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Risk factors and value at risk in publicly traded companies of the nonrenewable energy sector[☆]

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ABSTRACT

We analyze a sample of 64 oil and gas companies of the nonrenewable energy sector from 24 countries using daily observations on return on stock from July 15, 2003 to August 14, 2012.

We show that specific and common risk factors are priced. Specific risk factors including company size and leverage are important in explaining returns of energy companies and those companies became more exposed to credit concerns after the financial crisis of 2008. Common risk factors including the U.S. Dow Jones market excess return, the VIX, the WTI price of crude oil, and the FX of the Euro, Chinese yuan, Brazilian real, Japanese yen and British pound vis-à-vis the U.S. dollar are also important in explaining energy company returns. The foreign exchange effect accounts for the fact that many companies in the sector receive revenues denominated in domestic currency while their costs are in foreign currency.

1. Introduction

In the last few years, the U.S. has been moving towards energy self-sufficiency and, in December 2013, the nation produced more oil than it imported for the first time in nearly two decades. At the same time period, states in the union have implemented policies promoting alternative renewable energy uses and sources. The debate regarding the merits of nonrenewable versus renewable sources of energy in policy circles can potentially spillover on the financial returns of nonrenewable energy companies.[2] This paper studies how common factors and specific factors affect equity returns for publicly traded nonrenewable energy sector companies and their effect on value at risk for those companies. Our sample is in the realm of global capital markets. We set out to measure and analyze the exposure of the nominal equity returns of a company denominated in the currency of the stock exchange of the country of origin. Those nominal returns may or may not be exposed to company specific and/or common risk factors.

From a theoretical perspective, if we assume complete global financial markets, the conditional CAPM implies that specific idiosyncratic factors are fully diversified and only global risk is priced. On the other extreme of full absence of international risk sharing, specific idiosyncratic risk is fully priced and non-diversified. The potential for an in-between case of partial risk sharing is plausible under the common assumptions of information asymmetries. In this case, equity returns are exposed to both global risks and specific risks and our main objective is to measure and price those risks.

The core of our empirical methodology is as follows. First, we use conditional heteroskedasticity methods applied to the panel. Second, we use multivariate conditional heteroskedastic and dynamic conditional correlation methods applied to each company. While the full panel assumes homogeneity of the factor loadings, we estimate the model to better understand, on average, the key common and specific factors that affect returns. We then use the multivariate models by company to uncover heterogeneity across companies.

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2 See e.g. the review of Xie (2013).

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Table 1
Key codes of companies in the sample.[a]

Code	Full name	Country	Code	Full name	Country
AOIL_SS_Equity	Alliance Oil Company	Russia	LUPE_SS_Equity	Lundin Petroleum	Sweden
1605_JT_Equity	International Petroleum Exploration Corp.	Japan	MUR	Murphy Oil Corporation	U.S.
3_HK_Equity	Hong Kong and China Gas Co Limited	China	NES1V_FH_Equity	Neste Oil	Finland
386_HK_Equity	China National Petroleum Corporation	China	NG_LN_Equity	National Grid PLC	UK
6_HK_Equity	Power Assets Holdings Limited	China	OGXP3_BZ_Equity	OGX Petróleo e Gás Participações S.A.	Brazil
857_HK_Equity	PetroChina Company Limited	China	OINL_IN_Equity	Oil India Limited	India
883_HK_Equity	China National Offshore Oil Corporation	China	OMV_AV_Equity	Österreichische Mineralölverwaltung	Austria
APA	Apache Corporation	U.S.	OPHR_LN_Equity	Ophir Energy PLC	UK
BANE_RU_EQUITY	Bashneft	Russia	OXY	Occidental Petroleum Corporation	U.S.
BG_LN_Equity	BG Group	UK	PCG	Pacific Gas And Electric Company	U.S.
BP_LN_Equity	British Petroleum	UK	PEG	Public Service Enterprise Group Inc.	U.S.
CNA_LN_Equity	Centrica PLC	UK	PETR3_BZ_Equity	Petróleo Brasileiro S.A.	Brazil
CNE_LN_Equity	Cairn Energy plc	UK	PFC_LN_Equity	Petrofac	U.S.
CNP	CenterPoint Energy	U.S.	PMO_LN_Equity	Premier Oil PLC	UK
CNQ_CN_EQUITY	Canadian Natural Resources Limited	Canada	PRE_CN_Equity	Pacifc Rubiales Energy Corporation	Canada
COP	ConocoPhillips Company	U.S.	QGEP3_BZ_Equity	Grupo Queiroz Galvão S.A.	Brazil
CVE_CN_EQUITY	Cenovus Energy Inc.	Canada	RDSA_NA_Equity	Royal Dutch Shell	UK
CVX	Chevron Corporation	U.S.	REP_SM_EQUITY	Repsol S.A.	Spain
ECOPTL_CB_Equity	Empresa Comlombiana de Petróleos S.A.	Colombia	ROSN_RU_Equity	Rosneft	Russia
ENEL_IM_Equity	Ente Nazionale per l'energia Elettrica	Italy	RWE_GR_Equity	Rheinisch-Westfälisches E. AG	Germany
ENG_SM_Equity	Enagás S.A.	Spain	SBMO_NA_Equity	SBM Offshore N.V.	Holland
EXC	Exelon Corporation	U.S.	SDRL_NO_Equity	Seadrill Limited	Norway
FP_FP_Equity	Total S.A.	France	SOL_SJ_Equity	Sasol Limited	S. Africa
Galp_PL_Equity	Galp energia	Portugal	SPM_IM_EQUITY	Saipem S.p.A.	Italy
GAZP_RU_Equity	Gazprom	Russia	SRG_IM_Equity	Snam Rete Gas S.p.A	Italy
GSZ_FP_Equity	GDF Suez S.A.	France	STL_NO_Equity	Statoil ASA	Norway
HER_IM_Equity	Holding Energia Risorse Ambiente	Italy	SU_CN_EQUITY	Suncor Energy Inc.	Canada
HES	Hess Corporation	U.S.	SUBC_NO_Equity	Subsea UK	UK
HRTP3_BZ_Equity	HRT participações em petroleo	Brazil	TLW_LN_EQUITY	Tullow Oil plc	UK
HTG_LN_Equity	Hunting PLC	UK	UNF_SM_Equity	Unión Fenosa, S.A.	Spain
IBE_SM_Equity	Iberdrola Group	Spain	WMB	Williams Companies, Inc.	U.S.
LKOH_RU_Equity	LUKoil	Russia	XOM	Exxon Mobil Corporation	U.S.

[a] Company descriptions and additional information are presented in the extended version Table A1 in the Appendix.

We cover 64 companies from the oil and gas sector from 24 countries using daily data from July 15, 2003 to August 14, 2012. While the energy market can be regarded as a sector that supports the entire economy, our focus is on the systematic risk faced by companies in the non-renewable energy sector.[3] Our measurements indicate that specific factors relating to firm size and firm debt-to-equity financial policy are robustly priced factors.[4] In the space of common factors, the market premium of the U.S. Dow Jones industrials, the VIX U.S. S&P500 options volatility index, the price of West Texas Intermediate (WTI) crude oil and several exchange rates relative to the U.S. dollar are robustly priced common factors.

There is a vast literature on the effect of oil prices on energy markets, but our main focus is much broader and includes oil prices as one potential factor among many others.[5] Giovannini et al. (2004) investigate the correlations of volatilities in the stock returns and their determinants for integrated oil companies and find low to extreme interdependence between the volatilities of companies' stock returns and the relevant stock market indexes or crude oil prices. Chiou and Lee (2009) study the relationship of the S&P500 and the WTI oil transactions and find that high fluctuations in oil prices have asymmetric unexpected impacts on S&P500 returns. Elyasiani et al. (2011) examine the impact of changes in the oil returns and oil return volatility on U.S. industries' excess stock returns and return volatilities and find evidence that oil price fluctuations constitute a systematic asset price risk at the industry level. Mohanty and Nandha (2011) estimate oil price risk exposures of the U.S. oil and gas sector using the Fama and French (1992, 1995) framework. They show that the Fama–French factors as well as momentum characteristics of stocks and changes in oil prices are significant determinants of returns for the sector. Lombardi and Ravazzolo (2012) find that the joint modeling of oil and equity prices produces more accurate point and density forecasts for oil prices.[6] Our results regarding the change in oil prices as a common factor confirm the positive effect of WTI crude oil prices on company stock returns under several alternative estimation procedures.

Closer to our analysis is Ramos and Veiga (2011) who also analyze the exposure of the oil and gas industry returns of 34 countries to oil prices using panel data methods. They find that oil price is a globally priced factor for the oil industry. Our main contribution to this strand of the literature is to show that specific factors such as size and leverage and common factors such as the VIX U.S. options' volatility index are important factors that are robustly priced as well. In particular, we find that energy companies in the energy sector became more exposed to credit concerns since the financial crisis of 2008. In addition, we find significant heterogeneity across companies and move beyond the panel data framework.[7]

[3] Ferson and Harvey (1994) study the sources of risk and expected returns in global equity markets, see also Karolyi and Stulz (2003) for a survey. Alternatively, Pierret (2012) studies the systemic risk that emanates from energy markets. Hamilton (1983) is the classic reference on the broad effects of oil on the macroeconomy in the US.

[4] By robust we mean statistically significant across several specifications. Haushalter (2000) shows that the extent of hedging is related to financing costs for oil and gas industry firms and finds that companies with greater financial leverage manage price risks more extensively.

[5] The focus of this paper is on the energy sector (i.e., energy companies).

[6] In addition, several authors study the exposure of Canadian oil and gas companies to risk factors including Sadorsky (2001) and Boyer and Filion (2007).

[7] Our paper also differentiates from Ramos and Veiga (2011) by examining more factors such as the specific factors including firm size and leverage ratio. Related to this strand, Sadorsky (2008) investigates the impact that global oil market risk factors have on the oil price risk of oil company stock prices. He finds that oil prices and market risk are both positive and statistically significantly priced risk factors, and that oil price risk is negatively impacted by increases in oil reserves, is positively impacted by increases in oil production, and is more sensitive to changes in production rates than to changes in reserve addition rates. More recently, Bianconi and Yoshino (2013) apply a variant of the methodology of this paper to a small sample of oil and gas companies in the emerging countries of Brazil, Russia, India, China and South Africa (BRICS).

Table 2
Descriptive statistics.
Daily return on stock.

	Retur_ck
Mean	0.001
Median	0.000
StDev	0.024
Skewness	0.542
Kurtosis	30.062
Max	0.750
Min	−0.530
N	124,111

Legend:
Retur_ck = return on stock, continuous daily change in domestic currency.

Table 3a
Descriptive statistics — specific factors.

	lTotAs_e	z_BOOK_t	log_de_y	z_net__e
Mean	−0.621	0.000	3.874	0.000
Med	0.008	−0.106	3.898	−0.107
Std	2.101	1.000	1.130	1.000
Skewness	−0.994	12.381	−0.962	12.760
Kurtosis	3.160	179.994	8.222	176.071
Max	4.639	22.642	7.158	16.389
Min	−7.361	−0.238	−4.328	−0.227
N	121,807	121,773	119,346	122,379

Legend:
lTotAs_e = total assets divided by the price of equity in logarithms.
z_BOOK_t = book to market ratio as a z-score.
log_de_y = debt to equity ratio in logarithms.
z_net__e = net income as a z-score.

Our results on the exposure of returns to exchange rates are in line with other results in the literature.[8] De Santis and Gerard (1998) study the size of the premium for currency risk and find strong support for models that includes both market and foreign exchange risk. However, Roache (2008) assesses the macrorisk exposure offered by commodity futures and test whether those risks are priced thus finding that although some commodities are also a hedge against U.S. dollar depreciation, this risk is not priced. We find robust evidence that exchange rate risk is priced, but currencies such as the Russian ruble and the Indian rupee are not important in our sample. What is important is that for certain countries such as China and Brazil their revenues from the sector are denominated in domestic currency while their costs are in foreign currency making their exchange rates impact significantly on company returns.

In this paper, first we use a panel with threshold ARCH (TARCH) and ARMA effects. In this case, specific factors for size and leverage are statistically significant and exposure to the U.S. Dow Jones market premium, the VIX, and the foreign exchange (FX) rates of the Euro, Chinese yuan, Brazilian real, Japanese yen and British pound vis-a-vis the U.S. dollar is robustly priced.

We extend the empirical analysis to multivariate GARCH with dynamic conditional correlation (DCC) methods on a company by company basis. Here, we use bivariate conditional correlations with the market to estimate the systematic risk of firms as in Brownlees and Engle (2011). We find significant heterogeneity across firms by examining the quantile distribution of the multivariate GARCH-DCC parameter estimates. We compute one-day horizon value at risk based on the estimated first and second moments and evaluate the performance of value at risk with a back-testing procedure. Our value at risk estimation, conditional on specific and common factors, shows the oil and gas companies that emerge as less risky benchmarks and the ones that are more risky so that the market is charging excess risk premium of those companies relative to the low risk benchmark.

We use the framework to make comparisons between our estimated measures of volatility, dynamic conditional correlations and value at risk with and without exposure to common and specific factors. Not surprisingly, we find that the financial crisis of 2008 is the period of largest volatility under exposure and largest conditional correlations. However, a naïve calculation based on raw data would overestimate the value at risk considerably over the sample period relative to the value at risk accounting for exposure while GARCH models without taking into account exposure underestimate the value at risk.

The rest of the paper is organized as follows. Section 2 presents and analyzes the data sample and Section 3 discusses the econometric methods and models. Section 4 presents the empirical evidence and Section 5 concludes. The appendix provides the description of the firms in the sample.

2. Data

The focus of this paper is on oil and gas companies of the nonrenewable energy sector, publicly traded in exchange markets around the world. We have a sample of 64 companies and daily observations from July 15, 2003 to August 14, 2012, when assets are traded. Table 1 presents the key codes, names and country of origin of the companies while Table A1 in the appendix provides more detailed information in terms of the description, stock exchange listed and the currency denomination of the stock. We have companies from 24 countries, namely Austria, Brazil, Canada, Chile, China, Colombia, Denmark, Finland, France, Germany, Greece, Holland, India, Italy, Japan, Norway, Portugal, Russia, South Korea, South Africa, Spain, Sweden, UK and the US.

The main variables in the analysis are as follows.[9] The return on stock is calculated as the continuous daily change in the price of the stock denominated in the currency of the traded stock. Table 2 shows the descriptive statistics of the daily returns in the sample. The returns are severely leptokurtic in the panel. Most companies have a healthy cumulative sum of returns in the period, however some are much less successful. British Petroleum, Cenovos of Canada (CVE_CN), Enel of Italy, GazProm of Russia, HRT from Brazil, OINL from India, Queiroz-Galvao of Brazil, and Royal Dutch had particularly flat cumulative returns and did not perform well in the period.

Table 3a presents descriptive statistics of the firm specific factors in the sample. The first two specific factors are the well-known Fama and French (1992, 1995) factors. As a proxy for size, we have the total assets scaled by the price of equity in logarithms (lTotAs_e). The proxy for value is the book value scaled by the market value of equity normalized to mean zero and variance one, i.e. as a z-score (z_BOOK_t). As a measure of leverage/financial policy of the company we have the debt-to-equity ratio in logarithms (log_de_y);[10] and gauging revenues we have net income normalized to mean zero and variance one, i.e. as a z-score (z_net__e). Book-to-market (value), leverage and net income are leptokurtic.

Table 3b presents descriptive statistics for the time series of the common factors. First, the variable premium_mkt is the daily continuous return of the U.S. Dow Jones Industrials minus the daily yield of the 3-month U.S. Treasury bill rate all denominated in U.S. dollars.[11] The variable ch_VIX is the continuous daily change of the VIX options' volatility index of the U.S. S&P500 from the Chicago Board of Exchange,

[8] Recently, Katechos (2011) investigates the relationship between stock markets and exchange rates and finds strong linkages among exchange rates and global stock market returns, see e.g. references therein.

[9] The company data are from Bloomberg unless otherwise noted.

[10] We also used the variable financial leverage (FNCL_LVG) but it showed to be highly correlated with debt-to-equity and we choose to include debt-to-equity as a measure of leverage. We use the z-score transformation due to the large range in the raw data.

[11] We choose the U.S. Dow Jones industrials, as opposed to the broader S&P500, for the purpose of measuring international exposure to the systematic risk from a narrow, but widely covered market.

Table 3b
Descriptive statistics — common factors.

	premiu_t	ch_VIX	ch_eur_x	ch__na_x	ch_ind_x	ch_jap_x	ch_uk_x	ch_rus_x	ch_brl_x	ch_wti
Mean	1.55E−04	−0.001	−4.11E−05	−1.15E−04	−8.17E−05	1.63E−04	−2.22E−05	−2.19E−05	−1.56E−04	3.75E−04
Med	2.05E−04	−0.007	−1.86E−04	0	0	0	0	0	−1.14E−04	0.001
Sd	0.012	0.066	0.007	0.001	0.005	0.007	0.007	0.006	0.010	0.025
skewness	0.209	0.686	0.124	−2.802	−0.148	1.045	−1.105	−1.932	0.336	−0.059
kurtosis	14.863	7.634	6.016	63.411	11.590	16.947	20.203	27.746	11.899	7.283
Max	0.111	0.496	0.047	0.007	0.033	0.080	0.051	0.032	0.071	0.164
Min	−0.079	−0.351	−0.040	−0.020	−0.032	−0.035	−0.082	−0.077	−0.091	-0.128
N	2309	2206	2326	2326	2326	2326	2326	2326	2220	2260

Legend:
premium_mkt = daily return of the Dow Jones Industrial minus the daily yield of the 3-month U.S. Treasury bill rate (in US$ dollars).
ch_VIX = continuous daily change of the VIX index.
ch_euro_x = continuous daily change of the Euro/US$ dollar exchange rate.
ch_china_x = continuous daily change of the China–$/US$ dollar exchange rate.
ch_india_x = continuous daily change of the India–$/US$ dollar exchange rate.
ch_japan_x = continuous daily change of the Japan–Y$/US$ dollar exchange rate.
ch_uk_x = continuous daily change of the UK Pound$/US$ dollar exchange rate.
ch_russia_x = continuous daily change of the Russia–$/US$ dollar exchange rate.
ch_brl_x = continuous daily change of the BR–R$/US$ dollar exchange rate.
ch_wti = continuous daily change of the West Texas crude oil price per barrel in US$ dollar.

measuring the volatility of options in the market, known as the 'fear' index. We include several nominal exchange rates vis-à-vis the US dollar to account for exchange risk.[12] They are the Euro, Chinese yuan, Indian rupee, Japanese yen, UK Pound, Russian ruble, and the Brazilian real. The variable ch_wti is the continuous daily change of the West Texas Intermediate (WTI) crude oil price per barrel in U.S. dollars. The data are shown to be leptokurtic as well and, in the group of exchange rates, the Brazilian real has the highest variability in the sample while the Chinese yuan has the lowest. The change in the VIX, followed by the crude oil price, has the highest variability of all common factors in the sample.

Table 4 presents the statistically significant unconditional correlations among the returns and factors used in the analysis. The return on stock is highly correlated with the Dow Jones premium and the VIX and significantly correlated with most other factors. The Dow Jones premium is significantly correlated with all other common factors, but not with firm specific factors. The premium of the market and the VIX has the highest unconditional (negative) correlation in the sample. Most exchange rates are significantly correlated with one another as well. The crude oil price is significantly correlated with firm's net income, with the return on stock and with all other common factors.

Fig. 1A–E shows the exposure of the return on stock in domestic currency to the specific and common factors selected.[13] Fig. 1A shows return exposure to specific factors total assets scaled by the price of equity in logarithms (Size) and Leverage ratio in logarithms. Size shows negative exposure and leverage shows mostly positive but some negative exposure. In both cases, there is heterogeneity among some companies. Fig. 1B shows heterogeneous return exposure and company net income has more spread relative to value.

Fig. 1C–E presents return exposure to common factors. Fig. 1C shows first the market premium common factor, the Dow Jones Industrials market premium in U.S. dollars. Most companies are in the northwest quadrant with positive expected returns and a factor loading below unity indicating positive but low exposure to the market premium common factor. The notable exceptions in the southeast quadrant are Queiroz-Galvao and HRT from Brazil with negative expected returns and factor loading above unity indicating high exposure to the market premium common factor. Exposure to the common factor WTI oil price change has similar pattern to the market premium but with much less spread while the change in the VIX has uniformly negative returns exposure. Fig. 1D presents mostly negative return exposure to the Euro, Chinese yuan and Brazilian real exchange rate vis-à-vis the U.S. dollar. Lastly, Fig. 1E shows heterogeneous return exposure to the Indian rupee, Japanese yen, UK pound and Russian ruble exchange rate with the U.S. dollar. In summary, we find evidence of heterogeneous return exposure to the specific and common factors in the sample.

3. Econometric models

The core of our methodology is to measure the effect of systematic risk on the returns of the nonrenewable energy sector with a sample of oil and gas companies. We use conditional heteroskedasticity methods applied to the panel and multivariate conditional heteroskedastic and dynamic conditional correlation methods applied to each company. While the full panel assumes homogeneity of the factor loadings, we estimate the model to better understand, on average, the key common and specific factors that affect returns. We then use the multivariate models by company to uncover the heterogeneity.

3.1. Common and specific factors with the panel

Given the potential for autocorrelation and heteroskedasticity in the sample, we estimate a conditional heteroskedasticity family of models that include the threshold ARCH or TARCH formulation for conditional

[12] The list of the foreign exchange variables is: ch_euro_x is the continuous daily change of the Euro/US dollar exchange rate; ch_china_x is the continuous daily change of the Chinese yuan versus the US dollar exchange rate; ch_india_x is the continuous daily change of the Indian rupee versus the US dollar exchange rate; ch_japan_x is the continuous daily change of the Japanese yen versus the US dollar exchange rate; ch_uk_x is the continuous daily change of the UK Pound/US dollar exchange rate; ch_russia_x is the continuous daily change of the Russian ruble versus the US dollar exchange rate and ch_brl_x is the continuous daily change of the Brazilian real versus the US dollar exchange rate.

[13] The data for Fig. 1A–E are obtained using the Fama and MacBeth (1973) procedure of estimating a time series OLS regression of the returns on stock for each company on each factor separately and relating the average return on stock of each company to the factor loading of each regression.

Table 4
Unconditional correlation matrix of returns, common factors and specific factors (significant at 5% or less only).

	Retur_ck	lTotAs_e	z_BOOK_t	log_de_y	z_net__e	premiu_t
Return_Stock	1					
lTotAsset__e	−0.0151	1				
z_BOOK_to__t	−0.0089	0.2908	1			
log_debt_e_y		0.1915	−0.0268	1		
z_net_income		0.0198	0.0382	−0.1047	1	
premium_mkt	0.3672					1
ch_VIX	−0.3081					−0.7398
ch_euro_x	−0.1805					−0.1448
ch_china_x	−0.0492	0.0081				−0.0088
ch_india_x	0.0145					0.0362
ch_japan_x	0.0154					0.011
ch_uk_x						−0.0202
ch_russia_x						−0.0116
ch_brl_x	−0.1706				0.0059	−0.1944
ch_wti	0.2961				−0.0057	0.267

	ch_VIX	ch_eur_x	ch__na_x	ch_ind_x	ch_jap_x	ch_uk_x	ch_rus_x	ch_brl_x
ch_VIX	1							
ch_euro_x	0.1267	1						
ch_china_x	−0.0136	0.2336	1					
ch_india_x	−0.0238	0.0105	0.0104	1				
ch_japan_x	−0.0189	0.0214	0.025	−0.0721	1			
ch_uk_x	0.0121	0.0279	−0.0231	0.3206	0.0348	1		
ch_russia_x	0.0164		0.0058	0.3676	−0.0192	0.3862	1	
ch_brl_x	0.2054	0.2132	0.0485			0.0078	0.0149	1
ch_wti	−0.209	−0.1917	−0.0742		0.0244	−0.0246	0.0082	−0.1452

Return_Stock = daily continuous return on equity.
lTotAs_e = Total assets divided by the price of equity in logarithms.
z_BOOK_t = Book to market ratio as a z-score.
log_de_y = debt to equity ratio in logarithms.
premium_mkt = daily return of the Dow Jones Industrial minus the daily yield of the 3-month U.S. Treasury bill rate (in US$ dollars).
z_net_income = z_net__e = net income for company as a z-score.
ch_VIX = continuous daily change of the VIX index.
ch_euro_x = continuous daily change of the Euro/US$ dollar exchange rate.
ch_china_x = continuous daily change of the China–$/US$ dollar exchange rate.
ch_india_x = continuous daily change of the India–$/US$ dollar exchange rate.
ch_japan_x = continuous daily change of the Japan–Y$/US$ dollar exchange rate.
ch_uk_x = continuous daily change of the UK Pound$/US$ dollar exchange rate.
ch_russia_x = continuous daily change of the Russia–$/US$ dollar exchange rate.
ch_brl_x = continuous daily change of the BR–R$/US$ dollar exchange rate.
ch_wti = continuous daily change of the West Texas crude oil price per barrel in US$ dollar.

heteroskedasticity,[14] and autoregressive and moving average components for the mean equation with the whole panel. It is of the form

$$Return\_Stock_{i,t} = \beta_0 + \beta_1 Return\_Stock_{i,t-1} + \boldsymbol{\alpha}' Specific\_Factors_{i,t} + \boldsymbol{\beta}\prime Common\_Factors_t + \gamma_i + \delta_t + u_{i,t} + \theta_1\ u_{i,t-1} \quad (1a)$$

$$h_{i,t} = \pi_0 + \pi_1 h_{i,t-1} + \pi_2 u^2_{i,t-1} + \pi_3 I^+_{i,t-1} u^2_{i,t-1} \quad (1b)$$

where γ_i is a vector of company fixed effects, δ_t is a vector of time fixed effects referring to year, month and day of the week dummies, $u_{i,t}$ is a random error term, $h_{i,t}$ is the variance of $u_{i,t}$, e.g. the heteroskedastic function, and $I^+_{i,t} = 1$ *if* $u_{i,t} > 0$. This specification has the ability to capture the potential tendency of volatility to change with news in an asymmetric way. In the case where $\pi_3 < 0$, volatility increases more with negative news as opposed to positive ones. We also include an interaction term between the financial policy debt-to-equity variable and a dummy variable for the start of the U.S. financial crisis in September 2008. This is meant to capture potential effects of the crisis on credit behavior of the companies. We estimate four models imposing restrictions on the parameter space of (1).

[14] The TARCH model is explained in Rabemananjara and Zakoian (1993), Glosten et al. (1993) and Zakoian (1994). The estimation technique is ML in all models including below.

3.2. Multivariate GARCH, dynamic conditional correlation and value at risk

In the multivariate GARCH framework with dynamic conditional correlation, we follow the procedure of estimating the model for each company in the panel separately, e.g. Engle (2002), and Brownlees and Engle (2011). For each company labeled *i*, we estimate a bivariate GARCH(1,1) model with dynamic conditional correlation between the return on stock and the premium on the market using a Student's *t* distribution for the errors with endogenous degrees of freedom.[15] The full model is given by the expressions

$$Return\_Stock_{t,\ each\ i} = \beta_0 + \beta_1 Return\_Stock_{t-1,\ each\ i} + \boldsymbol{\alpha}' Specific\_Factors_{t,each\ i} + \boldsymbol{\beta}\prime Common\_Factors_t + u_{t,each\ i} \quad (2a)$$

$$Premium\_mkt_t = \delta_0 + e_t \quad (2b)$$

$$\varepsilon_{t,\ each\ i} = (u_t e_t)\prime = H_t^{1/2} z_t \quad (2c)$$

$$H_{t,\ each\ i} = E[\varepsilon_t \varepsilon\prime_t |.] = D_t^{1/2} R_t D_t^{1/2} \quad (2d)$$

where the notation |. refers to the previous period information set, $u_{t,each\ i}$ and e_t are random error terms, $H_{t,each\ i}$ is the conditional covariance

[15] This is to mitigate the excess kurtosis found in the data, see e.g. Cochrane (2005).

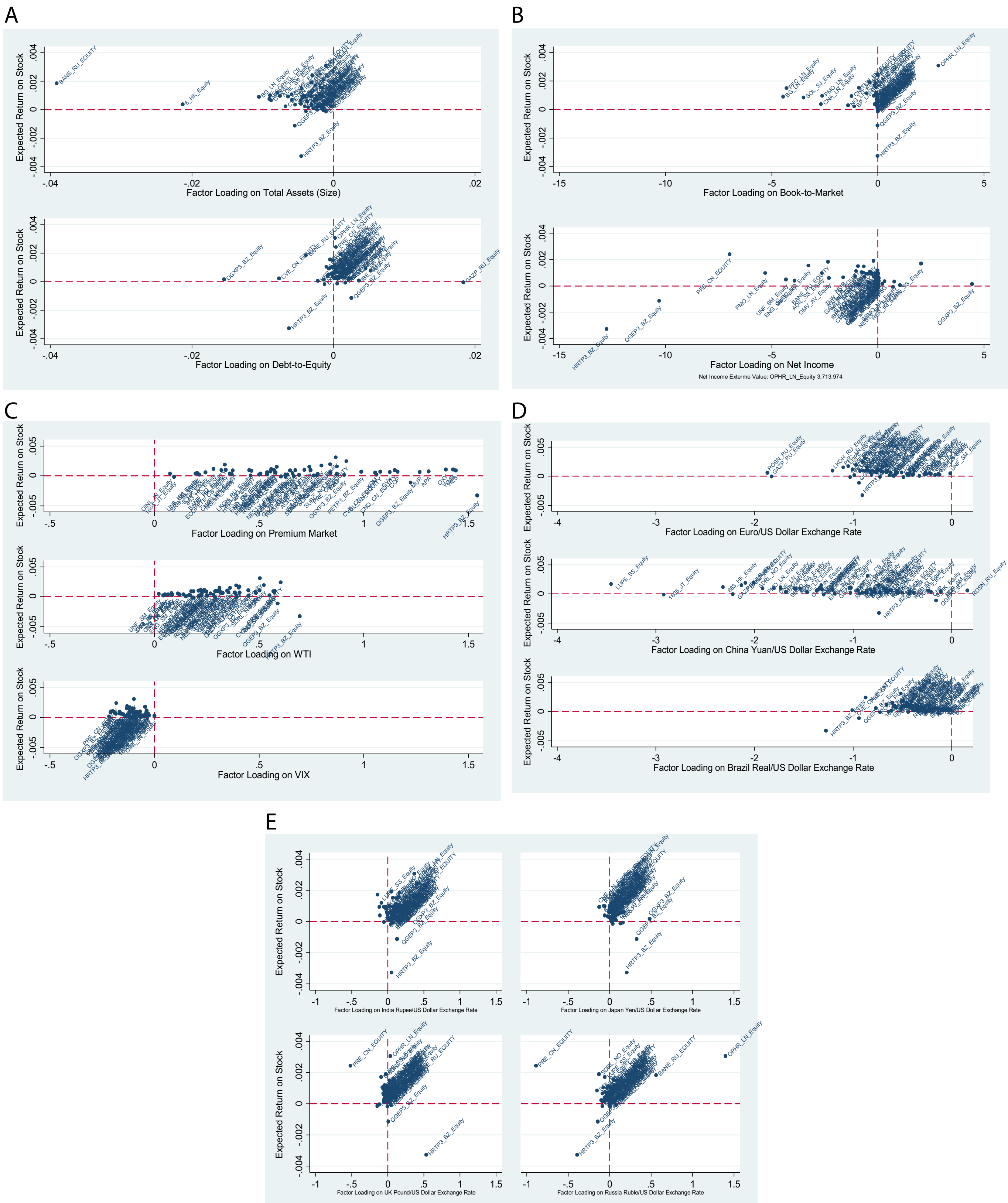


Fig. 1. A: Exposure of return on stock in domestic currency to specific factor: i. Total assets scaled by the price of equity in logarithms (size). ii. Leverage ratio in logarithms. B: Exposure of return on stock in domestic currency to specific factor: i. Book-to-market ratio as a z-score (value). ii. Net income for company as a z-score. C: Exposure of return on Stock in domestic currency to common factor: i. Dow Jones Industrials Market Premium in U.S. Dollars. ii. West Texas Intermediate oil price change. iii. VIX change. D: Exposure of return on stock in domestic currency to common factor: i. Euro/US dollar exchange rate change. ii. China yuan/US dollar exchange rate change. iii. Brazil real/US dollar exchange rate change. E: Exposure of return on stock in domestic currency to common factor: i. India rupee/US dollar exchange rate change. ii. Japan yen/US dollar exchange rate change. iii. UK pound/US dollar exchange rate change. iv. Russia ruble/US dollar exchange rate change.

Table 5
TARCH estimation.

	(1) Return_Stock	(2) Return_Stock	(3) Return_Stock	(4) Return_Stock
lTotAsset__e		−0.000120***	−0.0000866**	−0.00149***
z_BOOK_to__t		0.0000517	−0.0000359	−0.0000624
log_debt_e_y			0.0000275	0.000304*
z_net_income			0.0000628	0.000125
debt_eq_fi_s			−0.000129***	0.0000906
premium_mkt	0.665***	0.667***	0.505***	0.509***
ch_VIX			−0.0134***	−0.0129***
ch_euro_x			−0.157***	−0.160***
ch_china_x			−0.223***	−0.219***
ch_india_x			0.0198	0.0134
ch_japan_x			0.0210**	0.0218**
ch_uk_x			0.0183*	0.0217**
ch_russia_x			0.00227	−0.000653
ch_brl_x			−0.0982***	−0.0964***
ch_wti			0.137***	0.136***
Year				Y
Month				Y
Day of Week				Y
Company				Y
_cons	0.000383***	0.000334***	0.000381*	−0.00197
ARMA				
L.ar	0.662***	0.656***	0.490***	0.518***
L.ma	−0.692***	−0.688***	−0.541***	−0.570***
ARCH				
L.ARCH	0.110***	0.109***	0.173***	0.176***
L.TARCH	−0.0328***	−0.0354***	−0.0514***	−0.0555***
L.GARCH	0.904***	0.906***	0.848***	0.846***
_cons	0.00000320***	0.00000323***	0.00000563***	0.00000568***
N	123,555	121,031	109,371	109,371

Legend: Return_Stock = daily continuous return on equity.
lTotAs_e = total assets divided by the price of equity in logarithms.
z_BOOK_t = book to market ratio as a z-score.
fin_le_s = financial leverage divided by total assets.
log_de_y = debt to equity ratio in logarithms.
debt_eq_fi_s = debt to equity ratio in logarithms interacted with a dummy variable for financial crisis = 1 if after September 15, 2008 (Lehman Brothers failure).
z_net_income = net income for company as a z-score.
premium_mkt = daily return of the Dow Jones Industrial minus the daily yield of the 3-month U.S. Treasury bill rate (in US$ dollars).
ch_VIX = continuous daily change of the VIX index.
ch_euro_x = continuous daily change of the Euro/US$ dollar exchange rate.
ch_china_x = continuous daily change of the China–$/US$ dollar exchange rate.
ch_india_x = continuous daily change of the India–$/US$ dollar exchange rate.
ch_japan_x = continuous daily change of the Japan–Y$/US$ dollar exchange rate.
ch_uk_x = continuous daily change of the UK Pound$/US$ dollar exchange rate.
ch_russia_x = continuous daily change of the Russia–$/US$ dollar exchange rate.
ch_brl_x = continuous daily change of the BR–R$/US$ dollar exchange rate.
ch_wti = continuous daily change of the West Texas crude oil price per barrel in US$ dollar.
Year, month, day of week, company fixed effects.
ARCH = autocorrelation parameter estimate for the innovations in the conditional heteroskedasticity of returns on stock.
TARCH = autocorrelation parameter estimate for the positive innovations in the conditional heteroskedasticity of returns on stock.
GARCH = autocorrelation parameter estimate for the conditional heteroskedasticity of returns on stock.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

matrix, z_t is a vector of i.i.d. innovations, D_t is a diagonal matrix conditional variances from the GARCH(1,1) models and R_t is the matrix of conditional pseudo (or quasi) correlations of company and market returns.[16]

The one-day horizon value at risk (VaR) is then calculated based on the predictions of model (2a–d).[17] Using the one-step ahead forecasts of the estimated mean and conditional variances, we estimate the measure α% value at risk for each company i as

$$VaR_{t+1,\ each\ i} = E\left[\mu_{t+1,each\ i} + t_\alpha H^{1/2}_{t+1,each\ i}|\cdot\right] \tag{3a}$$

where μ_{t+1} is the mean forecast and t_α is the corresponding quantile for the Student's t distribution adjusted by the estimated degrees of freedom.

We proceed with the back-testing for the VaR using the likelihood ratio test via the Kupiec (1995) approach. The null hypothesis of the failure probability π^* is tested against the alternative that the failure probability differs from a given π^*_0. The likelihood function can be written as

$$LR = -2\log\left((1-\pi*)^{n0-n1}\pi*^{n1}\right) + 2\log\left((1-\hat{\pi}*)^{n0-n1}\hat{\pi}*^{n1}\right) \sim \chi^2(1) \tag{3b}$$

which has a chi-square distribution with one degree of freedom under the null hypothesis; where $\hat{\pi}*$ is the estimated probability of failure, n_0 is the total number of trials and n_1 is the number of failures observed.

We apply model (2) and measure (3) to four alternative cases. First, we use the raw data for the daily return on stock as a measure of the mean component and the daily return on stock squared as a measure of the daily variance of the return on stock. Second, we impose the restriction of no exposure to any factors by estimating (2)–(3) with the restriction that $\beta_1 = \boldsymbol{\alpha}'_1 = \boldsymbol{\beta}' = 0$ and no dynamic conditional correlation. Third, we impose the restriction of no exposure to any factors on expression (4a), or $\beta_1 = \boldsymbol{\alpha}'_1 = \boldsymbol{\beta}' = 0$, but allow dynamic conditional correlation. Fourth, we estimate the full unrestricted model (2) and measure (3).

4. Empirical results

4.1. Common and specific factors with the panel

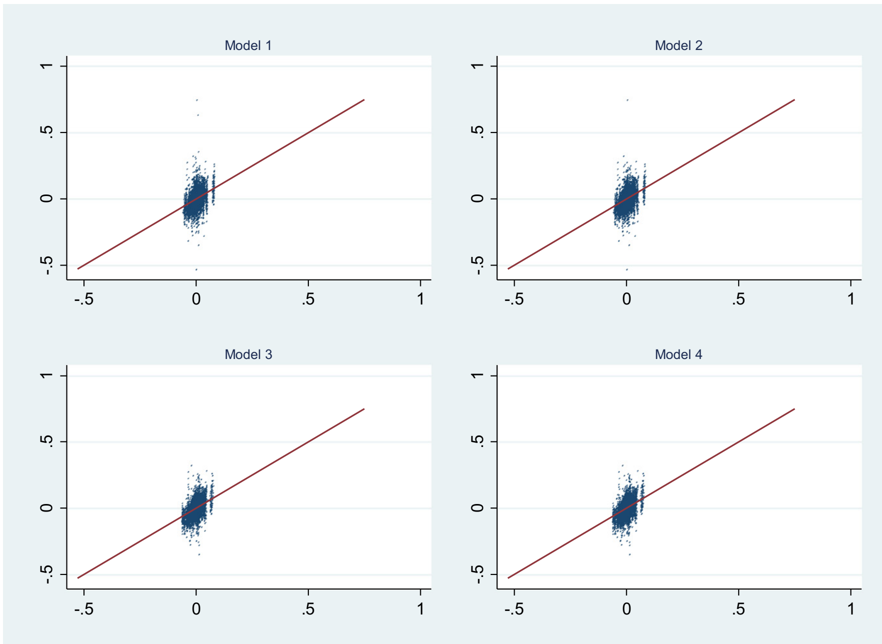
Table 5 presents four alternative specifications of the model in expressions (1a)–(1b). Model (1) is the single exposure to the premium common factor while model (2) includes the premium common factor and the size and value specific factors. Model (3) includes all common and specific factors and model (4) is the most general with all common and specific factors plus all fixed effects.

The constant term is statistically significant in models (1)–(3) but not in the full model (4) with all fixed effects accounted for. A statistically significant constant term indicates undesirable arbitrage opportunities from a theoretical perspective. In the group of specific factors only the size factor is significant and robust, while leverage is marginally significant in model (4). However, leverage after the financial crisis is significantly negative in specification (3). This potentially shows evidence that companies with more debt after the financial crisis had lower return on stock and thus became more exposed to credit concerns. In the group of common factors, as expected, exposure to the U.S. Dow Jones market premium is significant across models; however it declines in magnitude towards the full model (4) with all factors and fixed effects. The VIX has a robust negative effect while the price of crude oil has a robust positive effect on company returns. Both are expected since the VIX represents higher expected market volatility and the price of crude is a main determinant of company revenue in the energy sector. The FX group of factors shows that a devaluation (an increase in

[16] The matrix of conditional pseudo correlations is given by $R_t = diag(Q_t)^{-1/2}Q_t diag(Q_t)^{-1/2}$ where Q_t is a symmetric positive definite matrix whose dynamics evolve according to the error correction mechanism $Q_t = \overline{Q}(1-\lambda_1-\lambda_2) + \lambda_1\eta_{t-1}\eta'_{t-1} + \lambda_2 Q_{t-1}$ where $\overline{Q}$ is the constant unconditional correlation of company and market returns, η are standardized residuals of company and market returns and λ_1, and λ_2 are the adjustment parameters in the error correction mechanism, see e.g. Engle (2002) and Brownlees and Engle (2011). Khalfaoui and Boutahar (2012) estimate a similar class of models. Engle (2012) proposes an alternative approach to study the time-varying characteristics of an asset beta which is beyond our scope.

[17] We use the negative of the return on stock for the VaR calculation since the return refers to a long position.

Return on Stock versus Predicted Return on Stock
TARCH Estimation



Notes: The Diebold and Mariano (1995) predictive accuracy test among and across models tested two-by-two for Table 5 do not reject the null that the predictive accuracy across the econometric methods is similar. Results are available upon request.

Fig. 2. Return on stock versus predicted return on stock. TARCH estimation. Notes: the Diebold and Mariano (1995) predictive accuracy test among and across models tested two-by-two for Table 5 does not reject the null that the predictive accuracy across the econometric methods is similar. Results are available upon request.

the magnitude) of the Euro, Chinese currency, and Brazilian currency relative to the U.S. dollar have a robust negative impact on stock returns while a devaluation (an increase in magnitude) of the Japanese and British currencies have a robust positive effect on stock returns. This is a plausible result also seen in the panel regressions since many companies from emerging markets like Brazil and China have significant, if not all, share of revenues in domestic markets denominated in domestic currency, but face major costs in foreign currency. Our results here indicate that the market values costs more when a devaluation of the country's currency occurs. But, for Japanese and British companies the market values revenues relatively more. The Indian and the Russian currency rates are the only ones which are not statistically significant.

The autoregressive and moving average components of the mean equation are robust and significant across specifications. The ARCH parameters in the heteroskedastic function are robust and significant for all specifications as well. The TARCH asymmetry parameter is negative for all specifications showing that volatility increases more with negative innovations in this sample period.[18] Fig. 2 shows the actual versus the model predicted return on stock where the line represents the 45° angle. Models (1), (2), (3), and (4) refer to columns labeled 1, 2, 3, and 4 in Table 5. The predictive power of the models show that model (4) has a relatively better fit.[19]

The evidence from specification (4) indicates lack of arbitrage opportunities from the zero constant term, but shows significant positive autocorrelation in daily returns. The effects of common and specific factors are similar to the other cases. Clearly, we show here that specific factors are significantly globally priced in the oil and gas industry beyond the common factors examined by Ramos and Veiga (2011). We find that risky companies in the oil and gas sector tend to be large, with high leverage after the financial crisis and with high exposure to the VIX, the exchange rate of the US dollar vis-à-vis the Euro, the Chinese yuan and the Brazilian real.

Table 6a
Parameter estimates for specific factors.

	ltotas_e	z_book_t	log_de_y	z_net__e
10th quantile	−0.0075	−0.5054	−0.0012	−0.5122
25th quantile	−0.0034	−0.0741	−0.0007	−0.1119
Median	0.0001	−0.0069	0.0003	0.0149
75% quantile	0.0013	0.0046	0.0016	0.1297
90th quantile	0.0080	0.0172	0.0044	0.2585

Legend:
lTotas_e = total assets divided by the price of equity in logarithms.
z_book_t = book to market ratio as a z-score.
fin_le_s = financial leverage divided by total assets.
log_de_y = debt to equity ratio in logarithms.
z_net_income = net income for company as a z-score.

4.2. Multivariate GARCH, dynamic conditional correlation and value at risk

As noted in Section 2, there is potential heterogeneity of factor loadings in the sample. The estimates for the model (2a–d) indicate heterogeneity among firms in the sector in response to specific and common factors and conditional volatility and correlation estimates. Tables 6a, 6b, and 6c present select quantiles of the parameter estimates of the full model (2a–d).

First, Table 6a shows specific factor parameters. Size and value factor parameters are negative in the lower quantiles but become mildly positive at the upper quartiles. Size is negligibly positive at the median,

[18] This is a common feature of models that cover the financial crisis period, see e.g. Brownlees and Engle (2011).
[19] Cochrane (2005) refers to the comparison of actual versus predictive returns as 'back-tests.' Diebold and Mariano (1995) provide a simple test for predictive accuracy; we discuss the test results in Fig. 2 for all models.

Table 6b
Parameter estimates for common factors.

	premiu_t	ch_VIX	ch_eur_x	ch_chi_x	ch_ind_x	ch_jap_x	ch_uk_x	ch_rus_x	ch_brl_x	ch_wti
10th quantile	−0.3766	−0.0517	−0.4152	−0.6396	−0.0732	−0.0622	−0.0373	−0.0731	−0.1756	0.0175
25th quantile	0.0347	−0.0313	−0.2400	−0.4246	−0.0138	−0.0203	−0.0131	−0.0184	−0.1397	0.0305
Median	0.6049	−0.0066	−0.1173	−0.1507	0.0139	0.0141	0.0116	−0.0008	−0.0734	0.1266
75% quantile	1.0568	0.0037	−0.0675	0.0270	0.0495	0.0503	0.0395	0.0333	-0.0362	0.2597
90th quantile	1.2877	0.0111	0.0000	0.2151	0.0771	0.0715	0.0697	0.1182	0.0221	0.3220

Legend:
premium_mkt = daily return of the Dow Jones Industrial minus the daily yield of the 3-month U.S. Treasury bill rate (in US$ dollars).
ch_VIX = continuous daily change of the VIX index.
ch_euro_x = continuous daily change of the Euro/US$ dollar exchange rate.
ch_china_x = continuous daily change of the China–$/US$ dollar exchange rate.
ch_india_x = continuous daily change of the India–$/US$ dollar exchange rate.
ch_japan_x = continuous daily change of the Japan–Y$/US$ dollar exchange rate.
ch_uk_x = continuous daily change of the UK Pound$/US$ dollar exchange rate.
ch_russia_x = continuous daily change of the Russia–$/US$ dollar exchange rate.
ch_brl_x = continuous daily change of the BR–R$/US$ dollar exchange rate.
ch_wti = continuous daily change of the West Texas crude oil price per barrel in US$ dollar.

but value is negative at the median. The leverage factor is the one that has the smallest range across the quantiles. The effect is negative in the lower quantiles, but positive at the median and upper quantiles. The net income factor has a wide range with a positive median but a large negative effect at the lower 10th quantile. One key result is that the financial leverage (debt-to-equity) factor has a small magnitude across quantiles in the sample indicating that firms in this sector have smaller differences in terms of credit concerns. However, the effects of value and net income are of large magnitude in the lower quantiles.

Table 6b shows the common factor parameter estimates. The VIX volatility factor has the smallest range of impact, thus showing that firms in this sector have smaller differences in terms of the impact of the VIX upon them. The effect of the VIX is mostly negative, but becomes positive at the upper quantiles. The market premium factor ranges from 0.035 at the 25th quantile to 1.29 at the 90th quantile with a sizable negative effect at the lower 10th quantile. The price of crude oil in the last column shows a uniformly positive impact with potentially large responses at the upper 90th quantile as expected. The nominal exchange rates vis-à-vis the U.S. dollar have distinct patterns. The Chinese yuan exchange rate has the largest range across quantiles with a median negative impact on stock returns, but positive effects at the upper quantiles. This is not surprising since China is a sizable trading partner with nations worldwide. The Euro exchange rate has the second largest magnitude effects and an almost uniformly negative impact on stock returns. The Indian rupee, Japanese yen, UK pound and Russian ruble have similar patterns across quantiles with a small range across quantiles from the negative to the positive spectrum. Lastly, the Brazilian real exchange rate has a larger negative impact at the lower quantiles and a small positive effect at the 90th quantile only. The qualitative results at the median are roughly consistent with the panel estimates of Section 4.1 above where the Russian ruble and Indian rupee are not statistically significant.

Table 6c shows the multivariate conditional heteroskedasticity and dynamic conditional correlation parameter estimates as well as the parameters of the error correction for the dynamic conditional correlations, λ_1, and λ_2. In particular, conditional correlations refers to the conditional pseudo standardized residuals of the company and the market, λ_1 is the news parameter which captures the deviations of the standardized residuals from the unconditional correlation, while λ_2 is the decay adjustment parameter that captures the autocorrelation of the dynamic conditional correlations themselves, e.g. Engle (2002). The ARCH innovation effects vary from 0.07 at the 10th quantile to 0.24 at the 90th quantile. The correlations between the company return on stock and the market premium common factor shows significant heterogeneity among firms as well. While the median is positive, but close to zero, the correlations can be as low as −35% at the 10th quantile to 43% at the upper 90th quantile. This indicates that some companies can provide hedge opportunities within the oil and gas sector.

The key result of Tables 6a–6c is that the companies in the oil and gas sector have significant heterogeneity in response to specific factors and common factors. The financial leverage (debt-to-equity) specific factor and the VIX common factor have a small range of impact across quantiles in the sample indicating that firms in this sector differ less in terms of credit concerns and the impact of the VIX. The only two common factors that show robust qualitative effects across quantiles are the Euro–U.S. dollar rate, which is negative across all quantiles, and the change in the crude oil price which is positive across all quantiles. The Euro effect indicates that as the currency devalues, the rate of change increase relative to the U.S. dollar, company stock returns decline showing particular exposure to the Euro–U.S. dollar exchange risk. The change in the crude oil price shows robust exposure to the price of oil with higher oil prices increasing stock returns in the sector.

Table 7a shows the selected quantiles of the per company average estimates of the one-day horizon 5% value at risk from expression (3a). The estimates range from 1.8% value at risk for the lowest 10th quantile to

Table 6c
Parameter estimates for conditional heteroskedasticity and conditional correlations.

	ARCH	GARCH	DCC	λ_1	λ2
10th quantile	0.0737	0.6240	−0.3515	0.0013	0.8016
25th quantile	0.0878	0.7807	−0.2423	0.0057	0.8822
Median	0.1162	0.8528	0.0054	0.0205	0.9393
75% quantile	0.1697	0.8839	0.3032	0.0425	0.9802
90th quantile	0.2366	0.9100	0.4289	0.0579	0.9927

Legend:
ARCH = autocorrelation parameter estimate for the innovations in the conditional heteroskedasticity of returns on stock.
GARCH = autocorrelation parameter estimate for the conditional heteroskedasticity of returns on stock.
DCC = conditional correlation estimate between return on stock and market premium factor.
λ_1 = conditional correlation innovations parameter estimate.
λ_2 = autocorrelation of conditional correlations parameter estimate.

Table 7a
Value at risk. $\alpha = 0.05$, 5% value at risk.

	5% VaR
10th quantile	0.0184
25th quantile	0.0224
Median	0.0270
75% quantile	0.0355
90th quantile	0.0464

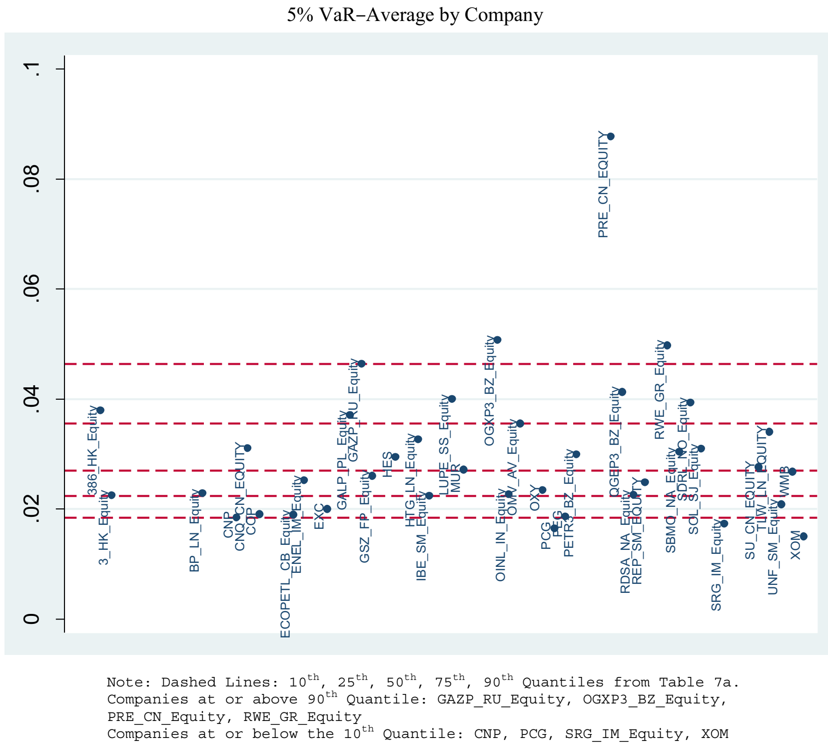


Fig. 3. 5% VaR — average by company. Note: dashed lines: 10th, 25th, 50th, 75th, 90th quantiles from Table 7a. Companies at or above 90th quantile: GAZP_RU_Equity, OGXP3_BZ_Equity, PRE_CN_Equity, RWE_GR_Equity. Companies at or below the 10th quantile: CNP, PCG, SRG_IM_Equity, XOM.

4.6% value at risk at the 90th quantile while the median is at 2.7% one-day horizon value at risk.

Fig. 3 shows the estimated average one-day horizon 5% value at risk per company in the sample with the dashed lines representing the respective quantiles of Table 7a. The companies that are above the 90th quantile are clearly riskier while the companies below the 10th quantile face much less value at risk. The four companies on or below the 10th quantile are potential benchmarks for risk in the sector, they are Center Point Energy of the U.S., Pacific Gas and Electric of the U.S., Snam-Rete Gas of Italy and Exxon-Mobil of the U.S. The four companies clearly on or above the 90th quantile value at risk in the sample are much riskier relative to the benchmark: GazProm of Russia, RWE of Germany, OGX of Brazil and Pacific Rubiales of Canada. In particular, Pacific Rubiales shows extreme average value at risk in the period. While the companies above differ in their sizes in the order listed, the key result is that when conditioning on the specific and common factors, they emerge as the riskier ones in the sample. Hence, the importance of measuring the impact of specific factors such as size and leverage and the common factors such as the VIX and the exchange rates of the Euro, Chinese yuan and Brazilian real for analysis of company returns in the oil and gas sector worldwide.

Table 7b presents the back-testing for the one-day horizon 5% value at risk estimates using expression (3b). The model performance gives 58% probability within the estimated 5% VaR range, and 9% probability outside the estimated 5% VaR range with 10% significance level. The remaining 33% of the sampled firms did not converge for the full model specification (2a–d). The companies outside the estimated 5% VaR range for the 5% significance level were ENEL_IM_Equity from Italy, OXY of the U.S. and Pacific Rubiales of Canada; while for the 10% significance level we note HES of the U.S., SBMO_SJ_Equity of Holland and SOL_SJ_Equity of South Africa.

Finally, Figs. 4–6 present comparisons of heteroskedasticity, dynamic correlations and value at risk for the raw data, the GARCH(1,1) model without any exposure nor dynamic conditional correlations, the GARCH(1,1) model without any exposure in the returns equation but with dynamic conditional correlations with the market premium common factor, and the full model (2a–d) with dynamic conditional correlations with the market premium common factor. Fig. 4, panel a. shows the absolute value of the daily returns, a measure of the unconditional volatility of stock returns. Panel b. shows the standard deviation of conditional variance of stock returns without exposure to any factor and panel c. shows the same variable estimated with exposure to all factors. The results show that raw volatility is very large relative to model based volatility. While volatility is smoother when exposure is taken into account, panel c. shows that the financial crisis of 2008 is the period of largest volatility under exposure while panels a. and b. show that volatility is more uniform and larger when exposure to specific and common factors are not accounted for.

Fig. 5 shows dynamic conditional correlations (DCC) between returns and the market premium in two alternative cases. Panel a. shows the conditional correlations in the M-GARCH(1,1) model without any exposure in the returns equation but with dynamic conditional correlations with the market premium common factor and panel b. shows

Table 7b
Value at risk $\alpha = 0.05$, 5% value at risk — back-testing.

Number of companies	Number of companies in the sample (% of total)	Back-test outcome
21	32.8%	No convergence of M-GARCH(1,1)
3	4.7%	Reject null of 5% VaR at 10% significance level[a]
3	4.7%	Reject null of 5% VaR at 5% significance level[b]
37	57.8%	Do not reject null of 5% VaR
64	100.0%	Total companies in the sample

[a] Companies: HES, SBMO_NA_Equity, SOL_SJ_Equity.
[b] Companies: ENEL_IM_EQUITY, OXY, PRE_CN_EQUITY.

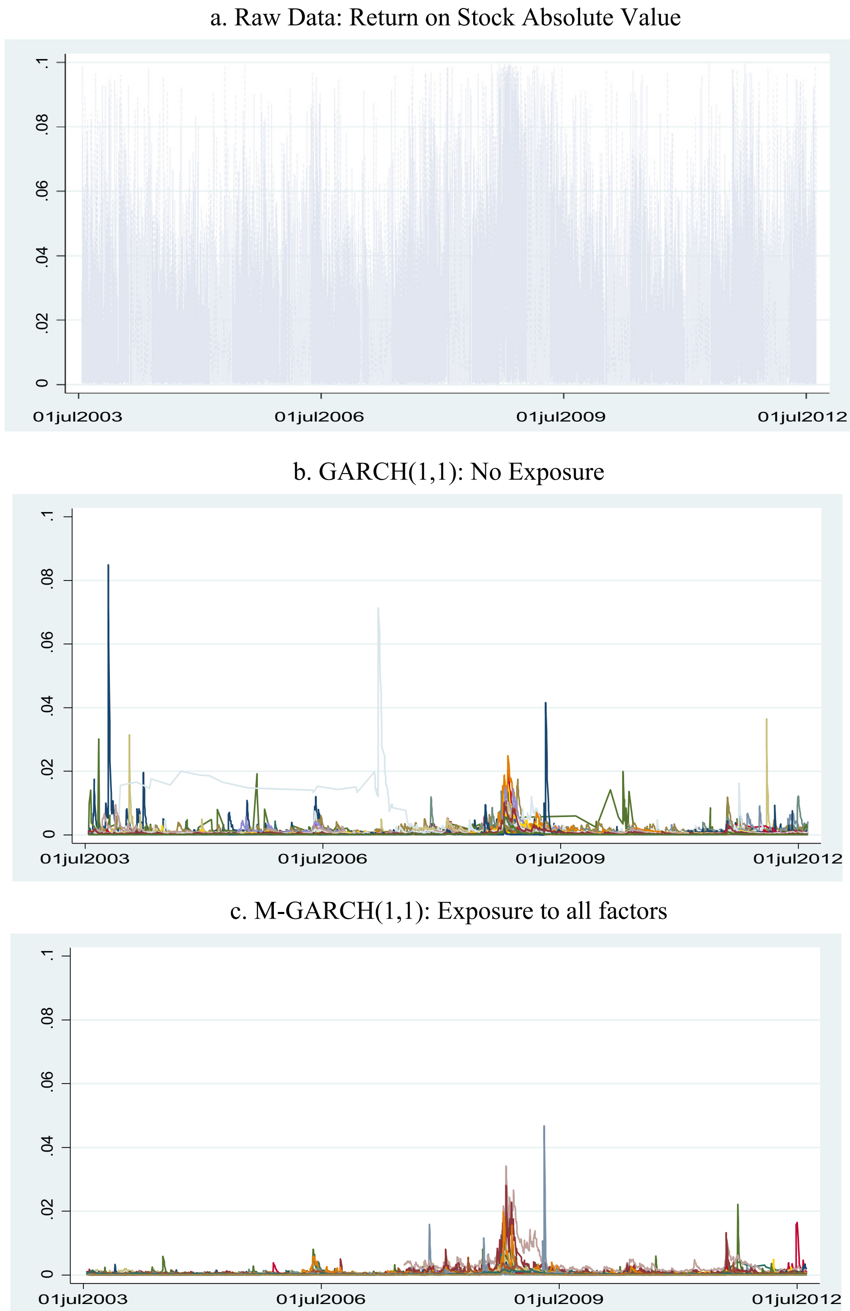


Fig. 4. Unconditional and conditional heteroskedasticity: exposure comparisons. a. Raw data: return on stock absolute value. b. GARCH(1,1): no exposure. c. M-GARCH(1,1): exposure to all factors.

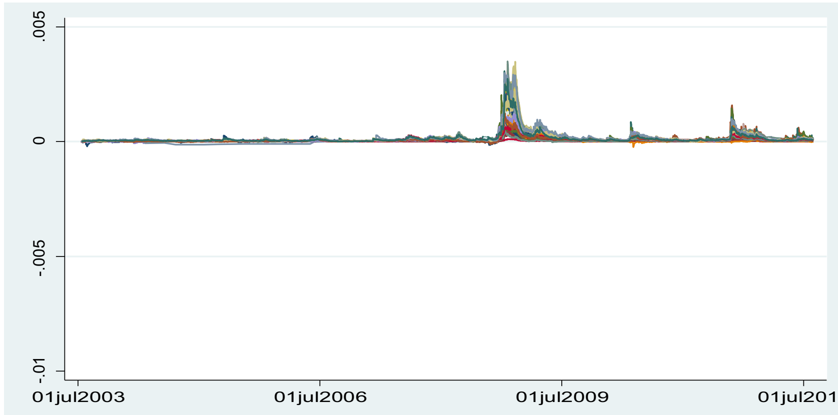
the full model with exposure in the returns equation. The model based conditional correlations in the absence of exposure is very smooth and shows a critical period of burst during the financial crisis on 2008 to early 2009. However, under exposure the conditional correlations become larger in magnitudes and with more significant range after the financial crisis of 2008. In particular, under exposure some companies emerge as clear hedges against the market risk with significant negative conditional correlations from the crisis period onwards.

Fig. 6 shows the one-day horizon 5% value at risk estimations for each of the cases. Panel a. shows value at risk based on raw data. Panel b. shows value at risk without exposure to any factor and panel c. shows the same variable estimated with exposure to all factors. Panel a. shows that a naïve calculation based on raw data would overestimate the value at risk considerably over the sample period relative to the value at risk accounting for exposure in panel c. The calculation without taking into account exposure in panel b. underestimates the value at risk relative to both panels a. and c. In accounting for the exposure to all factors, panel c. shows that value at risk increases considerably during the financial crisis and remains larger in magnitude after the financial crisis of 2008.

5. Conclusions

The empirical evidence presented from panel model regressions shows that in a model with moderate fit in the class of TARCH models

a. M-GARCH(1,1): No Exposure in Return on Stock Equation



b. M-GARCH(1,1): Exposure to all factors

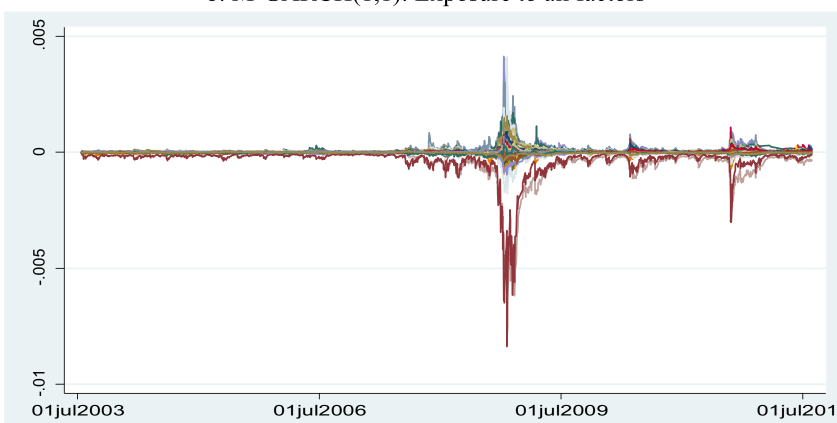


Fig. 5. Dynamic conditional correlations: exposure comparisons. a. M-GARCH(1,1): no exposure in return on stock equation. b. M-GARCH(1,1): exposure to all factors.

with all fixed effects taken into account, specific factors for size and leverage are statistically significant. The leverage effect is shown to be more important after the financial crisis of 2008, thus companies in the sector are more sensitive to credit concerns after the financial crisis. In terms of common factors, exposure to the U.S. Dow Jones market premium, the VIX, the price of crude oil, the Euro, Chinese yuan, the Brazilian real, the Japanese yen and British pound is robust and priced. The FX effects are potentially related to the extent to which market value costs denominated in domestic currency versus revenues denominated in foreign currency for companies in this sector.

However, there is clear evidence of heterogeneity among factor loadings in this sample confirmed by the evidence from multivariate GARCH-DCC models. The financial leverage (debt-to-equity) specific factor has a more uniform impact across quantiles in the sample indicating that firms in this sector differ less in relation to credit concerns. The only two common factors that show robust qualitative effects across quantiles are the Euro–U.S. dollar rate, which is negative across all quantiles, and the change in the crude oil price which is positive across all quantiles. The Euro effect indicates that as the currency devalues, the rate of change increases relative to the U.S. dollar, company stock returns decline showing particular exposure to the Euro–U.S. dollar exchange risk. The change in the crude oil price shows significant exposure to the price of oil with higher oil prices increasing stock returns in the sector.

The one-day horizon value at risk estimation, conditional on the specific and common factors, shows companies on or below the 10th quantile as potential benchmarks for risk in the sector; and other four companies clearly on or above the 90th quantile value at risk in the sample are much riskier relative to the benchmark.

Comparisons of heteroskedasticity, conditional correlations and value at risk for the raw data, the GARCH(1,1) model without any exposure nor dynamic conditional correlations, the M-GARCH(1,1) model without any exposure but with dynamic conditional correlations with the market premium factor, and the full model with dynamic conditional correlations with the market premium factor show that the financial crisis of 2008 is the period of largest volatility under exposure, and the period of largest conditional correlations under exposure. Comparisons of value at risk show that a naïve calculation based on raw data would overestimate the value at risk whereas calculation without taking into account exposure underestimates the value at risk. In accounting for the exposure to all factors, both conditional correlations and one-day horizon value at risk increase considerably during the financial crisis and remains larger in magnitude after the financial crisis of 2008 in this sample. Hence, companies in the oil and gas sector were not insulated from the financial crisis of 2008.

There are several potential avenues for further research. First, we did not consider here the potential for the joint distribution of mean returns and an extension in this direction could be valuable from a time series perspective. Other extensions with a broader sample of firms or a more segmented analysis of exposure for sectoral groups of firms and subgroups by regions and by country income levels could also be fruitful.

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2014.06.018.

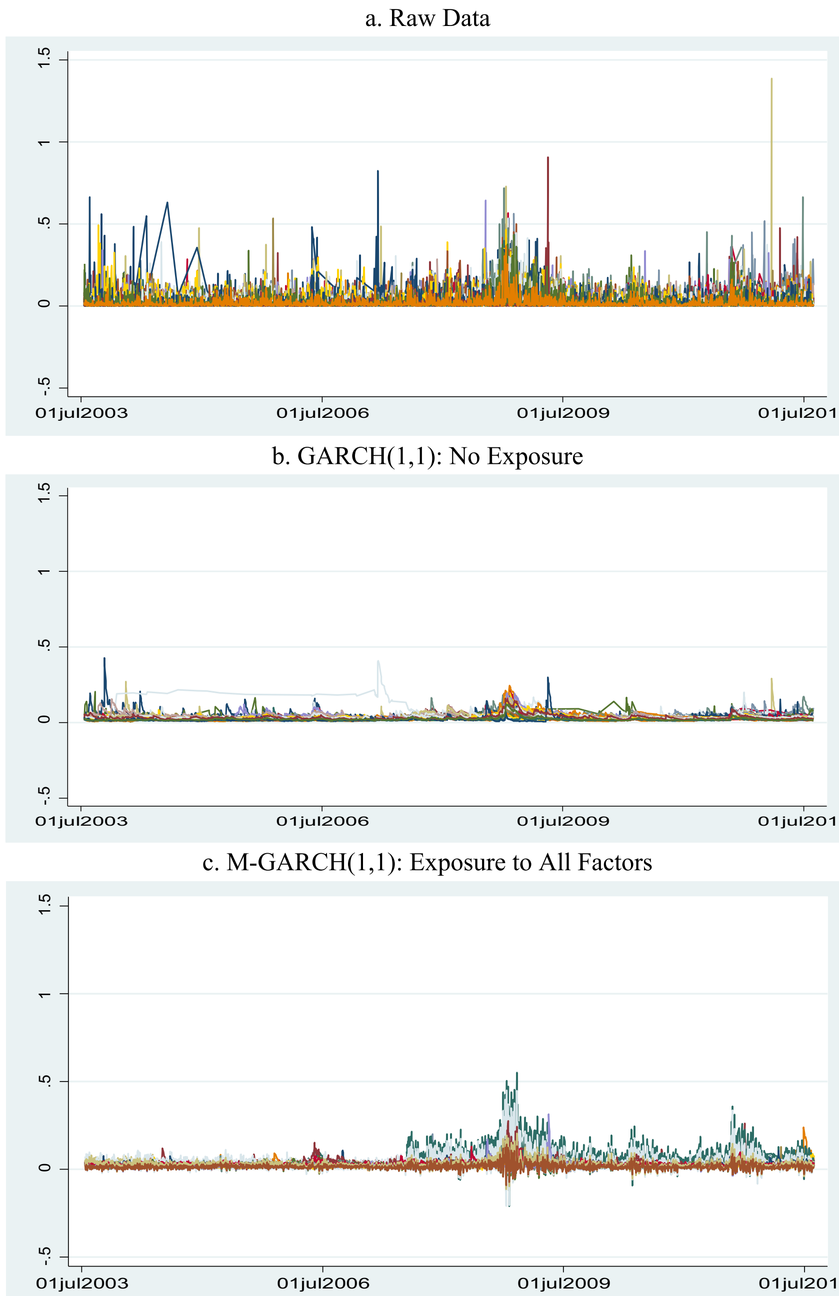


Fig. 6. 5% VaR: exposure comparisons. a. Raw data. b. GARCH(1,1): no exposure. c. M-GARCH(1,1): exposure to all factors.

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