-endogenous variables are not considered in the model specification. Therefore, by constraining the testable model specifications to a subset of only endogenous and exogenous variables, I can save computational cost. Parts A and B of Table 7.4 show chi-squared statistics for the Granger-causality test, respectively: (1) whether local variables anticipate changes in CDS spreads, and (2) whether the opposite holds true. A variable is deemed eligible when it is weakly exogenous or endogenous. Table 7.5 shows the subset of eligible variables for each country, that is, the weakly exogenous and endogenous variables

Table 7.4 Granger-causality test

	Part A					*Part B*				
	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$
Germany	8.8	2.5	10.5*	11.5**	10.7*	6.5	12.7**	4.5	12.9**	4.4
France	5.1	2.6	7.9	11.9**	20.0***	9.5*	7.7	6.2	6.9	16.5***
Finland	5.0	5.7	4.5	7.2	8.9	7.2	19.4***	9.5*	3.5	28.9***
Netherlands	7.5	10.0*	9.6*	11.1**	5.6	9.9*	14.7**	14.1**	9.5*	6.1
Austria	8.5	3.8	10.5*	26.4***	13.2**	12.1**	8.8	11.9**	7.2	21.2***
Belgium	1.6	5.9	16.1***	30.3***	12.9**	5.7	11.9**	4.8	10.6*	11.9**
Slovakia	8.4	8.3	8.5	5.5		15.0**	5.6	8.8	28.4***	
Spain	4.5	6.3	7.7	17.5***	31.5***	1.8	4.6	9.8*	18.9***	29.5***
Italy	8.8	3.7	38.0***	29.1***	30.8***	10.0*	5.7	4.2	8.9	21.9***
Ireland	2.2	2.4	5.9	12.8**	7.8	7.8	10.4*	17.1***	24.5***	19.1***
Portugal	4.1	1.7	10.5*	19.9***	25.8***	12.8**	8.1	49.9***	50.7***	17.6***
Denmark	20.9***	4.8	17.3***	5.3	7.4	24.3***	13.8**	11.2**	1.6	8.3
Sweden	23.3***	18.5***	6.0	14.8**	11.6**	14.1**	19.9***	9.9*	0.8	25.7***
Poland	5.4	19.1***	13.7**	12.8**		9.4*	8.8	7.6	5.9	
Czech Rep.	5.7	33.4***	24.7***	1.6		44.6***	9.0	31.4***	4.9	
Hungary	6.9	20.5***	12.5**	10.0*		21.2***	25.5***	8.0	24.5***	
Turkey	11.8**	28.5***	16.7***	5.3	90.4***	12.6**	20.0***	8.9	12.4**	173.5***
Russia	36.1***	15.1**	10.5*	10.5*	52.8***	8.5	16.4***	4.2	4.3	85.8***
Australia	10.7*	4.5	18.4***	17.7***	38.8***	11.6**	15.3***	6.5	10.8*	12.9**
New Zealand	6.1	15.9***	2.4	6.1		7.3	7.1	0.6	6.4	
Japan	14.3**	3.7	4.1	1.9	7.9	6.3	2.3	3.0	6.1	15.8***
Hong Kong	22.2***	2.3	3.6	15.8***	27.9***	10.5*	6.5	6.8	21.4***	9.8*
Korea	39.5***	71.9***	5.2	11.0*	105.8***	11.5**	41.2***	19.8***	4.3	174.5***
China	12.6**	1.9	25.7***	7.0	17.4***	21.5***	9.8*	11.0*	5.0	64.8***
Philippines	33.5***	3.3	8.3	7.4		26.0***	15.5***	11.2**	14.1**	

(*continued*)

Table 7.4 (continued)

	Part A					*Part B*				
	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$
Indonesia	42.5***	81.4***	117.7***	12.6**		42.8***	100.2***	62.0***	16.4***	
Thailand	27.4***	8.2	8.4	20.3***		43.8***	6.3	17.5***	2.0	
Malaysia	11.7**	18.4***	14.4**	14.1**	3.9	21.1***	6.9	4.2	7.8	38.3***
South Africa	15.3***	26.4***	11.7**	36.4***		14.8**	9.2	21.5***	0.9	
Israel	6.2	14.7**	6.3	5.3		13.6**	8.2	9.6*	2.5	
Brazil	13.9**	30.3***	5.3	1.9		10.2*	22.4***	7.5	9.4*	
Mexico	35.7***	34.6***	13.5**	3.9		13.1**	9.6*	4.7	2.5	
Peru	3.5	22.8***	16.0***	6.4		18.4***	7.8	10.7*	4.1	
Chile	23.5***	10.5*	14.8**	10.1*		7.9	8.8	14.2**	10.6*	
Colombia	11.2**	20.6***	17.5***	2.3		4.4	2.4	4.8	1.3	

Each column in Part A shows the chi-squared statistics with *n* degrees of freedom (χ_n^2) for the hypothesis test that the corresponding factor f_t does not "Granger cause" the first difference of CDS spreads of the country in the corresponding row. The Granger-causality test is a Wald test on the restrictions that the β_ls are jointly zero at the estimation of equation: $\Delta\text{spread}_{i,t} = \alpha_0 + \sum_{k=1}^{5}\alpha_k \Delta\text{spread}_{t-k} + \sum_{l=1}^{5}\beta_l \Delta f_{t-l} + \varepsilon_t$. Part B shows the chi-squared statistics for whether the opposite holds true, that is, for the hypothesis test that the first difference of CDS spreads of the country in the corresponding row does not "Granger cause" the corresponding factor f_t. The Granger-causality test is a Wald test on the restrictions that the δ_ls are jointly zero at the estimation of equation:

$$\Delta f_t = \gamma_0 + \sum_{k=1}^{5}\gamma_k \Delta f_{t-k} + \sum_{l=1}^{5}\delta_l \Delta\text{spread}_{t-l} + \eta_t$$

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level

Table 7.5 Set of eligible explanatory variables

	Global variables				*Local variables*					
	$sp500_t$	vix_t	$Slope_t$	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$
Germany	(*)	(*)	(*)	(*)	(*)			*	&	*
France	(*)	(*)	(*)	(*)	(*)				*	&
Finland	(*)	(*)	(*)	(*)	(*)					
Netherlands	(*)	(*)	(*)	(*)	(*)		&	&	&	
Austria	(*)	(*)	(*)	(*)	(*)			&	*	&
Belgium	(*)	(*)	(*)	(*)	(*)			*	&	&
Slovakia	(*)	(*)	(*)	(*)	(*)					
Spain	(*)	(*)	(*)	(*)	(*)				&	&
Italy	(*)	(*)	(*)	(*)	(*)			*	*	&
Ireland	(*)	(*)	(*)	(*)	(*)				&	
Portugal	(*)	(*)	(*)	(*)	(*)			&	&	&
Denmark	(*)	(*)	(*)	(*)	(*)	&		&		
Sweden	(*)	(*)	(*)	(*)	(*)	&	&		*	&
Poland	(*)	(*)	(*)	(*)	(*)		*	*	*	
Czech Rep.	(*)	(*)	(*)	(*)	(*)		*	&		
Hungary	(*)	(*)	(*)	(*)	(*)		&	*	&	
Turkey	(*)	(*)	(*)	(*)	(*)	&	&	*		&
Russia	(*)	(*)	(*)	(*)	(*)	*	&	*	*	&
Australia	(*)	(*)	(*)	(*)	(*)	&		*	&	&
New Zealand	(*)	(*)	(*)	(*)	(*)		*			
Japan	(*)	(*)	(*)	(*)	(*)	*				
Hong Kong	(*)	(*)	(*)	(*)	(*)	&			&	&
Korea	(*)	(*)	(*)	(*)	(*)	&	&		*	&
China	(*)	(*)	(*)	(*)	(*)	&		&		&
Philippines	(*)	(*)	(*)	(*)	(*)	&				
Indonesia	(*)	(*)	(*)	(*)	(*)	&	&	&	&	
Thailand	(*)	(*)	(*)	(*)	(*)	&			*	
Malaysia	(*)	(*)	(*)	(*)	(*)	&	*	*	*	
South Africa	(*)	(*)	(*)	(*)	(*)	&	*	&	*	
Israel	(*)	(*)	(*)	(*)	(*)		*			
Brazil	(*)	(*)	(*)	(*)	(*)	&	&			
Mexico	(*)	(*)	(*)	(*)	(*)	&	&	*		
Peru	(*)	(*)	(*)	(*)	(*)		*	&		
Chile	(*)	(*)	(*)	(*)	(*)	*	*	&	&	
Colombia	(*)	(*)	(*)	(*)	(*)	*	*	*		

(*) stands for exogeneity by assumption

* and & stand for weak exogeneity and non-weak exogeneity, as for the Granger-causality test, at 10% significance level, respectively

Blank accounts for non-significance at 10% significance level; in this case, the corresponding variable is not part of any estimation model for the corresponding country marked with the labels "*" and "&", respectively. Let's take the case of Italy. Their eligible variables are the global variables (*sp*500, *vix*, *Slope*, and *oil*) and the local variables $spread_i - 1$, $localTY_i$, $localSlope_i$, and $bank_i$. The first five variables are assumed to be exogenous *a priori*. Weak exogeneity is attributed to $localTY_i$ and $localSlope_i$, as their chi-squared statistics are significant at the 10% level in Part A (Table 7.4), while their Part B's (Table 7.4) chi-squared statistics are non-significant at the 10% level. $bank_i$ is set as endogenous, as their chi-squared statistics are significant at the 10% level in both Part A and Part B. When there is no label, the corresponding variable is not taken as eligible. Variables labelled as "(*)" in Table 7.5 are set as exogenous by assumption, that is, the global variables and the first lag of the dependent variable are not expected to be affected by the dependent variable in any sense.

I run the change in the weekly CDS spread over the four global factors (*sp*500, *vix*, *Slope*, and *oil*), the lagged first difference of the corresponding CDS spread, and the local factors chosen following Granger-causality test results. Second, I run the large-scale engine in Stata (Baum 2003) for choosing the best-fit model for each country *i*, testing as many econometric models as possible, according to Eq. (7.1):

$$\Delta \text{spread}_{i,t} = \alpha_i + \sum_{j=1}^{4} \beta_{i,j} . \Delta X_{j,t} + \lambda_i . \Delta \text{spread}_{i,t-1} + \sum_{k=1}^{5} \gamma_{i,k} . \Delta Z_{i,k,t} + \varepsilon_{i,t} \tag{7.1}$$

where α_i = constant term for country *i*, $X_{j,\,t}$ = set of global factors for week *t*: *sp*500, *vix*, *Slope*, or *oil*, $Z_{i,\,k,\,t}$ = set of local factors for country *i* and week *t*: $stock_i$, xr_i, $localTY_i$, $localSlope_i$, or $bank_i$, $\varepsilon_{i,\,t}$ = error term for country *i* and week *t*.

Variable transformations are such that "rate" variables are transformed first into absolute values, that is, CDS spreads, originally in basis points, are divided by 10,000; the other "rate" variables are divided by 100, when originally obtained in percentage format (*USA slope factor, Local Short-Term Yield*, and *Local slope* factor). "Price" variables are transformed into their logarithms: S&*P* 500 *index, VIX index, Oil price, Local Stock Index*, and *Exchange Rate*. I take the first differences of the resulting variables.

In the second step, I let the algorithm selects the model specification for each country constrained by the following pre-defined set of criteria.[6] First, I require that at least one variable with significance at the 10% level has the expected sign as in Table 7.3 is included in the model. Within the space of such models, I select the one with the highest Adjusted R^2 which is statistically superior to all possible nested models.[7] After testing 255 model specifications for Italy, for instance, the engine comes out with a model comprising *S&P*500, *Slope*, *spread* − 1, and *localTY* factors, as shown in Table 7.6. The Italy's S&P 500 estimator value of −0.025 means that a 1% weekly variation of the S&P500 index would be consistent, *ceteris paribus*, with a 2.5 basis points contemporaneous reduction in the Italy's CDS spreads. Blank cells in Table 7.6 mean that models including the corresponding factor are superseded by the prevailing model specification as presented in the table; or simply that this variable is not selected in the selection procedure. Finally, I assess the goodness-of-fit of the estimations and their forecast accuracy.

7.5.1 Results

The most striking result of Table 7.6 is that the *sp*500 estimator not only shows up as significant for most of the countries (22 out of 35), but one can also notice a remarkable difference in sensitivity magnitudes to this global factor between emerging markets and advanced economics. For countries where *sp*500 doesn't show up as statistically significant in the specification (Germany, the Netherlands, Austria, Portugal, Denmark, Poland, Turkey, Australia, Hong Kong, Korea, China, Mexico, and Chile), different combinations of global and local factors (*oil*, *spread* − 1, *xr*, *localTY*, and *bank*) are found by the algorithm to be their best-fit models. Quite noticeably, *vix*, *oil*, and *stock*, which are exactly the variables orthogonalized against *sp*500, barely show up as significant for any country's model specification.[8] In line with the usual finding that most emerging markets and advanced economies are typically well integrated into the global markets, no local variable shows up as a significant driver of sovereign CDS spreads for 16 out of the 35 countries.[9]

The pervasiveness of *sp*500 is consistent with the results reported by other authors (Longstaff et al. 2011; Pan and Singleton 2008). The results in Table 7.6 also confirm the intuition that CDS spreads of emerging market sovereigns are more sensitive to global factors than spreads of developed countries.

That the CDS spreads of Israel, Malaysia, South Africa, Mexico, Peru, Chile, and Colombia are significantly sensitive to the exchange rate is in line with the evidence (Broner et al. 2013; Broto et al. 2011; Calvo 2007) that emerging markets' debt riskiness is tightly linked to the dynamics of global capital flows or commodity prices.

Table 7.6 GMM results

	Const	*Global variables*				*Local variables*						*Adj.* $R^{2[c]}$	$U_1^{a,d}$	$U_2^{a,d}$	$PHM^{b,d}$	*#obs.*[c]
		$sp500_t$	vix_t	$Slope_t$	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$					
Germany	4.0E-06					0.26***						6%	0.749	0.777	42%	383
France	2.0E-05	−0.013***				0.09						19%	0.563	0.754	35%	374
Finland	9.0E-06	−0.007***	−0.0004									24%	0.608	0.792	44%	353
Netherlands	1.0E-05					0.18**						3%	0.818	0.787	53%	352
Austria	1.7E-05				−0.003*						0.28	39%	0.650	1.231	43%	241
Belgium	3.0E-05	−0.017***										13%	0.589	0.880	41%	383
Slovakia	4.0E-05	−0.022***										21%	0.618	0.987	42%	383
Spain	1.0E-04	−0.025***										10%	0.675	0.695	34%	313
Italy	6.9E-05	−0.025***		−0.16***		0.09			0.45***			44%	0.509	0.616	24%	383
Ireland	6.0E-05	−0.026***										3%	0.629	0.783	37%	353
Portugal	5.0E-05								0.84***	0.50		55%	0.305	0.469	25%	359
Denmark	1.0E-05					0.30***						8%	0.767	0.733	47%	352
Sweden	6.0E-06	−0.009***	−0.0008									17%	0.636	0.977	47%	353
Poland	3.0E-05								0.39***			10%	0.599	0.706	44%	378
Czech Rep.	3.0E-05	−0.022***										21%	0.622	0.872	34%	383
Hungary	1.0E-04	−0.040***				0.13			0.39***			51%	0.468	0.661	28%	295
Turkey	1.1E-04			−0.26					0.32***			36%	0.386	0.499	29%	333
Russia	4.0E-05	−0.033**		0.13			−0.014**	0.05	0.29**	0.17		99%	0.224	0.308	22%	96
Australia	8.0E-06	−0.008			−0.002*						0.38	39%	0.402	0.649	30%	252
New Zealand	2.0E-05	−0.012***										12%	0.541	0.705	36%	313
Japan	2.0E-05	−0.011***										19%	0.608	0.745	36%	383
Hong Kong	3.0E-06										0.28***	44%	0.643	0.726	42%	213
Korea	1.0E-05					−0.15					1.05***	87%	0.215	0.309	15%	252
China	2.0E-06					−0.31					1.03**	46%	0.315	0.481	19%	252
Philippines	−5.0E-05	−0.060***										32%	0.451	0.893	28%	383
Indonesia	2.0E-06	−0.092***	−0.0017									34%	0.461	0.764	32%	383

Thailand	3.0E-05	−0.036***										26%	0.454	0.646	31%	383
Malaysia	5.0E-05	−0.029***						0.04***				30%	0.405	0.597	24%	383
South Africa	−1.0E-05	−0.044***						0.04***		−0.12		59%	0.371	0.525	23%	206
Israel	4.0E-05	−0.018***	−0.0005		0.001			0.01*				25%	0.530	0.706	37%	383
Brazil	5.0E-06	−0.048***					−0.032					44%	0.471	0.563	28%	383
Mexico	−5.8E-05	−0.009						0.06**	−0.04			97%	0.352	0.502	26%	86
Peru	−6.0E-05	−0.042***						0.05**	−0.07			92%	0.415	0.633	30%	112
Chile	1.0E-05							0.05**		−0.29		43%	0.467	0.687	29%	84
Colombia	5.0E-06	−0.047***			−0.003		−0.006	0.02***	0.12***			49%	0.340	0.466	27%	372

This table reports, for each country, results of models: (1) with at least one 10%-significant coefficient with expected signs according to Table 7.3, (2) with the highest Adjusted R^2, and (3) statistically superior to all possible nested models. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and out-of-sample (November 2012 to July 2016) periods. Only permutations of explanatory variables labelled with "(*)", "*", and "&" in Table 7.5 are taken as eligible estimation models. The explanatory variables were selected according to 10% significance level when applying the Granger-causality tests. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 7.5. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. *Vix* and *Local Slope* don't show up as significant for any country

Source: Capital IQ, Bloomberg, Datastream and author's calculations

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

[a]and [b] stand for Theil's U_i and percent hit misses, respectively

[b]and [d] stand for in-sample and out-of-sample calculations, respectively

Another interesting finding is that Portugal, Italy, Russia, Poland, Hungary, Turkey, and Colombia appear in Table 7.6 with local two-year yields being significant. While Portugal's and Italy's short-term debts might have been eventually under rollover risk between 2010 and 2012, as per the Eurozone debt crisis, the CDS spreads and yields co-movements of Russia, Poland, Hungary, Turkey, and Colombia are consistent with the usual view that a large part of their higher yields is presumably related to credit risk itself. In any case, these dynamics are arguably consistent with protection-sellers charging higher premiums on CDS contracts with those debts as reference obligations.

The fact that *bank* barely shows up as significant might be due to the general assessment that the transmission of distress from the banking sector to sovereign credit may occur more like a structural break than gradually over time.[10] It could perhaps have been expected that increases in *bank*, as a stress indicator of the banking sector, could have gradually spilled over into the risk perception of sovereign bonds. Thus, the apparent underpricing of the spillover effect from the financial stability stance to the sovereign debt risk during the period leading to the 2010–2012 European sovereign debt crisis can be tentatively explained by the expectation that governments would: (1) monetize their debts (perhaps more in the case of the USA than for Eurozone countries), (2) wipe out defaulted bank's shareholders and subordinated debtholders, or (3) be simply bailed out by economically stronger sovereigns. While not having been noticeably impacted by the global financial crisis, Hong Kong, Korea, and China are three jurisdictions where the banking sector remained relatively stable during the 2005–2012 period and where the governments are perceived to be very supportive of their domestic big banks. This may be the reason why, in these three cases, the sovereign and their banking system CDS spreads tend to co-move, that is, why their coefficients of the *bank* variable showed up as significant.

Next, I perform a goodness-of-fit analysis and compare the contemporaneous-variable model estimation outcomes with those of Autoregressive Moving Average (ARMA) structural models and lagged-explanatory variables specifications.

The goodness-of-fit of the GMM estimations is evaluated by means of Adjusted R^2, Theil's U_1, Theil's U_2, and percent hit misses (PHM) statistics. I calculate Adjusted R^2s for the in-sample period, whereas for calculating Theil's U_1, Theil's U_2, and PHM out-of-sample statistics, I use the first two-thirds of the data for estimation and perform out-of-sample tests on the remaining sample. Normalizing the root mean squared error by the dispersion of actual and forecasted series or calculating the root mean squared percentage errors relative to naive forecast (random walk), Theil's U_1 and Theil's U_2 stand, respectively, as intuitive assessments of forecast accuracy. PHM assesses whether the direction of the prediction is accurate or not, that is:

$$PHM = {}^{\#\,HitMisses}\!\big/_{N}$$

where $\#HitMisses$ = number of times the prediction does not have the same sign as the realized value and N = total number of observations.

It is well known that higher values of Adjusted R^2 imply better model fit; however, lower Theil's U_1, Theil's U_2, and PHM values indicate better forecasting ability.

The goodness-of-fit statistics of Table 7.6 suggest that emerging market economies' models presumably show more forecasting power than the developed countries'. Sorting into ascending (Adjusted R^2) or descending order (Theil's U_1, Theil's U_2, and PHM), these statistics confirm that countries at the bottom rows of the table, broadly composed of emerging market economies, are associated with better goodness-of-fit measures.

As a benchmark for this chapter's GMM estimations, ARMA model specifications are also estimated. The ARMA(p,q) process is estimated by full-information maximum likelihood estimation (FIMLE), following Box et al. (1994) and Enders (2004). I select the best model according to the following criteria: (1) the AR and MA terms are significant at the 10% level; (2) the residuals behave as a white-noise process (all autocorrelations of the residuals should be indistinguishable from zero), (3) the model has to have the lowest Bayesian Information Criteria (BIC) statistic, (4) it is non-degenerate, that is, there are no gaps within AR or MA terms, and (5) when (1) and (2) don't hold, then I only take criteria (3) and (4) into account. I use Ljung and Box (1978) Q-statistic in eq. (2) at 10% significance level for testing (2).

$$Q = T(T+2)\sum_{k=1}^{s} {}^{r_k^2}\!\big/_{(T-k)} \tag{7.2}$$

If Q exceeds the critical value of χ^2 with $s - p - q$ degrees of freedom, then at least one value of r_k, which is the sample autocorrelation coefficient of order k, is statistically different from zero (I set s to 10).

Table 7.7 shows that the goodness-of-fit statistics (Adjusted R^2, Theil's U_1, Theil's, U_2 and PHM) of are noticeably worse than the respective contemporaneous model statistics (Table 7.6).

Table 7.7 ARMA results

	AR terms			*MA terms*					*Adj.* R$^{2[c]}$	$U_1^{a,d}$	$U_2^{a,d}$	*PHM*^{b,d}
	α_1	α_2	α_3	β_1	β_2	β_3	β_4	β_5				
Germany	0.3***								6%	**0.748**	**0.776**	**39%**
France				0.1					1%	0.862	0.778	35%
Finland				0.4***					10%	0.751	**0.748**	45%
Netherlands				0.2**					**3%**	**0.807**	**0.781**	**44%**
Austria				0.4***					11%	0.710	**0.780**	**38%**
Belgium				0.2*					3%	0.817	**0.755**	**40%**
Slovakia				0.3***					10%	0.767	**0.760**	51%
Spain				0.05					0%	0.948	0.744	39%
Italy	1.7***	−1.2***	0.2*	−1.7***	1.0***				8%	0.753	0.787	53%
Ireland				0.2***	−0.3				**10%**	0.733	0.798	50%
Portugal	1.0***			−0.8***	−0.4***	0.1	−0.1	0.2***	13%	0.691	0.929	39%
Denmark				0.3***					**9%**	**0.763**	0.738	**44%**
Sweden				0.3***	0.1	0.2			13%	0.765	**0.768**	**46%**
Poland				0.4***					**11%**	0.767	0.765	**42%**
Czech Rep.				0.4***					12%	0.804	**0.746**	56%
Hungary				0.3**	−0.1				11%	0.735	0.763	44%
Turkey				0.2	−0.3				8%	0.765	0.732	44%
Russia				0.2	−0.4	0.1	0.3**		22%	0.698	0.804	45%
Australia	0.3***								12%	0.732	0.788	42%
New Zealand	0.3***								9%	0.783	0.751	39%
Japan	0.1								0%	0.923	0.804	**34%**
Hong Kong				0.2*					4%	0.821	0.756	**39%**
Korea	−0.6***	−0.2		0.8***					11%	0.738	0.808	53%
China				0.3***	−0.3**				14%	0.724	0.822	49%
Philippines	−0.5***	−0.3		0.6***					11%	0.759	**0.807**	47%

Indonesia				0.3	−0.3*	16%	0.699	0.825	45%
Thailand	−0.6***	−0.2		0.8***		13%	0.741	0.838	48%
Malaysia	−0.6***	−0.3		0.7***		17%	0.711	0.812	45%
South Africa	0.2	−0.2	0.2*			11%	0.745	0.742	42%
Israel	−0.4**			0.7***		8%	0.756	0.776	42%
Brazil				0.2*	−0.2	9%	0.749	0.729	39%
Mexico	0.3*	−0.2				11%	0.741	0.737	47%
Peru	−1.1***	−0.7***		1.3***	0.8***	10%	0.737	0.745	43%
Chile	−0.7***			0.9***		6%	0.775	0.744	39%
Colombia	−1.1***	−0.7***		1.4***	0.8***	9%	0.728	0.746	42%

When the goodness-of-fit statistics are better than those of Table 7.6, they are highlighted in bold

This table reports, for each country, the ARMA coefficients α_i's and β_i's estimated from the FIMLE equation: $\Delta\text{spread}_{t,i} = \sum_{i=1}^{p} \alpha_i \Delta\text{spread}_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}$

Source: Capital IQ

***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively

[a] and [b] stand for Theil's U_i and percent hit misses, respectively; [c] and [d] stand for in-sample and out-of-sample calculations, respectively

As for the lagged-factor specifications, Table 7.8 shows that they are noticeably less robust than those comprising contemporaneous factors. Except for a few occurrences (10 out of 124), the lagged-variable models' goodness-of-fit metrics are worse than those of contemporaneous-variable models (Table 7.6). Besides, the "best-fit" lagged-variable model specifications (which I am able to obtain for all but France, Italy, Spain, and Ireland) are even worse than those of ARMA models (Table 7.7).[11]

7.5.2 Robustness Check

This subsection shows that even altering the algorithm criteria significantly (changing the significance level of the Granger-causality test at which variables are included in the analysis, or substituting other goodness-of-fit statistics for the Adjusted R^2) or repeating the analysis across different sub-periods does not give rise to results substantially challenging this chapter's two main claims, that is, that the S&P 500 index is statistically significant and contemporaneously negatively related to the CDS spreads for most of the countries, and that emerging market's coefficients on the S&P 500 variable are higher in magnitude than those of advanced economies. To be sure, the S&P 500 coefficient's statistical significance and its magnitude do change when modifying the algorithm criteria or the sample period, leading to different country ranking orders. The coefficient on the S&P 500 for Russia (statistically significant and with the expected negative sign in Table 7.6), for instance, is not available in the July 2005–June 2010 and January 2008–December 2010 sub-periods' models, while ranging from −0.073 to −0.028 as for the other four sub-periods (Tables 7.15 and 7.16). Although the individual coefficient estimates somewhat vary between the different specifications, those of the S&P 500 remain higher (in absolute terms) for emerging markets.

Interestingly, eliminating the criterion (1) (choosing models with at least one coefficient significant at the 10% level with the expected sign) altogether from the algorithm, or modifying the restriction (2) (choosing models with the highest Adjusted R^2), the engine still generates models (see Tables 7.9, 7.10, 7.11, and 7.12) with statistically significant negative coefficients on the *sp*500 variable, higher in absolute terms for emerging market countries than for advanced economies. Table 7.9 shows that the characteristics of the sole 6 (out of 35 models; highlighted in bold) models which happen to be distinct from those of Table 7.6 don't lead to a different assessment regarding the coefficient of the *sp*500 variable. By the same token, no dramatic changes take place regarding the quantity and the magnitude of statistically significant *sp*500 coefficients. It continues to play a dominant role in explaining the CDS spreads in nearly all of our sample countries, and the higher sensitivity of emerging markets to this variable, when substituting other goodness-of-fit statistics for the Adjusted R^2 as a criterion for selecting the best-fit models (Tables 7.10, 7.11, and 7.12).

Aiming to evaluate, to a fairly large extent, whether changing the Granger-causality test significance level from 10% to 5% would lead to the rejection of this chapter's main claims, I ran the algorithm over the six sub-periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis). As it turns out, had I imposed a stricter cutoff (a 5% significance level, instead of 10%), it wouldn't materially have changed this chapter's main outcomes (Table 7.13).

Changing the significance level to 5% reduces the set of eligible variables either by excluding previously selected variables, or by switching previously endogenous variables to weakly exogenous ones. As expected, supressing previously elected variables from the set of eligible variables leads to the algorithm generating a different model. For instance, when excluding the *LocalTY* factor from the set of eligible variables, Portugal's alternative model (Table 7.14) ends up presenting a statistically significant S&P 500 estimator, when it was not the case previously (Table 7.6). Less obviously, when the changed cutoff of the level of significance switches a previously endogenous variable into a weakly exogenous one using the Granger-causality test, the algorithm may prefer a different model. The Netherlands' alternative model (Table 7.14), for example, shows a statistically significant coefficient on the S&P 500, when the previously endogenous variable *localSlope* (at the 10% significance level) turns into a weakly exogenous variable (at the 5% level) and further excluding *xr* and *localTY* from the set of eligible variables, even though none of these three variables were part of the originally selected model (see Table 7.6). As it turns out, this unintended consequence is due to the change in the instrumental variables setting: endogenous variables are transformed into lags when running the GMM regressions, while weakly exogenous ones are not.

Jointly, the results of Tables 7.15 and 7.16 show that the net effect of reducing the significance level from 10% to 5% in the Granger-causality test is almost neutral in terms of the quantity of statistically significant

Table 7.8 GMM results with lagged-explanatory variables

	const	*Global variables*				*Local variables*	
		sp500–1	*vix – 1*	*Slope – 1*	*oil – 1*	*spread – 1*	*stock – 1*
Germany	4.0E-06					0.26***	
Finland	5.0E-06					0.32***	
Netherlands	9.0E-06					0.18**	
Austria	1.0E-05					0.30***	
Belgium	2.0E-05		0.0001			0.17*	
Slovakia	2.0E-05					0.30***	
Portugal	1.0E-04			0.08		0.19*	
Denmark	1.0E-05					0.30***	
Sweden	3.0E-06					0.32**	
Poland	1.0E-05					0.29***	
Czech Rep.	1.0E-05					0.33***	
Hungary	1.0E-04						
Turkey	−1.0E-04	0.01	0.0007		−0.01*	0.50	0.024
Russia	5.0E-05					0.27*	
Australia	1.0E-05					0.35***	
New Zealand	1.0E-05					0.30***	
Japan	2.0E-05	−0.005***					
Hong Kong	1.0E-05	−0.01***					
Korea	1.0E-05	−0.02**	−0.002				
China	2.0E-05	−0.01**					
Philippines	−1.0E-04	−0.02*	−0.002				
Indonesia	−2.0E-05	−0.03*	−0.004			0.06	
Thailand	2.0E-05	−0.01*					
Malaysia	2.0E-05	−0.01*					
South Africa	1.0E-05						
Israel	4.0E-05	−0.01***					
Brazil	−1.0E-04	−0.01*	−0.001				
Mexico	−5.0E-05			−0.24*			
Peru	1.0E-06					0.14	
Chile	2.0E-05	−0.01***					
Colombia	−3.0E-05						

This table reports, for each country, the models' results with the same explanatory variables as in Table 7.6, but in lags. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and the out-of-sample (November 2012 to July 2016) periods. The explanatory variable itself is used as instrument for the GMM estimation. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield, and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. When the goodness-of-fit statistics are better than those of Table 7.6, they are highlighted in bold. The engine didn't generate any model specifications for France, Italy, Spain, and Ireland. *Vix, stock, localSlope, and bank* don't show up as significant for any country

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

[a] and [b] stand for Theil's U_i and percent hit misses, respectively

[c] and [d] stand for in-sample and out-of-sample calculations, respectively

				Adj. $R^{2[c]}$	$U_1^{a,d}$	$U_2^{a,d}$	$PHM^{b,d}$	#obs.^{c}
xr − 1	*localTY − 1*	*localSlope − 1*	*bank − 1*					
				6%	0.749	0.777	42%	383
				10%	0.774	**0.746**	**44%**	352
				3%	0.818	0.787	53%	352
				9%	0.728	**0.783**	**37%**	383
				3%	0.826	**0.759**	43%	383
				9%	0.802	**0.751**	51%	383
				3%	0.801	0.825	42%	383
				8%	0.767	0.733	47%	352
				10%	0.775	**0.739**	50%	352
				8%	0.815	0.730	**42%**	383
				11%	0.834	**0.723**	53%	383
	0.20**			5%	0.803	0.767	46%	294
0.08			−0.8	31%	0.660	0.943	47%	240
	−0.24	−0.19		96%	0.799	0.699	56%	95
				12%	0.734	0.790	38%	312
				9%	0.785	0.753	39%	312
				3%	0.828	0.823	48%	383
				10%	0.740	0.768	46%	383
				4%	0.741	0.848	48%	383
				3%	0.826	0.754	49%	383
				2%	0.760	**0.804**	48%	383
				6%	0.776	0.816	48%	383
				2%	0.817	0.789	47%	383
				3%	0.824	0.775	49%	383
0.03***				10%	0.709	0.715	43%	383
				6%	0.731	0.791	49%	383
				3%	0.899	0.734	54%	383
	0.04			93%	0.820	0.750	53%	85
0.04*				5%	0.750	0.757	45%	383
				8%	0.775	0.763	46%	383
	0.10*			2%	0.781	0.666	46%	372

Table 7.9 GMM results without the criterion “with at least one 10%-significant coefficient with expected signs according to Table 7.3”

	const	*Global variables*				*Local variables*						*Adj.* $R^{2[c]}$	$U_1^{a,d}$	$U_2^{a,d}$	$PHM^{b,d}$	*#obs.*[c]
		$sp500_t$	vix_t	$Slope_t$	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$					
Germany	4.0E-06					0.26***						6%	0.749	0.777	42%	383
France	**2.0E-05**	**−0.012**		**−0.07**						**0.03**	**0.09**	**37%**	**0.505**	**0.731**	**29%**	**252**
Finland	9.0E-06	−0.007***	−0.0004									24%	0.608	0.792	44%	353
Netherlands	1.0E-05					0.18**						3%	0.818	0.787	53%	352
Austria	**1.7E-05**	**−0.020*** **	**−0.002***									**24%**	**0.609**	**1.197**	**40%**	**383**
Belgium	3.0E-05	−0.017***										13%	0.589	0.880	41%	383
Slovakia	4.0E-05	−0.022***										21%	0.618	0.987	42%	383
Spain	1.0E-04	−0.025***										10%	0.675	0.695	34%	313
Italy	**6.0E-05**	**−0.026*** **		**−0.21*** **		**0.07**			**0.67*** **	**0.40** **		**48%**	**0.420**	**0.536**	**21%**	**383**
Ireland	6.0E-05	−0.026***										3%	0.629	0.783	37%	353
Portugal	5.0E-05								0.84***	0.50		55%	0.305	0.469	25%	359
Denmark	1.0E-05	−0.010***	−0.001*									17%	0.648	0.979	47%	353
Sweden	6.0E-06	−0.009***	−0.0008									17%	0.636	0.977	47%	353
Poland	3.0E-05								0.39***			10%	0.599	0.706	44%	378
Czech Rep.	3.0E-05	−0.022***										21%	0.622	0.872	34%	383
Hungary	1.0E-04	−0.040***				0.13			0.39***			51%	0.468	0.661	28%	295
Turkey	1.1E-04			−0.26					0.32***			36%	0.386	0.499	29%	333
Russia	4.0E-05	−0.033**		0.13			−0.014**	0.05	0.29**	0.17		99%	0.224	0.308	22%	96
Australia	**5.0E-06**	**−0.008**									**0.37**	**38%**	**0.393**	**0.603**	**27%**	**252**
New Zealand	2.0E-05	−0.012***										12%	0.541	0.705	36%	313
Japan	2.0E-05	−0.011***										19%	0.608	0.745	36%	383
Hong Kong	3.0E-06										0.28***	44%	0.643	0.726	42%	213
Korea	1.0E-05					−0.15					1.05***	87%	0.215	0.309	15%	252
China	**2.0E-05**	**−0.023**		**−0.10**			**0.002**				**0.14**	**55%**	**0.450**	**0.586**	**26%**	**252**

Philippines	−5.0E-05	−0.060***										32%	0.451	0.893	28%	383
Indonesia	2.0E-06	−0.092***	−0.0017									34%	0.461	0.764	32%	383
Thailand	3.0E-05	−0.036***										26%	0.454	0.646	31%	383
Malaysia	5.0E-05	−0.029***						0.04***				30%	0.405	0.597	24%	383
South Africa	−1.0E-05	−0.044***						0.04***		−0.12		59%	0.371	0.525	23%	206
Israel	4.0E-05	−0.018***	−0.0005		0.001			0.01*				25%	0.530	0.706	37%	383
Brazil	1.0E-05	−0.048***					−0.032					44%	0.471	0.563	28%	383
Mexico	**−1.9E-05**	**−0.020**				**0.08**		**0.03**	**0.07**			**98%**	**0.346**	**0.463**	**27%**	**86**
Peru	−6.0E-05	−0.042***						0.05**	−0.07			92%	0.415	0.633	30%	112
Chile	1.0E-05							0.05**		−0.29		43%	0.467	0.687	29%	84
Colombia	5.0E-06	−0.047***			−0.003		−0.006	0.02***	0.12***			49%	0.340	0.466	27%	372

This table reports, for each country, results of models: (1) with the highest Adjusted R^2 and (2) statistically superior to all possible nested models. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and out-of-sample (November 2012 to July 2016) periods. Only permutations of explanatory variables labelled with "(*)", "*", and "&" in Table 7.5 are taken as eligible estimation models. The explanatory variables were selected according to 10% significance level when applying the Granger-causality tests. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 7.5. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield, and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. When model specifications show up as different from Table 7.6, they are highlighted in bold. *Oil* doesn't show up as significant for any country. *Vix* and *oil* estimators aren't significant for any model

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

[a] and [b] stand for Theil's U_i and percent hit misses, respectively

[c] and [d] stand for in-sample and out-of-sample calculations, respectively

Table 7.10 GMM results substituting Theil's U_1 for Adjusted R^2 in criteria (2) "with the highest Adjusted R^2"

	const	*Global variables*				*Local variables*						*Adj. $R^{2[c]}$*	*$U_1^{a,d}$*	*$U_2^{a,d}$*	*$PHM^{b,d}$*	*#obs.^{c}*
		$sp500_t$	*vix_t*	*$Slope_t$*	*oil_t*	*$spread_{i,t-1}$*	*$stock_{i,t}$*	*$xr_{i,t}$*	*$localTY_{i,t}$*	*$localSlope_{i,t}$*	*$bank_{i,t}$*					
Germany	4.0E-06					0.26***						6%	0.749	0.777	42%	383
France	**−3.0E-05**		**−0.0006**		**−0.001**	**−0.07**				**0.10**	**0.85****	**18%**	**0.530**	**1.260**	**26%**	**252**
Finland	9.0E-06	−0.007***	−0.0004									24%	0.608	0.792	44%	353
Netherlands	**1.0E-05**	**−0.009*****	**−0.0003**									**17%**	**0.622**	**0.890**	**42%**	**353**
Austria	**7.0E-06**					**0.30*****						**9%**	**0.728**	**0.783**	**37%**	**383**
Belgium	**2.0E-05**	**−0.017*****				**0.16***						**15%**	**0.578**	**0.861**	**38%**	**383**
Slovakia	4.0E-05	−0.022***										21%	0.618	0.987	42%	383
Spain	1.0E-04	−0.025***										10%	0.675	0.695	34%	313
Italy	**6.5E-05**			**−0.20*****					**0.46*****			**33%**	**0.590**	**0.646**	**26%**	**383**
Ireland	6.0E-05	−0.026***										3%	0.629	0.783	37%	353
Portugal	5.0E-05								0.84***	0.50		55%	0.305	0.469	25%	359
Denmark	**1.0E-05**	**−0.010*****	**−0.0010**				**−0.001**					**17%**	**0.646**	**0.974**	**49%**	**353**
Sweden	6.0E-06	−0.009***	−0.0008									17%	0.636	0.977	47%	353
Poland	3.0E-05								0.39***			10%	0.599	0.706	44%	378
Czech Rep.	3.0E-05	−0.022***										21%	0.622	0.872	34%	383
Hungary	**1.4E-04**			**−0.26****					**0.56*****			**43%**	**0.528**	**0.692**	**36%**	**295**
Turkey	**−6.7E-05**					**−0.25**			**0.03**		**1.09*****	**49%**	**0.352**	**0.499**	**17%**	**241**
Russia	**−2.0E-05**	**−0.026***			**0.008**		**−0.016*****	**0.05**	**0.31****	**0.17**		**99%**	**0.222**	**0.308**	**24%**	**96**
Australia	8.0E-06	−0.008			−0.002*						0.38	39%	0.402	0.649	30%	252
New Zealand	2.0E-05	−0.012***										12%	0.541	0.705	36%	313
Japan	**2.0E-05**	**−0.011*****				**0.07**						**19%**	**0.596**	**0.731**	**34%**	**383**
Hong Kong	**3.0E-06**									**−0.05**	**0.29*****	**44%**	**0.639**	**0.729**	**40%**	**213**
Korea	1.0E-05					−0.15					1.05***	87%	0.215	0.309	15%	252
China	2.0E-06					−0.31					1.03**	46%	0.315	0.481	19%	252
Philippines	−5.0E-05	−0.060***										32%	0.451	0.893	28%	383
Indonesia	2.0E-06	−0.092***	−0.0017									34%	0.461	0.764	32%	383
Thailand	3.0E-05	−0.036***										26%	0.454	0.646	31%	383

Malaysia	5.0E-05	−0.029***						0.04***				30%	0.405	0.597	24%	383
South Africa	−1.0E-05	−0.044***						0.04***		−0.12		59%	0.371	0.525	23%	206
Israel	**4.0E-05**	**−0.018*****|			**0.16**		**0.01***				**28%**	**0.510**	**0.719**	**34%**	**383**
Brazil	**−2.0E-05**	**−0.026**				**0.15***		**0.05**				**42%**	**0.397**	**0.499**	**24%**	**383**
Mexico	−5.8E-05	−0.009						0.06**	−0.04			97%	0.352	0.502	26%	86
Peru	**3.0E-05**	**−0.045*****						**0.06*****				**41%**	**0.384**	**0.574**	**25%**	**383**
Chile	**3.0E-05**	**−0.023*****					**−0.003**	**0.01****				**37%**	**0.401**	**0.510**	**27%**	**383**
Colombia	5.0E-06	−0.047***			−0.003		−0.006	0.02***	0.12***			49%	0.340	0.466	27%	372

This table reports, for each country, results of models: (1) with at least one 10%-significant with expected signs according to Table 7.3, (2) with the lowest Theil's U_1, and (3) statistically superior to all possible nested models. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and out-of-sample (November 2012 to July 2016) periods. Only permutations of explanatory variables labelled with "(*)", "*", and "&" in Table 7.5 are taken as eligible estimation models. The explanatory variables were selected according to 10% significance level when applying the Granger-causality tests. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 7.5. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield, and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. When model specifications show up as different from Table 7.6, they are highlighted in bold. *Vix* and *localSlope* estimators aren't significant for any model

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

[a] and [b] stand for Theil's U_i and percent hit misses, respectively

[c] and [d] stand for in-sample and out-of-sample calculations, respectively

Table 7.11 GMM results substituting Theil's U_2 for Adjusted R^2 in criteria (2) "with the highest Adjusted R^2"

	const	*Global variables*				*Local variables*						*Adj. $R^{2[c]}$*	$U_1^{a,d}$	$U_2^{a,d}$	*PHM*^{b,d}	*#obs.*^{c}
		$sp500_t$	vix_t	$Slope_t$	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$					
Germany	4.0E-06					0.26***						6%	0.749	0.777	42%	383
France	2.0E-05	−0.013***				0.09						19%	0.563	0.754	35%	374
Finland	9.0E-06	−0.007***	−0.0004									24%	0.608	0.792	44%	353
Netherlands	**1.0E-05**	**−0.009*** **	**−0.0003**									**17%**	**0.622**	**0.890**	**42%**	**353**
Austria	**7.0E-06**					**0.30*** **						**9%**	**0.728**	**0.783**	**37%**	**383**
Belgium	**2.0E-05**			**−0.10*** **								**2%**	**0.771**	**0.782**	**44%**	**383**
Slovakia	**2.0E-05**					**0.30*** **						**9%**	**0.802**	**0.751**	**51%**	**383**
Spain	1.0E-04	−0.025***										10%	0.675	0.695	34%	313
Italy	6.9E-05	−0.025***		−0.16***		0.09			0.45***			44%	0.509	0.616	24%	383
Ireland	**5.0E-05**			**−0.21** **	**0.002**	**0.15***						**2%**	**0.758**	**0.762**	**41%**	**352**
Portugal	**6.0E-05**			**−0.28*** **					**0.82*** **	**0.48**		**56%**	**0.298**	**0.459**	**19%**	**359**
Denmark	1.0E-05					0.30***						8%	0.767	0.733	47%	352
Sweden	6.0E-06	−0.009***	−0.0008									17%	0.636	0.977	47%	353
Poland	3.0E-05								0.39***			10%	0.599	0.706	44%	378
Czech Rep.	**3.0E-05**				**−0.004***							**1%**	**0.748**	**0.723**	**50%**	**383**
Hungary	**1.1E-04**	**−0.040*** **							**0.42*** **			**50%**	**0.471**	**0.667**	**31%**	**295**
Turkey	1.1E-04			−0.26					0.32***			36%	0.386	0.499	29%	333
Russia	4.0E-05	−0.033**		0.13			−0.014**	0.05	0.29**	0.17		99%	0.224	0.308	22%	96
Australia	8.0E-06	−0.008			−0.002*						0.38	39%	0.402	0.649	30%	252
New Zealand	**2.0E-05**	**−0.011*** **	**−0.0006**									**12%**	**0.564**	**0.679**	**34%**	**313**
Japan	**2.0E-05**	**−0.011*** **				**0.07**						**19%**	**0.596**	**0.731**	**34%**	**383**
Hong Kong	3.0E-06										0.28***	44%	0.643	0.726	42%	213
Korea	1.0E-05					−0.15					1.05***	87%	0.215	0.309	15%	252
China	2.0E-06					−0.31					1.03**	46%	0.315	0.481	19%	252

Philippines	−5.0E-05	−0.060***								32%	0.451	0.893	28%	383
Indonesia	2.0E-06	−0.092***	−0.0017							34%	0.461	0.764	32%	383
Thailand	3.0E-05	−0.036***								26%	0.454	0.646	31%	383
Malaysia	5.0E-05	−0.029***						0.04***		30%	0.405	0.597	24%	383
South Africa	**2.0E-05**	**−0.035*** **		**−0.04**				**0.03*** **		**48%**	**0.378**	**0.478**	**24%**	**383**
Israel										–	–	–	–	–
Brazil	**−2.0E-05**	**−0.026**				**0.15***		**0.05**		**42%**	**0.397**	**0.499**	**24%**	**383**
Mexico	**−6.0E-05**					**0.04**		**0.05*** **	**−0.04**	**97%**	**0.394**	**0.505**	**27%**	**86**
Peru	**3.0E-05**	**−0.045*** **						**0.06*** **		**41%**	**0.384**	**0.574**	**25%**	**383**
Chile	**3.0E-05**	**−0.023*** **					**−0.003**	**0.01** **		**37%**	**0.401**	**0.510**	**27%**	**383**
Colombia	5.0E-06	−0.047***			−0.003		−0.006	0.02***	0.12***	49%	0.340	0.466	27%	372

This table reports, for each country, results of models: (1) with at least one 10%-significant with expected signs according to Table 7.3, (2) with the lowest Theil's U_2, and (3) statistically superior to all possible nested models. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and out-of-sample (November 2012 to July 2016) periods. Only permutations of explanatory variables labelled with "(*)", "*", and "&" in Table 7.5 are taken as eligible estimation models. The explanatory variables were selected according to 10% significance level when applying the Granger-causality tests. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 7.5. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield, and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. When model specifications show up as different from Table 7.6, they are highlighted in bold. *Vix* and *localSlope* estimators aren't significant for any model

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

[a] and [b] stand for Theil's U_i and percent hit misses, respectively

[c] and [d] stand for in-sample and out-of-sample calculations, respectively

Table 7.12 GMM results substituting percent hit misses (PHM) for Adjusted R^2 in criteria (2) “with the highest Adjusted R^2”

	const	*Global variables*				*Local variables*						Adj. $R^{2[c]}$	$U_1^{a,d}$	$U_2^{a,d}$	$PHM^{b,d}$	#obs.[c]
		$sp500_t$	vix_t	$Slope_t$	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$					
Germany	4.0E-06					0.26***						6%	0.749	0.777	42%	383
France	**2.0E-05**			**−0.09*****		**0.12**				**0.07**		**5%**	**0.773**	**0.758**	**41%**	**374**
Finland	9.0E-06	−0.007***	−0.0004									24%	0.608	0.792	44%	353
Netherlands	**1.0E-05**	**−0.009*****	**−0.0003**									**17%**	**0.622**	**0.890**	**42%**	**353**
Austria	**7.0E-06**					**0.30*****						**9%**	**0.728**	**0.783**	**37%**	**383**
Belgium	3.0E-05	−0.017***										13%	0.589	0.880	41%	383
Slovakia	4.0E-05	−0.022***										21%	0.618	0.987	42%	383
Spain	1.0E-04	−0.025***										10%	0.675	0.695	34%	313
Italy	6.9E-05	−0.025***		−0.16***		0.09			0.45***			44%	0.509	0.616	24%	383
Ireland	6.0E-05	−0.026***										3%	0.629	0.783	37%	353
Portugal	**6.0E-05**			**−0.28*****					**0.82*****	**0.48**		**56%**	**0.298**	**0.459**	**19%**	**359**
Denmark	1.0E-05					0.30***						8%	0.767	0.733	47%	352
Sweden	6.0E-06	−0.009***	−0.0008									17%	0.636	0.977	47%	353
Poland	**4.0E-05**	**−0.034*****								**0.05**		**33%**	**0.554**	**0.894**	**33%**	**378**
Czech Rep.	3.0E-05	−0.022***										21%	0.622	0.872	34%	383
Hungary	**5.0E-05**	**−0.035*****				**0.21***			**0.74*****	**1.19**		**35%**	**0.513**	**1.091**	**24%**	**294**
Turkey	**−6.7E-05**					**−0.25**			**0.03**		**1.09*****	**49%**	**0.352**	**0.499**	**17%**	**241**
Russia	4.0E-05	−0.033**		0.13			−0.014**	0.05	0.29**	0.17		99%	0.224	0.308	22%	96
Australia	**1.5E-05**	**−0.013*****		**−0.05**						**0.17**		**26%**	**0.455**	**0.708**	**29%**	**313**
New Zealand	**2.0E-05**	**−0.011*****	**−0.0006**									**12%**	**0.564**	**0.679**	**34%**	**313**
Japan	**2.0E-05**	**−0.011*****				**0.07**						**19%**	**0.596**	**0.731**	**34%**	**383**
Hong Kong	**3.0E-06**									**−0.05**	**0.29*****	**44%**	**0.639**	**0.729**	**40%**	**213**
Korea	1.0E-05					−0.15					1.05***	87%	0.215	0.309	15%	252
China	2.0E-06					−0.31					1.03**	46%	0.315	0.481	19%	252
Philippines	−5.0E-05	−0.060***										32%	0.451	0.893	28%	383
Indonesia	2.0E-06	−0.092***	−0.0017									34%	0.461	0.764	32%	383

Thailand	3.0E-05	−0.036***							26%	0.454	0.646	31%	383
Malaysia	5.0E-05	−0.029***					0.04***		30%	0.405	0.597	24%	383
South Africa	**−3.0E-05**	**−0.039*** **	**−0.0018**				**0.04*** **	**−0.03**	**56%**	**0.386**	**0.515**	**21%**	**240**
Israel	**3.0E-05**	**−0.020*** **	**−0.0003**		**0.16**				**27%**	**0.524**	**0.719**	**32%**	**383**
Brazil	**−2.0E-05**	**−0.026**			**0.15***		**0.05**		**42%**	**0.397**	**0.499**	**24%**	**383**
Mexico	−5.8E-05	−0.009					0.06**	−0.04	97%	0.352	0.502	26%	86
Peru	**3.0E-05**	**−0.045*** **					**0.06*** **		**41%**	**0.384**	**0.574**	**25%**	**383**
Chile	**3.0E-05**	**−0.023*** **				**−0.003**	**0.01*** *		**37%**	**0.401**	**0.510**	**27%**	**383**
Colombia	**3.0E-06**	**−0.047*** **		**−0.002**		**−0.008*** *	**0.02*** **		**48%**	**0.343**	**0.509**	**25%**	**383**

This table reports, for each country, results of models: (1) with at least one 10%-significant with expected signs according to Table 7.3, (2) with the lowest percent hit misses (PHM) and (3) statistically superior to all possible nested models. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and out-of-sample (November 2012 to July 2016) periods. Only permutations of explanatory variables labelled with "(*)", "*", and "&" in Table 7.5 are taken as eligible estimation models. The explanatory variables were selected according to 10% significance level when applying the Granger-causality tests. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 7.5. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield, and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. When model specifications show up as different from Table 7.6, they are highlighted in bold. *Vix*, *oil*, and *localSlope* estimators aren't significant for any model

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level

** Significant at the 5% level

*** Significant at the 1% level

^{a} and ^{b} stand for Theil's U_i and percent hit misses, respectively

^{c} and ^{d} stand for in-sample and out-of-sample calculations, respectively

Table 7.13 5%-significant level Granger-causality test

	Global variables				*Local variables*					
	$sp500_t$	vix_t	$Slope_t$	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localSlope_{i,t}$	$bank_{i,t}$
Germany	(*)	(*)	(*)	(*)	(*)				&	
France	(*)	(*)	(*)	(*)	(*)				*	&
Finland	(*)	(*)	(*)	(*)	(*)					
Netherlands	(*)	(*)	(*)	(*)	(*)				*	
Austria	(*)	(*)	(*)	(*)	(*)				*	&
Belgium	(*)	(*)	(*)	(*)	(*)			*	*	&
Slovakia	(*)	(*)	(*)	(*)	(*)					
Spain	(*)	(*)	(*)	(*)	(*)				&	&
Italy	(*)	(*)	(*)	(*)	(*)			*	*	&
Ireland	(*)	(*)	(*)	(*)	(*)				&	
Portugal	(*)	(*)	(*)	(*)	(*)				&	&
Denmark	(*)	(*)	(*)	(*)	(*)	&		&		
Sweden	(*)	(*)	(*)	(*)	(*)	&	&		*	&
Poland	(*)	(*)	(*)	(*)	(*)		*	*	*	
Czech Rep.	(*)	(*)	(*)	(*)	(*)		*	&		
Hungary	(*)	(*)	(*)	(*)	(*)		&	*		
Turkey	(*)	(*)	(*)	(*)	(*)	&	&	*		&
Russia	(*)	(*)	(*)	(*)	(*)	*	&			&
Australia	(*)	(*)	(*)	(*)	(*)			*	*	&
New Zealand	(*)	(*)	(*)	(*)	(*)		*			
Japan	(*)	(*)	(*)	(*)	(*)	*				
Hong Kong	(*)	(*)	(*)	(*)	(*)	*			&	*
Korea	(*)	(*)	(*)	(*)	(*)	&	&			&
China	(*)	(*)	(*)	(*)	(*)	&		*		&
Philippines	(*)	(*)	(*)	(*)	(*)	&				
Indonesia	(*)	(*)	(*)	(*)	(*)	&	&	&	&	
Thailand	(*)	(*)	(*)	(*)	(*)	&			*	
Malaysia	(*)	(*)	(*)	(*)	(*)	&	*	*	*	
South Africa	(*)	(*)	(*)	(*)	(*)	&	*	&	*	
Israel	(*)	(*)	(*)	(*)	(*)		*			
Brazil	(*)	(*)	(*)	(*)	(*)	*	&			
Mexico	(*)	(*)	(*)	(*)	(*)	&	*	*		
Peru	(*)	(*)	(*)	(*)	(*)		*	*		
Chile	(*)	(*)	(*)	(*)	(*)	*		&		
Colombia	(*)	(*)	(*)	(*)	(*)	*	*	*		

Set of eligible explanatory variables

(*) stands for Exogeneity by Assumption. * and & stand for Weak Exogeneity and Non-Weak Exogeneity, as for the Granger-causality test, at 10% significance level, respectively. Blank accounts for non-significance at 10% significance level, in this case, the corresponding variable is not part of any estimation model for the corresponding country

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

coefficients of the S&P 500 within each sub-period. What is more, the algorithm's outcomes still provide support to this chapter's two main findings. Tables 7.15 and 7.16 also show that the differences between the quantities of statistically significant S&P 500 estimators across the six sub-periods aren't large: 5, 1, 0, 0, 0, and 2 out of 35 countries, respectively, for the sub-periods July 2005–October 2012, Before July 2010, After July 2010, Before July 2008, Subprime Crisis, and Euro Crisis. Overall, whether or not the S&P 500 is selected by the algorithm does depend on the specific setting. Let's take the models for New Zealand and the Colombia models for the July 2005–June 2010 period ("Before Jul 2010" column in Table 7.16).[12] Supressing *localSlope* from the set of eligible variables for New Zealand gives rise to an alternative model where the previously non-significant coefficient of the S&P 500 (see the corresponding column in Table 7.15) now becomes statistically significant. In contrast, the S&P 500 is no longer selected by the algorithm for Colombia, when the Granger-causality test leads to the exclusion of the variable *stock* from the set of eligible variables. Quite conspicuously, apart from slight differences in other factor estimators for just three countries, the statistical significance of the coefficients of the S&P 500 is pretty much the same for the July 2005 to June 2008 ("Before Jul 2008" column in Tables 7.15 and 7.16).[13]

Ordering Adjusted R^2 statistics from low to high values and the other goodness-of-fit statistics (Theil's U_1, Theil's U_2, and PHM) the other way around (descending) according to the column "After Jul 2010", Tables 7.17, 7.18, 7.19, and 7.20 support the finding that emerging markets model specifications (mostly at the bottom rows of the tables) tend toshow better goodness-of-fit and forecast accuracy statistics as a group than advanced economies across all the different sub-periods.

Tables 7.21 and 7.22 show respectively that ARMA models' and lagged-variable models' goodness-of-fit statistics are mostly superseded by the contemporaneous models across the other five sub-periods as they are for the July 2005–October 2012 period.[14] However, comparing Table 7.21 values particularly with those of Tables 7.18 and 7.19, we find a couple of better ARMA Theil's U_1 values (highlighted in bold in Table 7.21, column "Before Jul 2008") and Theil's U_2 values (highlighted in bold in Table 7.21, columns "After Jul 2010" and "Euro Crisis"); yet this is the case for just less than half the number of countries. Showing mixed results in comparison to the corresponding ARMA-model statistics (Table 7.21)

Table 7.14 GMM results—5%-significant level Granger-causality-test set of eligible variables

	const	*Global variables*				*Local variables*						*Adj. $R^{2[c]}$*	*$U_1^{a,d}$*	*$U_2^{a,d}$*	*$PHM^{b,d}$*	*#obs.^{c}*
		$sp500_t$	*vix_t*	*$Slope_t$*	*oil_t*	*$spread_{i,t-1}$*	*$stock_{i,t}$*	*$xr_{i,t}$*	*$localTY_{i,t}$*	*$localSlope_{i,t}$*	*$bank_{i,t}$*					
Germany	4.0E-06					0.26***						6%	0.749	0.777	42%	383
France	2.0E-05	−0.013***				0.09						19%	0.563	0.754	35%	374
Finland	9.0E-06	−0.007***	−0.0004									24%	0.608	0.792	44%	353
Netherlands	**1.0E-05**	**−0.009*****	**−0.0003**									**17%**	**0.622**	**0.890**	**42%**	**353**
Austria	1.7E-05				−0.003*						0.28	39%	0.650	1.231	43%	241
Belgium	3.0E-05	−0.017***										13%	0.589	0.880	41%	383
Slovakia	4.0E-05	−0.022***										21%	0.618	0.987	42%	383
Spain	1.0E-04	−0.025***										10%	0.675	0.695	34%	313
Italy	6.9E-05	−0.025***		−0.16***		0.09			0.45***			44%	0.509	0.616	24%	383
Ireland	6.0E-05	−0.026***										3%	0.629	0.783	37%	353
Portugal	**1.0E-04**	**−0.029*****	**0.0017**	**−0.25****	**0.005**	**0.20***						**6%**	**0.671**	**0.773**	**28%**	**383**
Denmark	1.0E-05					0.30***						8%	0.767	0.733	47%	352
Sweden	6.0E-06	−0.009***	−0.0008									17%	0.636	0.977	47%	353
Poland	3.0E-05								0.39***			10%	0.599	0.706	44%	378
Czech Rep.	3.0E-05	−0.022***										21%	0.622	0.872	34%	383
Hungary	1.0E-04	−0.040***				0.13			0.39***			51%	0.468	0.661	28%	295
Turkey	1.1E-04			−0.26					0.32***			36%	0.386	0.499	29%	333
Russia	**3.0E-05**	**−0.073*****	**−0.0022**			**0.12**		**0.06**				**25%**	**0.334**	**0.473**	**29%**	**383**
Australia	8.0E-06	−0.008			−0.002*						0.38	39%	0.402	0.649	30%	252
New Zealand	2.0E-05	−0.012***										12%	0.541	0.705	36%	313
Japan	2.0E-05	−0.011***										19%	0.608	0.745	36%	383
Hong Kong	**1.0E-05**						**−0.005*****					**4%**	**0.799**	**0.771**	**49%**	**383**
Korea	1.0E-05					−0.15					1.05***	87%	0.215	0.309	15%	252
China	**2.0E-05**	**−0.026*****										**34%**	**0.479**	**0.611**	**29%**	**383**
Philippines	−5.0E-05	−0.060***										32%	0.451	0.893	28%	383
Indonesia	2.0E-06	−0.092***	−0.0017									34%	0.461	0.764	32%	383

Thailand	3.0E-05	−0.036***							26%	0.454	0.646	31%	383
Malaysia	5.0E-05	−0.029***				0.04***			30%	0.405	0.597	24%	383
South Africa	−1.0E-05	−0.044***				0.04***		−0.12	59%	0.371	0.525	23%	206
Israel	4.0E-05	−0.018***	−0.0005	0.001		0.01*			25%	0.530	0.706	37%	383
Brazil	**−1.0E-05**	**−0.049*** **			**−0.021*** **				**46%**	**0.507**	**0.568**	**27%**	**383**
Mexico	**−1.5E-05**	**−0.022*** **				**0.03*** **	**0.08**		**98%**	**0.349**	**0.459**	**25%**	**86**
Peru	**−2.0E-05**	**−0.041*** **				**0.05*** **	**−0.03**		**92%**	**0.412**	**0.621**	**26%**	**119**
Chile	**3.0E-05**	**−0.026*** **							**35%**	**0.451**	**0.566**	**28%**	**383**
Colombia	5.0E-06	−0.047***		−0.003	−0.006	0.02***	0.12***		49%	0.340	0.466	27%	372

This table reports, for each country, results of models: (1) at least one 10%-significant coefficient with expected signs according to Table 7.3, (2) with the highest Adjusted R^2, and (3) statistically superior to all possible nested models. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for the estimation sample (July 2005 to October 2012) and out-of-sample (November 2012 to July 2016) periods. Only permutations of explanatory variables labelled with "(*)", "*", and "&" in Table 7.13 are taken as eligible estimation models. Differently from the setting in Table 7.6, the explanatory variables were selected according to 5% significance level, instead of 10%, when applying the Granger-causality tests. Nine models (highlighted in bold) show up as different from those in Table 7.6. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 7.5. As for variable transformation, I apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, and Exchange Rate) and Δ(.) to "rate" variables (USA Slope, CDS spreads, Local Short-Term Yield, and Local Slope). The variance-covariance matrices are estimated according to White (1980) robust estimation. *Vix* and *localSlope* don't show up as significant for any country

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

* Significant at the 10% level
** Significant at the 5% level
*** Significant at the 1% level
[a] and [b] stand for Theil's U_i and percent hit misses, respectively
[c] and [d] stand for in-sample and out-of-sample calculations, respectively

Table 7.15 Coefficient estimators for $sp500_t$ across different sub-samples

	Jul 2005 to Oct 2012	*Before Jul 2010*	*After Jul 2010*	*Before Jul 2008*	*Subprime Crisis*	*Euro Crisis*
Australia	−0.008	−0.009***	−0.012***	−0.005	−0.008***	−0.006***
New Zealand	−0.012***		−0.013***			−0.018***
Ireland	−0.026***	−0.032***			−0.026***	
Sweden	−0.009***	−0.009***	−0.007***	−0.001*	−0.010***	
Germany		−0.003		−0.001***	−0.007***	
Finland	−0.007***	−0.004	−0.007***	−0.001***	−0.007***	
Denmark		−0.005*	−0.010***	−0.002*	−0.010***	
Netherlands		−0.008***	−0.002	−0.002***	−0.008***	−0.013***
Austria		−0.012	−0.012**	−0.002***	−0.013	−0.018*
France	−0.013***	−0.008***		−0.002***	−0.010***	
Belgium	−0.017***	−0.009***		−0.002***	−0.011***	
Hong Kong		−0.013***	−0.006***	−0.004**	−0.011**	−0.011***
Japan	−0.011***	−0.009***	−0.014***	−0.004**	−0.010***	−0.015***
Portugal		−0.017***	−0.046**	−0.004***		
Italy	−0.025***	−0.016***		−0.004***	−0.019***	
Slovakia	−0.022***	−0.017***	−0.023***	−0.005***	−0.018***	−0.033***
Spain	−0.025***	−0.017***	−0.028***	−0.005***	−0.018***	−0.057***
Czech Rep.	−0.022***	−0.020***		−0.006***	−0.017***	−0.020***
Israel	−0.018***	−0.013	−0.014***	−0.010***		−0.018***
Poland		−0.017***	−0.027***	−0.012***	−0.016***	
Chile		−0.025***	−0.022***	−0.012***	−0.030***	−0.022***
China			−0.022***	−0.014***		−0.023***
Korea			−0.025***	−0.017***		−0.031***
Malaysia	−0.029***	−0.031***	−0.023***	−0.019***	−0.042***	−0.016***
Thailand	−0.036***	−0.038***	−0.022***	−0.023***	−0.041***	−0.030***

Hungary	−0.040***	−0.026		−0.025***	−0.029	−0.061***
South Africa	−0.044***	−0.043***	−0.026***	−0.026***	−0.049**	−0.035***
Mexico	−0.009	−0.053***	−0.016*	−0.029***	−0.033***	−0.034***
Russia	−0.033**		−0.028	−0.029***		−0.030***
Turkey		−0.073***	−0.033***	−0.033***		−0.023***
Peru	−0.042***	−0.044***	−0.029***	−0.044***	−0.048***	−0.031***
Brazil	−0.048***	−0.053***		−0.052***	−0.053***	−0.033***
Philippines	−0.060***	−0.069***	−0.032***	−0.055***	−0.067***	−0.024***
Indonesia	−0.092***	−0.111***	−0.036***	−0.059***	−0.112***	−0.035***
Colombia	−0.047***	−0.053***	−0.028***	−0.062***	−0.051***	−0.032***

This table shows $sp500_t$ estimators ordered by the column "Before Jul 2008". Non-significant estimators are ranked as if they were not available. The columns show $sp500_t$ estimator values across six different periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis)

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively

Table 7.16 Coefficient estimators for $sp500_t$ across different sub-samples 5%-significant level Granger-causality-test set of eligible variables

	Jul 2005 to Oct 2012	*Before Jul 2010*	*After Jul 2010*	*Before Jul 2008*	*Subprime Crisis*	*Euro Crisis*
Australia	−0.008	−0.009***	−0.006***	−0.005	**−0.009*****	**−0.017*****
New Zealand	−0.012***	**−0.010****	−0.016***			−0.018***
Ireland	−0.026***	**−0.025*****			−0.026***	
Sweden	−0.009***	−0.009***		−0.001*	−0.010***	
Germany		−0.003		−0.001***	−0.007***	
Finland	−0.007***	−0.004		−0.001***	**−0.005***	
Denmark		−0.005*		−0.002*	−0.010***	
Netherlands	**−0.009*****	−0.008***		−0.002***	**−0.009*****	**NA**
Austria		−0.012		−0.002***	−0.013	−0.018*
France	−0.013***	−0.008***		−0.002***	−0.010***	
Belgium	−0.017***	−0.009***		−0.002***	**−0.008*****	
Hong Kong		−0.013***	−0.011***	−0.004**	**−0.011*****	−0.011***
Japan	−0.011***	−0.009***		−0.004**	−0.010***	−0.015***
Portugal	**−0.029*****	−0.017***		−0.004***		
Italy	−0.025***	−0.016***		−0.004***	−0.019***	
Slovakia	−0.022***	−0.017***	−0.029***	−0.005***	−0.018***	−0.033***
Spain	−0.025***	−0.017***	−0.051***	−0.005***	−0.018***	**NA**
Czech Rep.	−0.022***	**−0.016*****	−0.019***	−0.006***	−0.017***	−0.020***
Israel	−0.018***	−0.013		−0.010***		−0.018***
Poland		−0.017***	−0.037***	−0.012***	−0.016***	
Chile	**−0.026*****	**−0.026*****	−0.022***	−0.012***	−0.030***	**−0.025*****
China	**−0.026*****		−0.023***	−0.014***		−0.023***
Korea			−0.029***	−0.017***		−0.031***
Malaysia	−0.029***	**−0.039*****	−0.029***	−0.019***	−0.042***	**−0.022*****
Thailand	−0.036***	−0.038***	−0.031***	−0.023***	−0.041***	−0.030***
Hungary	−0.040***	−0.026		−0.025***	−0.029	−0.061***

South Africa	−0.044***	**−0.044*** **	−0.018***	−0.026***	−0.049**	**−0.044*** **
Mexico	**−0.022*** **	**−0.050*** **	**−0.014*** **	−0.029***	−0.033***	−0.034***
Russia	**−0.073*** **		**−0.046*** **	−0.029***		**−0.049*** **
Turkey		**NA**	−0.013***	−0.033***		−0.023***
Peru	**−0.041*** **	−0.044***	**−0.030*** **	−0.044***	**−0.042*** **	−0.031***
Brazil	**−0.049*** **	**−0.055*** **	−0.034***	−0.052***	−0.053***	−0.033***
Philippines	−0.060***	−0.069***	−0.035***	−0.055***	−0.067***	−0.024***
Indonesia	−0.092***	−0.111***	−0.036***	−0.059***	−0.112***	**−0.034*** **
Colombia	−0.047***	**NA**	−0.032***	**−0.066*** **	−0.051***	−0.032***

This table shows S&P500 estimators ordered by the column “Before Jul 2008”. Non-significant estimators are ranked as if they were not available. In contrast to Table 7.15, in this case, the engine generated the models corresponding to the associated S&P500 estimators below from a set of variables elected by means of a 5%-significant level (instead of 10%, as for Table 7.15) Granger-causality test. The columns show S&P500 estimator values across six different periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis). When S&P500 estimators show up as different from Table 7.15, they are highlighted in bold

Source: Capital IQ, Bloomberg, Datastream, and author’s calculations

***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively. Blank cells and NA stand for “non-available”

Table 7.17 Adjusted R^2 across different periods

	Jul 2005 to Oct 2012	*Before Jul 2010*	*After Jul 2010*	*Before Jul 2008*	*Subprime Crisis*	*Euro Crisis*
Israel	25%	77%	3%	17%	7%	22%
Ireland	3%	73%	4%	89%	9%	3%
Denmark	8%	25%	4%	2%	16%	18%
Hungary	51%	41%	6%	24%	47%	22%
Netherlands	3%	17%	9%	8%	17%	20%
Sweden	17%	21%	9%	3%	22%	54%
Japan	19%	21%	10%	1%	24%	25%
Austria	39%	51%	11%	18%	51%	38%
Spain	10%	29%	13%	19%	40%	15%
Belgium	13%	24%	18%	20%	13%	35%
Czech Rep.	21%	34%	19%	20%	30%	21%
Portugal	55%	36%	21%	13%	14%	18%
Slovakia	21%	40%	22%	17%	42%	25%
Hong Kong	44%	39%	30%	14%	68%	32%
Germany	6%	5%	31%	9%	24%	2%
Poland	10%	45%	34%	24%	49%	4%
Italy	44%	26%	36%	25%	17%	35%
Thailand	26%	24%	37%	36%	26%	39%
Chile	43%	43%	39%	26%	38%	41%
Brazil	44%	47%	40%	35%	47%	47%
Korea	87%	88%	41%	31%	88%	44%
Philippines	32%	33%	42%	53%	31%	53%
New Zealand	12%	95%	43%	0%	96%	46%
Colombia	49%	50%	45%	49%	47%	49%
Indonesia	34%	38%	45%	45%	39%	52%
Finland	24%	32%	47%	5%	24%	48%
Malaysia	30%	28%	47%	33%	28%	73%
Peru	92%	93%	47%	27%	90%	80%
South Africa	59%	55%	49%	24%	66%	38%
China	46%	67%	51%	33%	65%	60%
Russia	99%	78%	54%	43%	78%	58%
France	19%	28%	62%	8%	30%	64%
Mexico	97%	45%	68%	52%	53%	60%
Australia	39%	31%	68%	30%	33%	71%
Turkey	36%	36%	76%	63%	44%	71%

This table shows the Adjusted R^2 statistics ordered (ascending) by the column "After Jul 2010". The columns show the Adjusted R^2 statistics across six different periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis). The explanatory variables for each period were selected according to 10% significance level when applying the Granger-causality tests. Countries at the bottom of the table, broadly composed of emerging market economies, are associated with better goodness-of-fit measures

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

Table 7.18 Theil's U_1 across different periods

	Jul 2005 to Oct 2012	*Before Jul 2010*	*After Jul 2010*	*Before Jul 2008*	*Subprime Crisis*	*Euro Crisis*
Denmark	0.767	0.575	0.858	0.920	0.710	0.672
Israel	0.530	0.483	0.829	0.746	0.630	0.512
Sweden	0.636	0.474	0.805	0.838	0.467	0.568
Ireland	0.629	0.520	0.790	0.739	0.898	0.667
Belgium	0.589	0.765	0.784	0.678	0.827	0.535
Japan	0.608	0.676	0.692	0.732	0.673	0.477
Slovakia	0.618	0.629	0.650	0.664	0.593	0.650
Hong Kong	0.643	0.486	0.646	0.633	0.425	0.653
Czech Rep.	0.622	0.585	0.646	0.706	0.517	0.598
Italy	0.509	0.820	0.642	0.677	0.832	0.534
Hungary	0.468	0.351	0.641	0.739	0.331	0.520
Austria	0.650	0.498	0.619	0.841	0.477	0.620
Poland	0.599	0.436	0.584	0.649	0.413	0.746
Netherlands	0.818	0.721	0.583	0.872	0.689	0.645
Finland	0.608	0.553	0.571	0.705	0.633	0.602
Brazil	0.471	0.351	0.550	0.485	0.340	0.612
Spain	0.675	0.754	0.544	0.776	0.619	0.599
New Zealand	0.541	1.072	0.533	–	0.690	0.568
Germany	0.749	0.580	0.521	0.731	0.648	0.782
France	0.563	0.773	0.479	0.822	0.705	0.443
Colombia	0.340	0.359	0.470	0.447	0.340	0.576
Portugal	0.305	0.651	0.470	0.798	0.794	0.417
Malaysia	0.405	0.348	0.428	0.747	0.397	0.256
Chile	0.467	0.374	0.425	0.699	0.397	0.471
Thailand	0.454	0.438	0.396	0.707	0.442	0.529
Peru	0.415	0.439	0.386	0.477	0.396	0.620
South Africa	0.371	0.371	0.381	0.684	0.251	0.601
Korea	0.215	0.199	0.377	0.816	0.201	0.499
Mexico	0.352	0.382	0.348	0.575	0.331	0.449
Australia	0.402	0.347	0.347	0.553	0.265	0.445
Turkey	0.386	0.422	0.334	0.515	0.335	0.300
China	0.315	0.353	0.333	0.688	0.290	0.499
Philippines	0.451	0.438	0.318	0.553	0.424	0.361
Indonesia	0.461	0.500	0.310	0.629	0.488	0.374
Russia	0.224	0.237	0.305	0.838	0.225	0.286

This table shows the Theil's U_1 statistics ordered (descending) by the column "After Jul 2010". The columns show the U_1 statistics across the six out-of-sample periods: (1) November 2012 to July 2016, (2) July 2010 to December 2012, (3) July 2014 to July 2016, (4) July 2008 to November 2009, (5) January 2011 to June 2012, and (6) July 2013 to December 2014. These out-of-sample periods correspond, respectively, to the in-sample estimations over the periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis). The explanatory variables for each period were selected according to 10% significance level when applying the Granger-causality tests. Countries at the bottom of the table, broadly composed of emerging market economies, are associated with better goodness-of-fit measures

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

Table 7.19 Theil's U_2 across different periods

	Jul 2005 to Oct 2012	*Before Jul 2010*	*After Jul 2010*	*Before Jul 2008*	*Subprime Crisis*	*Euro Crisis*
Slovakia	0.987	0.716	1.370	0.777	0.705	1.192
Austria	1.231	0.606	1.206	0.838	0.573	1.422
Czech Rep.	0.872	0.654	1.086	0.814	0.620	0.665
Poland	0.706	0.562	1.080	0.752	0.553	0.778
Germany	0.777	0.662	1.028	0.810	0.641	0.828
New Zealand	0.705	1.115	0.840	–	0.862	1.214
Finland	0.792	0.676	0.837	0.799	0.655	0.946
Spain	0.695	0.634	0.813	0.685	0.587	1.004
Japan	0.745	0.636	0.794	0.689	0.626	0.705
Hong Kong	0.726	0.598	0.792	0.686	0.550	0.834
France	0.754	0.668	0.788	0.836	0.623	0.815
Netherlands	0.787	0.660	0.782	0.804	0.629	1.215
Belgium	0.880	0.691	0.757	0.777	0.689	0.826
Sweden	0.977	0.656	0.748	0.811	0.646	0.740
Ireland	0.783	0.708	0.747	0.818	0.736	1.493
Israel	0.706	0.664	0.742	0.700	0.673	0.716
Hungary	0.661	0.512	0.733	0.740	0.483	0.758
Denmark	0.733	0.704	0.697	0.863	0.704	1.313
Italy	0.616	0.688	0.687	0.740	0.708	0.616
Korea	0.309	0.331	0.686	0.673	0.344	0.811
Portugal	0.469	0.650	0.664	0.705	0.712	0.601
Thailand	0.646	0.634	0.585	0.622	0.677	0.658
Malaysia	0.597	0.566	0.568	0.630	0.634	0.353
Australia	0.649	0.439	0.559	0.765	0.371	0.702
Brazil	0.563	0.577	0.558	0.589	0.575	0.599
Peru	0.633	0.619	0.517	0.572	0.560	0.661
Chile	0.687	0.552	0.514	0.663	0.635	0.564
Philippines	0.893	0.799	0.509	0.570	0.758	0.542
Indonesia	0.764	1.080	0.495	0.646	1.065	0.553
Colombia	0.466	0.623	0.490	0.568	0.583	0.616
China	0.481	0.579	0.460	0.666	0.499	0.629
South Africa	0.525	0.636	0.446	0.650	0.692	0.652
Mexico	0.502	0.618	0.437	0.653	0.590	0.576
Turkey	0.499	0.671	0.410	0.555	0.585	0.366
Russia	0.308	0.356	0.402	0.703	0.355	0.382

This table shows the Theil's U_2 statistics ordered (descending) by the column "After Jul 2010". The columns show the U_2 statistics across the six out-of-sample periods: (1) November 2012 to July 2016, (2) July 2010 to December 2012, (3) July 2014 to July 2016, (4) July 2008 to November 2009, (5) January 2011 to June 2012, and (6) July 2013 to December 2014. These out-of-sample periods correspond, respectively, to the in-sample estimations over the periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis). The explanatory variables for each period were selected according to 10% significance level when applying the Granger-causality tests. Countries at the bottom of the table, broadly composed of emerging market economies, are associated with better goodness-of-fit measures

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

Table 7.20 PHM across different periods

	Jul 2005 to Oct 2012	*Before Jul 2010*	*After Jul 2010*	*Before Jul 2008*	*Subprime Crisis*	*Euro Crisis*
Belgium	41%	32%	53%	38%	38%	36%
Sweden	47%	31%	50%	33%	33%	48%
Israel	37%	27%	49%	32%	27%	34%
Denmark	47%	28%	46%	32%	38%	48%
Hungary	28%	15%	46%	34%	15%	42%
Ireland	37%	47%	45%	62%	42%	48%
Finland	44%	28%	44%	37%	40%	39%
Hong Kong	42%	32%	44%	25%	21%	43%
Germany	42%	26%	42%	38%	29%	34%
Slovakia	42%	31%	42%	27%	23%	42%
Austria	43%	25%	41%	32%	22%	39%
Japan	36%	37%	39%	34%	31%	32%
Spain	34%	28%	35%	32%	31%	40%
Czech Rep.	34%	25%	35%	34%	18%	29%
Netherlands	53%	36%	34%	38%	36%	43%
Italy	24%	28%	34%	30%	38%	23%
New Zealand	36%	29%	32%	0%	29%	38%
France	35%	33%	31%	34%	33%	29%
Portugal	25%	24%	31%	41%	23%	25%
Poland	44%	24%	30%	30%	21%	42%
Australia	30%	23%	29%	29%	17%	25%
Peru	30%	33%	28%	18%	30%	51%
Thailand	31%	29%	26%	29%	27%	40%
Russia	22%	22%	25%	25%	17%	26%
Philippines	28%	30%	24%	15%	28%	22%
Korea	15%	16%	23%	25%	14%	31%
Malaysia	24%	26%	22%	27%	27%	18%
Brazil	28%	25%	22%	18%	22%	38%
China	19%	22%	21%	29%	15%	27%
Indonesia	32%	32%	21%	25%	32%	29%
Colombia	27%	24%	20%	20%	23%	34%
South Africa	23%	20%	19%	25%	0%	36%
Mexico	26%	28%	19%	30%	21%	36%
Chile	29%	27%	17%	37%	27%	29%
Turkey	29%	32%	13%	9%	5%	10%

This table shows the percent hit misses (PHM) statistics ordered (descending) by the column "After Jul 2010". The columns show the PHM statistics across the six out-of-sample periods: (1) November 2012 to July 2016, (2) July 2010 to December 2012, (3) July 2014 to July 2016, (4) July 2008 to November 2009, (5) January 2011 to June 2012, and (6) July 2013 to December 2014. These out-of-sample periods correspond, respectively, to the in-sample estimations over the periods: (1) July 2005 to October 2012, (2) July 2005 to June 2010 (Before Jul 2010), (3) July 2010 to June 2014 (After Jul 2010), (4) July 2005 to June 2008 (Before Jul 2008), (5) January 2008 to December 2010 (Subprime Crisis), and (6) July 2010 to June 2013 (Euro Crisis). The explanatory variables for each period were selected according to 10% significance level when applying the Granger-causality tests. Countries at the bottom of the table, broadly composed of emerging market economies, are associated with better goodness-of-fit measures

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

Table 7.21 ARMA models' goodness-of-fit statistics

	Before Jul 2010				*After Jul 2010*				*Before Jul 2008*				*Subprime Crisis*				*Euro Crisis*			
	Adj. R^2	*U_1*	*U_2*	*PHM*	*Adj. R^2*	*U_1*	*U_2*	*PHM*	*Adj. R^2*	*U_1*	*U_2*	*PHM*	*Adj. R^2*	*U_1*	*U_2*	*PHM*	*Adj. R^2*	*U_1*	*U_2*	*PHM*
Germany	**21%**	0.703	0.986	43%	2%	0.852	**0.739**	42%	5%	0.759	0.841	49%	16%	0.697	0.816	49%	2%	0.809	0.837	**32%**
France	14%	**0.735**	0.833	54%	0%	0.903	**0.728**	38%	−1%	0.942	0.887	41%	18%	0.750	0.822	47%	0%	0.882	0.842	30%
Finland	18%	0.669	0.819	38%	5%	0.838	**0.716**	**43%**	**19%**	**0.684**	0.972	51%	17%	0.679	0.798	**37%**	5%	0.783	**0.791**	43%
Netherlands	10%	0.751	0.771	40%	0%	0.932	**0.724**	48%	**13%**	0.899	0.881	54%	10%	0.752	0.767	40%	0%	0.923	**0.894**	**34%**
Austria	14%	0.689	0.794	41%	6%	0.784	**0.768**	41%	0%	0.891	0.864	42%	13%	0.694	0.777	45%	6%	0.758	**0.812**	**32%**
Belgium	12%	**0.719**	0.779	40%	2%	0.872	**0.709**	**43%**	**24%**	**0.627**	0.898	48%	**17%**	**0.717**	0.798	41%	1%	0.828	**0.819**	39%
Slovakia	16%	0.672	0.825	38%	7%	0.843	**0.696**	55%	14%	**0.641**	0.788	29%	15%	0.674	0.814	33%	7%	0.800	**0.748**	57%
Spain	18%	**0.644**	0.977	45%	−1%	0.964	**0.707**	42%	**33%**	**0.687**	1.086	49%	7%	0.741	0.711	40%	−1%	0.966	**0.835**	**36%**
Italy	9%	**0.742**	0.769	42%	1%	0.901	0.707	44%	**35%**	0.745	0.983	**53%**	9%	**0.743**	0.774	50%	0%	0.893	0.757	49%
Ireland	11%	0.694	0.792	**44%**	**14%**	**0.747**	0.935	51%	3%	0.842	0.845	51%	4%	**0.756**	**0.734**	42%	**14%**	0.690	**1.292**	60%
Portugal	19%	0.752	1.868	42%	5%	0.769	0.786	44%	**31%**	**0.711**	0.869	48%	12%	**0.709**	0.765	42%	4%	0.760	0.819	42%
Denmark	15%	0.698	0.805	36%	4%	0.861	**0.696**	47%	**46%**	**0.759**	1.091	48%	15%	**0.695**	0.788	**35%**	4%	0.808	**0.782**	**44%**
Sweden	10%	0.718	0.816	38%	9%	**0.796**	**0.739**	54%	**31%**	**0.701**	1.226	51%	10%	0.712	0.810	40%	10%	0.801	**0.733**	48%
Poland	14%	0.675	0.802	43%	5%	0.837	**0.714**	44%	6%	0.735	0.810	34%	13%	0.663	0.793	41%	**5%**	0.736	**0.766**	**39%**
Czech Rep.	18%	0.708	0.814	48%	7%	0.866	**0.645**	53%	**26%**	**0.658**	1.048	46%	17%	0.711	0.809	42%	1%	0.909	**0.653**	51%
Hungary	16%	0.704	0.860	38%	**6%**	0.815	**0.733**	49%	17%	**0.642**	0.748	39%	14%	0.716	0.848	37%	6%	0.773	0.772	42%
Turkey	9%	0.755	0.760	50%	0%	0.934	0.745	45%	3%	0.833	0.742	44%	11%	0.736	0.751	51%	0%	0.925	0.746	43%
Russia	24%	0.697	0.839	47%	2%	0.858	0.731	46%	4%	**0.827**	0.746	37%	23%	0.686	0.832	44%	1%	0.897	0.766	47%
Australia	15%	0.734	0.777	40%	2%	0.840	0.773	40%	**37%**	0.614	0.867	41%	15%	0.730	0.777	45%	2%	0.817	0.768	35%
New Zealand	10%	**0.756**	**0.768**	38%	2%	0.860	**0.729**	44%	**3%**	0.793	0.873	28%	10%	0.751	**0.770**	44%	2%	0.794	**0.817**	38%
Japan	0%	0.930	0.725	40%	−306%	0.807	2.348	56%	**10%**	**0.697**	1.160	56%	3%	0.844	0.725	42%	−306%	0.767	2.139	53%
Hong Kong	6%	0.793	0.745	49%	0%	0.925	**0.743**	44%	**23%**	0.647	1.037	43%	5%	0.803	0.747	53%	0%	0.927	**0.761**	44%
Korea	11%	0.720	0.797	48%	3%	0.828	0.737	46%	11%	**0.740**	0.733	32%	9%	0.725	0.800	49%	3%	0.806	**0.732**	51%

China	21%	0.670	0.851	45%	2%	0.863	0.732	42%	7%	0.774	0.760	39%	18%	0.664	0.828	46%	1%	0.854	0.759	48%
Philippines	11%	0.740	**0.772**	45%	4%	0.808	0.748	39%	2%	0.867	0.712	39%	12%	0.702	0.765	50%	3%	0.802	0.768	43%
Indonesia	17%	0.673	**0.794**	46%	5%	0.785	0.752	42%	3%	0.839	0.759	33%	18%	0.660	**0.789**	49%	6%	0.762	0.772	48%
Thailand	14%	0.721	0.807	48%	5%	0.781	0.779	40%	8%	0.801	0.734	42%	12%	0.675	0.779	50%	5%	0.773	0.770	43%
Malaysia	19%	0.699	0.825	44%	4%	0.793	0.760	40%	9%	0.754	0.709	35%	18%	0.704	0.834	46%	3%	0.812	0.749	42%
South Africa	12%	0.718	0.771	48%	0%	0.983	0.713	47%	13%	0.773	0.785	46%	11%	0.693	0.733	46%	−1%	0.984	0.752	52%
Israel	8%	0.742	0.758	45%	**4%**	**0.796**	**0.741**	52%	**23%**	**0.705**	0.972	49%	**8%**	0.738	0.773	45%	3%	0.782	0.816	35%
Brazil	11%	0.757	0.795	48%	1%	0.896	0.722	44%	4%	0.776	0.749	41%	16%	0.685	0.805	44%	1%	0.894	0.722	43%
Mexico	11%	0.735	0.781	49%	1%	0.902	0.714	48%	8%	0.737	0.772	34%	11%	0.727	0.776	46%	1%	0.892	0.723	49%
Peru	12%	0.725	0.805	47%	0%	0.913	0.737	43%	14%	0.825	0.806	49%	10%	0.746	0.770	50%	1%	0.904	**0.722**	49%
Chile	6%	0.756	0.812	54%	5%	0.810	0.733	42%	5%	0.798	0.754	41%	5%	0.762	0.831	49%	6%	0.817	0.741	43%
Colombia	11%	0.727	0.800	48%	1%	0.884	0.752	34%	2%	0.833	0.753	34%	−7%	0.751	1.680	58%	2%	0.894	0.744	47%

This table shows goodness-of-fit statistics for ARMA model specifications corresponding to five sub-periods: (1) July 2005 to June 2010 (Before Jul 2010), (2) July 2010 to June 2014 (After Jul 2010), (3) July 2005 to June 2008 (Before Jul 2008), (4) January 2008 to December 2010 (Subprime Crisis), and (5) July 2010 to June 2013 (Euro Crisis). The Adjusted R^2 is calculated over the in-sample period, whereas we adopted the two-part split of the data for calculating Theil's U_1, Theil's U_2, and percent hit misses (PHM) out-of-sample statistics: estimation (2/3 of data) and out-of-sample test (1/3 of data). Better statistics than the corresponding contemporaneous models are highlighted in bold

Source: Capital IQ

Table 7.22 Lagged-explanatory variable models' S&P500 estimators and goodness-of-fit statistics

	Before Jul 2010					*After Jul 2010*					*Before Jul 2008*
	$sp500_t$	*Adj.* R^2	U_1	U_2	*PHM*	$sp500_t$	*Adj.* R^2	U_1	U_2	*PHM*	$sp500_t$
Germany	−0.004***	**7%**	0.887	0.782	52%		3%	0.838	**0.741**	46%	
France	−0.004***	6%	0.937	0.746	52%	0.004	1%	0.675	0.813	37%	
Finland		14%	0.713	0.792	36%		5%	0.838	**0.717**	44%	−0.002***
Netherlands	−0.006***	9%	0.864	0.755	48%		2%	0.728	0.974	44%	
Austria		11%	0.730	0.789	42%		5%	0.775	**0.775**	42%	
Belgium	−0.006**	6%	0.935	0.770	51%	0.003	0%	0.693	0.811	47%	
Slovakia		11%	0.724	0.796	41%		7%	0.848	**0.699**	53%	
Spain		3%	0.846	0.725	46%	0.016	**2%**	0.743	**0.758**	**50%**	
Italy	−0.009***	5%	0.953	0.751	50%	0.040	−3%	0.758	0.787	44%	
Ireland		4%	0.815	0.753	**45%**		–	–	–	–	
Portugal		–	–	–	–		4%	0.810	0.793	44%	−0.003***
Denmark		12%	0.728	0.785	35%		4%	0.858	0.697	46%	
Sweden		10%	0.720	0.814	42%		9%	0.805	0.748	50%	
Poland		9%	0.764	0.792	45%		5%	0.857	**0.709**	51%	−0.007*
Czech Rep.		15%	0.736	0.777	48%		1%	0.791	**0.705**	47%	
Hungary	−0.032**	8%	0.796	0.836	46%		**6%**	0.807	0.734	50%	
Turkey		–	–	–	–		3%	0.809	0.750	46%	
Russia	−0.047*	8%	0.668	0.886	41%		20%	0.789	0.642	57%	−0.012***
Australia	−0.008***	7%	0.778	0.788	47%		1%	0.780	0.833	47%	
New Zealand	−0.004	94%	1.307	1.250	44%		3%	0.745	**0.744**	39%	
Japan	−0.005***	6%	0.856	0.729	48%		–	–	–	–	
Hong Kong	−0.009***	15%	0.731	0.778	47%		3%	0.858	**0.739**	50%	
Korea	−0.026**	5%	0.709	0.876	44%		3%	0.740	0.779	44%	−0.011***
China	−0.011**	5%	0.804	0.792	50%		1%	0.762	0.768	51%	−0.008***
Philippines	−0.022*	3%	0.738	0.832	48%		3%	0.842	0.748	44%	−0.017*
Indonesia	−0.052*	8%	0.686	**0.995**	48%		4%	0.818	0.752	41%	−0.018*
Thailand	−0.013*	3%	0.800	0.822	49%		4%	0.814	0.774	40%	
Malaysia	−0.015*	3%	0.763	0.819	50%		2%	0.765	0.775	50%	−0.011***
South Africa		29%	0.812	1.287	54%		3%	0.847	0.704	45%	
Israel		69%	0.716	0.819	48%		3%	0.829	0.742	49%	−0.008***
Brazil	−0.019**	4%	0.721	0.771	42%		2%	0.886	0.709	37%	
Mexico	−0.023**	7%	0.700	0.796	46%		15%	0.859	0.750	56%	
Peru		81%	0.652	0.677	33%		2%	0.829	0.744	47%	
Chile	−0.015***	15%	0.690	0.779	46%		5%	0.824	0.739	44%	−0.003*
Colombia	−0.019**	4%	0.721	0.778	45%		**45%**	0.821	0.680	59%	

This table shows S&P500 estimators and goodness-of-fit statistics for lagged-explanatory variable model specifications corresponding to five sub-periods: (1) July 2005 to June 2010 (Before Jul 2010), (2) July 2010 to June 2014 (After Jul 2010), (3) July 2005 to June 2008 (Before Jul 2008), (4) January 2008 to December 2010 (Subprime Crisis), and (5) July 2010 to June 2013 (Euro Crisis). The explanatory variables for each period were selected according to 10% significance level when applying the Granger-causality tests. The Adjusted R^2 is calculated over the in-sample period, whereas we adopted the two-part split of the data for calculating Theil's U_1, Theil's U_2, and percent hit misses (PHM) out-of-sample statistics: estimation (2/3 of data) and out-of-sample test (1/3 of data). Better statistics than the corresponding contemporaneous models are highlighted in bold

Source: Capital IQ, Bloomberg, Datastream, and author's calculations

***, **, and * stand for significance at the 1%, 5%, and 10% level, respectively

				Subprime Crisis					*Euro Crisis*				
Adj. R^2	U_1	U_2	*PHM*	$sp500_t$	*Adj. R^2*	U_1	U_2	*PHM*	$sp500_t$	*Adj. R^2*	U_1	U_2	*PHM*
4%	0.762	0.846	46%		13%	0.735	0.771	46%		2%	0.782	0.828	34%
–	–	–	–		7%	0.801	0.736	47%		1%	0.622	0.891	36%
8%	0.755	0.840	42%	−0.004***	8%	0.834	0.780	44%		5%	0.776	**0.792**	44%
–	–	–	–	−0.006***	8%	0.855	0.729	46%		2%	0.707	**0.940**	45%
–	–	–	–		10%	0.737	0.779	44%		1%	**0.576**	**0.804**	44%
10%	0.711	0.811	39%		9%	**0.776**	0.750	45%	0.004	0%	0.663	0.909	48%
10%	0.706	0.818	35%		10%	0.725	0.792	36%		7%	0.799	**0.748**	53%
13%	**0.744**	0.766	41%		3%	0.838	0.726	51%	0.019	2%	0.821	**0.934**	47%
11%	0.723	0.789	38%	−0.009***	4%	0.937	0.754	51%		2%	0.725	0.856	44%
88%	**0.696**	**0.575**	**49%**		3%	**0.837**	0.738	42%		–	–	–	–
8%	0.870	0.746	46%		–	–	–	–		4%	0.687	0.792	39%
–	–	–	–		12%	0.730	0.777	**36%**		1%	0.677	**1.051**	49%
–	–	–	–		10%	0.712	0.810	38%		10%	0.775	**0.729**	**44%**
5%	0.880	0.862	54%		8%	0.733	0.796	45%		4%	0.746	0.778	42%
4%	0.766	0.857	**32%**		13%	0.692	0.740	36%	0.001	1%	0.834	**0.634**	51%
6%	0.757	0.796	38%	−0.033**	7%	0.775	0.814	44%		–	–	–	–
3%	0.834	0.742	44%		–	–	–	–		–	–	–	–
7%	0.940	0.739	44%	−0.054**	8%	0.648	0.883	33%		3%	0.823	0.784	44%
29%	0.622	0.833	38%	−0.008***	7%	0.764	0.786	49%	0.004	3%	0.719	0.803	43%
–	–	–	–		94%	1.090	1.135	38%		3%	0.657	**0.873**	**36%**
–	–	–	–	−0.006***	8%	0.842	0.714	45%		–	–	–	–
8%	0.758	0.777	32%	−0.010***	16%	0.725	0.778	45%		1%	0.863	**0.798**	44%
11%	0.906	0.714	48%	−0.027**	5%	0.694	0.883	44%		3%	0.733	**0.720**	43%
10%	0.845	0.742	54%	−0.011**	6%	0.783	0.794	40%		1%	0.862	0.779	43%
3%	0.872	0.690	48%	−0.030*	3%	0.744	0.878	49%	0.008	2%	0.843	0.785	49%
3%	0.896	0.761	46%	−0.052*	7%	0.679	**0.985**	46%		5%	0.798	0.774	48%
9%	0.803	0.732	39%	−0.021*	4%	0.792	0.886	49%	0.007	4%	0.790	0.779	42%
11%	0.872	0.684	52%	−0.015*	3%	0.757	0.827	47%		3%	0.803	0.731	43%
11%	0.749	0.768	43%		22%	1.343	2.055	33%		–	–	–	–
10%	0.818	0.740	39%		6%	0.747	0.781	46%		2%	0.821	0.825	34%
4%	0.814	0.763	46%	−0.019*	5%	0.716	0.772	41%		4%	0.843	0.730	53%
8%	0.748	0.789	34%		13%	0.623	0.815	45%		13%	0.830	0.735	49%
6%	0.781	0.765	35%	0.019	33%	0.592	0.874	44%		74%	0.840	0.752	63%
99%	1.362	1.102	46%	−0.015***	9%	0.670	0.818	35%		6%	0.826	0.745	49%
2%	0.849	0.759	38%	−0.018*	4%	0.726	0.771	45%		–	–	–	–

for the periods “Before Jul 2010”, “After Jul 2010”, “Before Jul 2008”, “Subprime Crisis”, and “Euro Crisis”, Table 7.22 indicates that the lagged-variable model statistics are worse than those of the ARMA models for the July 2005–October 2012 period and noticeably worse than the corresponding contemporaneous model statistics (Tables 7.17, 7.18, 7.19, and 7.20). In addition, one can also notice that no coefficient of the S&P 500 appears to be statistically significant for the two overlapping subperiods “After Jul 2010″ and “Euro Crisis”.

7.6 Conclusion

I find that the S&P 500 is significant in explaining CDS spreads across a range of countries, especially emerging markets. Moreover, the coefficients of *Exchange Rate* and *Local Two-Year Yield* variables have the expected sign, and are also significant for some important investable markets. On the other hand, variables such as *VIX, Oil, Local Stock index, Slope, Local Slope*, and *Banking System* are rarely found to be statistically significant in explaining sovereign CDS spreads. Strikingly, goodness-of-fit and forecast accuracy are much better for emerging markets than for developed countries. Models with contemporaneous variables provide better statistical fitness than lagged-variable models. As for ARMA models, except for a few occurrences, their goodness-of-fit and forecast accuracy statistics are worse than for contemporaneous fundamental models across the board. When generating fundamental models with lagged variables, however, the engine comes up with goodness-of-fit statistics even worse than those of pure time series-generated models (ARMA).

If the past is any guide (so far I still believe it is!) and risk assessments are to be made on a weekly basis, the proposed large-scale, econometric-based framework can be used as part of an early warning tool. While using this framework in practice, however, some caveats should be kept in mind. Models with contemporaneous variables need one-week-ahead predictions as inputs. Accordingly, the results point out that forecasting initiatives should be focused on global variables, particularly those conveying the overall risk aversion or the general state of the global economy, like the VIX or the S&P 500 factors. Not least, Longstaff et al.’s (2011) advice is worth considering: as the estimation period is “characterized by excess global liquidity, prevalence of carry trades and reaching for yield in thesovereign market", approaches like the one proposed in this chapter should be taken with a grain of salt when applied to periods not subject to those market forces. In addition, models based on historical information do not necessarily unveil the true relationship between variables under unusual circumstances, regardless of how sophisticated they are.

As for additional robustness assessments, I recommend applying randomization tests on a selected set of explanatory variables and compare the forecast accuracy ex-post. For example, if 60% of predictions of changes in S&P 500 had been correct, what would have been the value for PHM? Besides, while this chapter provides some evidence for the overall neutrality in terms of the quantity of statistically significant S&P 500 coefficients, there is an opportunity to more extensively check the robustness of the algorithm to potential unintended consequences when modifying the set of instrumental variables in the GMM estimation.

Finally, for future research, one could test other banking sector-related variables. While the well-functioning of the banking sector is key to fostering the economic development of any country, the opposite has proved so far to hold true: banking crisis can lead to economic recession. Not as a coincidence, the factor $bank_{i,\ t}$ strikes as indicating double causality between the sovereign and its corresponding banking system CDS spreads in almost all cases for which I could achieve data for banks' CDS spreads, as shown in Table 7.5.[15] As it turns out, distresses in the banking sector, when pervasive and impacting too-systemic-to-fail banks, as for the 2007–2009 crisis and the European debt crisis, might lead to negative views on the debt sustainability of the corresponding jurisdiction, which would presumably manifest themselves by increasing CDS spreads. Playing a pivotal role in paving the way for economic growth or where having a specific mandate for guaranteeing financial stability, central banks, as lenders of last resort, have an incentive to bailing the banking sector out. In this chapter, although using the average of banks' CDS spreads as a proxy for the distress in the banking sector, it didn't show up as significant in most of the cases.[16] I conjecture that movements in sovereign CDS spreads might not have fully captured the dynamics of the banking sector risk, as its transmission to sovereign credit deterioration may occur more like a structural break than continuously in time.

NOTES

1. Arce et al. (2012) find that due to the higher liquidity of the sovereign CDS market, the sovereign bonds led the price discovery process during the recent global financial crisis.
2. The Chinese Renminbi was officially added to the SDR basket on October 2016, after the sample period chosen for this paper analysis.
3. Longstaff et al. (2011), "How Sovereign is Sovereign Credit Risk?"
4. Notional amounts outstanding are defined as the gross nominal or notional value of all deals concluded and not yet settled on the reporting date. These amounts provide a measure of market size and a reference from which contractual payments are determined in derivatives markets.
5. According to the BIS, these declines are largely due to terminations of existing contracts, by netting gross notional outstanding through portfolio compression and clearing.
6. The total number of models tested comprises all possible permutations of factors labelled as "(*)", "*", or "&" in Table 7.5. For example, in the case of Italy, I have a set of 8 eligible factors (Table 7.5):$sp500$,vix,$Slope$,oil, $spread - 1$, xr, $localTY$, $localSlope$, and $bank$. Then, the engine is due to test as many as $$\binom{1}{8}+\binom{2}{8}+\binom{3}{8}+\binom{4}{8}+\binom{5}{8}+\binom{6}{8}+\binom{7}{8}+\binom{8}{8}=2^8-1=255$$ models.
7. A model nests another one when the first contains the same terms as the second and at least one additional term. I use the F-test (see Greene 2007) for testing the null hypothesis that the more comprehensive model does not contribute with additional information. When I reject this hypothesis at 5% significance level, then the more comprehensive model is not rejected to be superior to the nested one.
8. The only exceptions are Austria (*oil*), Australia (*oil*), and Russia (*stock*).
9. France, Finland, Austria, Belgium, Slovakia, Spain, Ireland, Sweden, Czech Republic, Australia, New Zealand, Japan, Philippines, Indonesia, Thailand, and Brazil.
10. The only exceptions are Hong Kong, Korea, and China.
11. The ARMA-model statistics are better in comparison to the corresponding lagged model (Table 7.8) in 88 out of 124 goodness-of-fit statistic values.
12. The corresponding complete model specifications are not shown, but are available at request.
13. Even generating different models for Hungary, Israel, and Colombia, their S&P500 estimators differ by less than 5%.
14. The corresponding complete model specifications are not shown, but are available at request.

15. The exception is Germany, for which we cannot reject that the variable *bank* is weakly exogenous.
16. The exceptions are Hong Kong, Korea, and China.

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