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Mean-variance portfolio methods for energy policy risk management☆

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ABSTRACT

The risks associated with current and prospective costs of different energy technologies are crucial in assessing the efficiency of the *energy mix*. However, energy policy typically relies on the evolution of average costs, neglecting the covariances in the costs of the different energy technologies in the mix. The Mean-Variance Portfolio Theory is implemented to evaluate jointly the average costs and the associated volatility of alternative energy combinations. In addition systematic and non-systematic risks associated to the energy technologies are computed based on a Capital Asset Pricing Model and considering time varying betas. It is shown that both electricity generation and fuel use imply risks that are idiosyncratic and with relevant implications for energy and environmental policy.

1. Introduction

Sustainability, competitiveness and security of supply are central objectives for energy policy in developed countries. The achievement of those goals requires in the near future a transition towards an energy mix more balanced among the different energy sources (IEA, 2010). The process is not at all free of uncertainties, from demand and supply challenges in the oil market to regulatory risks and factors related to energy security (EC, 2006). Further, climate change concerns cannot be disregarded in relation to sustainable alternatives while taking into account the uncertainty of CO_2 emission costs. Whereas the electricity sector seems in a stage of somewhat an efficient managing of aggregate risks [cf. Moselle, 2010], this does not appear to be the case at all for the road transport sector. In this context, identifying the optimal degree of fuel mix diversity for a country or a particular company requires valuation approaches of energy investments which trade off the risk and returns of diversification.

To analyze these issues, we build upon tools that have been widely used in the financial literature. First, we implement the *Mean-Variance Portfolio Theory* [MVPT; Markowitz (1952); Luenberger (1998)] to assess the trade-offs in risk management from the point of view of energy policy. In so doing, both the average cost and the associated risk of the different energy technologies are simultaneously taken into account for energy planning. This enables to compute minimum variance energy portfolios for any given level of expected generation cost. Such efficient portfolio therefore minimizes risk, as measured by the standard

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deviation of return, and shows directions for improvement in both average cost and risk while starting from a reference energy mix.[1]

Second, beyond the MVPT approach to the risk of an energy portfolio, a contribution in this paper is to consider the Capital Asset Pricing Model (CAPM) framework to compute systematic and non-systematic risks. Since the seminal papers by Sharpe (1964) and Lintner (1965), such a distinction has been commonly implemented in the financial literature [Boyle (1994); Jagannathan and McGrattan (1995); Fama and French (2004)] and recently considered in risk management analysis of commodity prices (Chen, 2010), but it has not been implemented to evaluate energy portfolios to the best of our knowledge. Clearly, though, if the main concern for energy policy risk management is hedging against oil price shocks then, systematic, that is, undiversifiable aggregate risk, rather total risk, has to be the instrument to characterize the efficient energy mix. In this framework, we check the time-varying properties of CAPM beta parameters.[2] We show that, from an energy policy perspective, it is important to consider the stability of parameters against time-varying risks rather than to capture the dynamics of these parameters.

Indeed, one key feature in the application of MVPT to energy portfolios is the complementarity among the various technologies in the mix. In that respect, Awerbuch (2000) analyzes US gas-coal generation mix, and shows that adding Wind, Photovoltaics and other fixed-cost renewables to a portfolio of conventional generation technologies serves to reduce overall portfolio cost and risk, even though their stand-alone generating cost may be higher. Several authors have elaborated on better characterizing that kind of complementarity. Krey and Zweifel (2006) refine the econometric evidence for Swiss and US power generation efficient frontiers, by implementing SURE to obtain reasonably time-invariant covariance matrices as an input to the determination of efficient electricity-generating portfolios. Roques, Newbery, and Nuttall (2008) introduce simulation techniques and portfolio optimization to illustrate the dominance of coal technologies in optimal portfolios due to the high degree of correlation between electricity and gas price in liberalized markets.

Another key feature of the approach is the potential for consideration of external costs. Marrero, Puch, and Ramos-Real (2011) considers CO_2 externalities to analyze the projected generating mix for Europe in 2020 (EU-BAU) highlighting the importance of complementarity between traditional and renewable energies to reduce not only portfolio risk and average cost but also total CO_2 emissions. Roques, Hiroux, and Saguan (2010) apply the MVPT to identify cross-country portfolios that minimize the total variance of wind production for a given level of production across Austria, Denmark, France, Germany and Spain. They find that projected portfolios for 2020 are far from the efficient frontier, suggesting that there could be large benefits in a more coordinated European renewable deployment policy.

Our contribution here is in the application of the MVPT and the CAPM tools to characterize both an electric generation and a transport fuel frontier. The scope of use of these tools is well established in finance, but it is not sufficiently developed for the very relevant question of energy portfolio management, despite its strong potential as we show. In addition, while most energy applications in existing literature focus on the generation of electricity, here we show that it turns out overly useful to simultaneously analyze the electricity and fuel mixes while addressing the tension between total and systematic risks in energy portfolios.[3] Finally, the approach we take in this paper is that of a quasi-social planner maximizing social welfare, which is the standard approach for energy policy purposes, as emphasized by Awerbuch and Berger (2003).[4] Thus, in the two applications (electricity and road transport fuels), we analyze the consequences of the complementarities between the different energy technologies (Thermal Classic and Renewables), and for the case of electricity we apply sensitivity analyses to test the effects of including CO_2 external costs or to discuss various counterfactuals that are key for energy planning. An integrated specification of the risks in a joint primary energy mix for an energy system has major difficulties and goes beyond the scope of this paper.

In all of the cases we report the corresponding findings, but we focus on the methodological contribution rather than in the seldom energy results. We do so even though we use for the quantitative experiments precise input data that are also relevant for related applications. The reason is not that those findings are field oriented. Rather, we consider that the contribution of the methods in this paper, namely to offer a measure of how diversifiable an energy portfolio is, as well as of the stringency of systematic energy risks, is key for energy policy and does not belong to common wisdom in the field. We find that the complementarities of the technologies in electricity and fuel portfolios have to be effectively balanced with the target of total and systematic risks.

The paper is organized as follows. Section 2 describes the theoretical framework. Section 3 organizes the evidence on the various production costs and energy prices. In Section 4, the estimation of the energy efficiency frontiers for both total risk and systematic risk is discussed. Section 5 examines the main results of the paper for electricity and fuel frontiers, and the last section concludes.

2. Methodology: the mean-variance energy portfolio approach

By maximizing a social welfare function, the energy portfolio is characterized by a set of weightings, each between zero and one, of all feasible energy alternatives. Those weightings, say $X_1, \ldots, X_n$, must add up to unity, and are subject to certain technological

[1] MVPT theory has been often used in the financial sector to identify portfolios of bonds or stocks [see, among many others, Merton (1973); Shefrin and Statman (2000); Levy and Levy (2004) and, more recently, Hsu and Szu-Lang (2012)]. Bar-Lev and Katz (1976) is the first application of MVPT to the U.S. electricity industry [see also Humphreys and McClain (1998)]. Galvani and Plourde (2009) apply MVPT within energy asset and commodity markets. Bazilian and Roques (2008) provide a complete survey of the research applying MVPT to energy planning.

[2] For an alternative analysis on risk management, see Hammoudeh, Araújo-Santos, and Al-Hassan (2013), which uses Value-at-Risk based optimal portfolios for precious metals, oil and stocks. See also Chang, McAleer, and Tansuchat (2013) on crude oil.

[3] Guerrero-Lemus et al. (2012) is an exception to the traditional focus of existing literature in the electricity sector. These authors analyze in detail the average costs and cost volatility of conventional and renewable fuels, and of electricity of either non-renewable or renewable nature for vehicles, and discuss the findings obtained from the MVPT when implemented to worldwide road transport sector.

[4] It is also possible to apply MVPT from a private investor perspective to identify optimal portfolios for energy suppliers. Roques et al. (2008) analyze optimal portfolios for electricity generators in the UK electricity markets with this approach, concentrating on profit risk rather than production cost risk. Muñoz, Sánchez- Nieta, Contreras, and Bernal-Agustín (2009) present a model for investing in renewable energies in the framework of the Spanish electricity market. These authors show that technologies that have the lowest risk and the lowest return (PV and Thermo electrical) increase their market quota in more conservative scenarios.

restrictions that determine the range of variation of each energy source in the portfolio under alternative scenarios. For instance, depending on whether we consider the short or the long run, different technical restrictions can be assumed. Such restrictions are discussed in Section 3 below.

The average cost of the energy portfolio is defined as the weighted average of the various individual costs according to those weights:

$$\overline{CC} = \sum_{i=1}^{n} X_i \cdot \overline{C_i}. \tag{1}$$

It is clear from this expression that, given the technological restrictions, the minimum average cost of the fuel mix will correspond to a combination of the less expensive technologies.

The MVPT approach combines the information on restricted average costs above, with the risk costs associated to each feasible portfolio. We consider a traditional approach, thus measuring risk involves the volatility of historical data: the greater the individual cost's volatility, the greater the uncertainty and the associated risk. In the case of a single technology, its risk can be calculated by using a measure of its cost dispersion (i.e., the standard deviation). However, when estimating the electricity portfolio risk, it is also necessary to consider the cross-correlation costs among all the different technologies.[5] Once the average cost and risks of all feasible generating or transport fuel portfolios are determined, an efficient mix minimizes the volatility, for a given level of the average cost and over every feasible combination given technological restrictions. The set of all efficient energy portfolios comprises what is known as the *Energy Efficient Frontier* (*EEF*).

Fig. 1 illustrates a hypothetical *EEF*. The average cost is along the y-axis and the measure of risk along the x-axis. The minimum cost (MC) mix includes the cheapest technologies, given technological restrictions. Starting from this mix, moving left along the frontier, more diversified portfolios would presumably increase the average cost while, simultaneously, reducing the variance until the minimum variance (MV) mix is reached. Given positive correlations among the different alternatives, as in general it is the case for energy, the more concave is the frontier, the greater is the possibility of reducing risk by diversification. As we will see in Section 4, this issue is important when distinguishing between total and systematic risk. Being situated to the left of the frontier would be unfeasible, while any portfolio above the MV or to the right of the frontier would be inefficient. In order to use a benchmark efficient mix, we can consider the one in the mean of the MC and the MV portfolio, i.e., the MC–MV mix.

The estimated frontier allows also to assess specific portfolios and to offer directions for improvement. Suppose, for instance, that we wish to assess portfolio A, which is clearly inefficient. We can define two portfolios, B and C, of particular interest with respect to the reference portfolio A. Portfolio B involves equal risk as the reference one but with lower cost by virtue of being on the frontier, while Portfolio C has the same cost as the initial one and involves moving to the frontier by reducing risk. In reality, any mix between portfolio B and C, as portfolio D in the figure, will be more efficient than the reference mix, since it would improve in both dimensions with respect to A.

As we have said, beyond the analysis of total risks (in percent change) of an energy portfolio, we further consider the Capital Asset Pricing Model (CAPM) framework to distinguish between systematic and non-systematic risk, applied both to a set of energy commodities and feedstock time series prices. The former refers to market risk, common to all technologies and hence with no possibilities to reduce it by technology diversification, while the second is a technology-specific risk and hence susceptible to be diversified in the own generation process.

Applied to the case of energy-related commodities and feedstock prices, the CAPM model states that the expected change in price of an individual commodity *i* should equal the change in prices of a risk-free commodity, *f*, plus a risk premium,

$$E(\Delta p_i) = \Delta p_f + \beta_i \left(E(\Delta p_m) - \Delta p_f \right), \tag{2}$$

where $E(\Delta p_i)$ is the expected change in prices of commodity *i*, Δp_f is the price change of a theoretical risk-free commodity, and $E(\Delta p_m)$ is the expected change in prices of the market portfolio of commodities (i.e., a basket of primary commodities in our case).

The term in parenthesis in Eq. (2) above is the risk-premium.[6] The associated β_i measures the sensitivity of the individual price commodity change to system-wide global fluctuations. Since the market variance is common to all individual commodities, estimated β_i is used to measure systematic risk (i.e., a volatility measure of the commodity relative to the market): $\beta_i = 1$ means an individual systematic risk equal to the market; $\beta_i > 1$ means individual risk above the market; $\beta_i < 1$ refers systematic risk below that of the market.

Note finally, that the relevant market portfolio can be established based upon energy and non-energy commodity prices, although we will elaborate more on the former, as we will discuss below along the empirical part.

3. Empirical data: mean-risk individual energy costs

This section revises the input data needed for the implementation of the Mean-Variance Portfolio Theory (MVPT) analysis for the two case studies (electricity and fuels). In the second part, the standard CAPM model is applied to distinguish between systematic and non-systematic risk; in the last part, the time-varying properties of beta parameters are analyzed.

For the MVPT analysis, the required empirical data consists of a vector of average costs and a matrix of variance–covariance costs of the alternative technologies or fuels for road transport considered. Regarding average cost, we review available data and existing

[5] See Awerbuch and Berger (2003), Awerbuch and Yang (2007) and Roques et al. (2008) for a more detailed discussion of this topic in the electricity sector.

[6] In finance, the market asset would be the Dow Jones or Standard & Poor's 500 Index, for example.

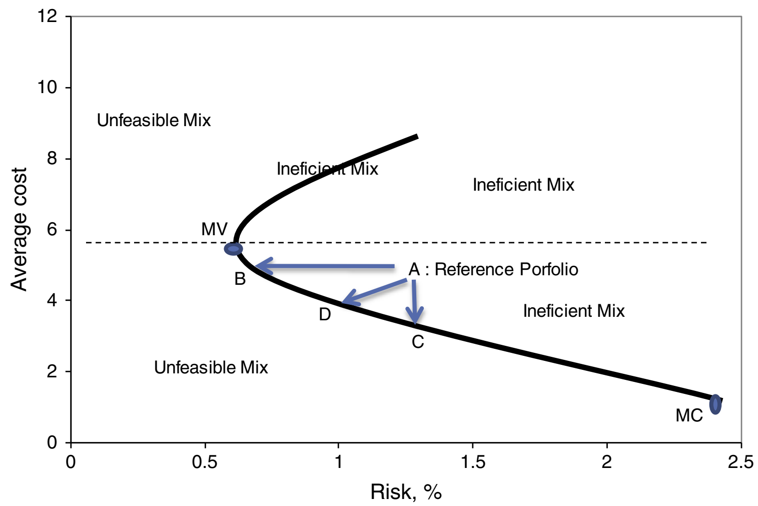

Fig. 1. Energy Efficient Frontier: an example.
Based on Marrero et al. (2011).

literature, and we use the most up-to-date results. For the electricity case study, building upon IEA (2010) special issue on electricity generating cost as our point of reference, we use the report published by Lazard (2012), which is referred to 2012 costs. As far as changes towards technologies with lower costs have been important in most of the cases (particularly in renewables) during the last years, it is relevant to use the most up-to-date information.[7] For transport data and based on Guerrero-Lemus et al. (2012), average production costs for the alternative fuels considered, can be obtained from the International Energy Agency (IEA) in terms of US dollars 2009.

In order to distinguish between systematic and non-systematic risk we estimate cost volatilities and cross-correlations of the various technologies for electricity and the transport fuel mix. Thus, we use the variability of the associated energy related commodities and feedstock prices. Data comes from the World Bank Commodity Price Data (Pink Sheet) and the IMF Commodities Unit Research Department (see Appendix A).

3.1. Average costs

3.1.1. Electricity

To calculate an average cost for each electricity generating technology we use the standard method, namely the levelized cost of electricity (LCOE). This method computes the costs over the electric plants' useful lifetimes and averages them to yield a total production cost. This measure is expressed in Euros (or US dollars) per MWh, so it is comparable across the various electricity generating technologies.[8] Under this model, cost cash flows are discounted back to the present using discount rates reflecting the opportunity cost of capital. LCOE does not take into account the various costs of transmission and distribution over the electricity system as a whole. Rather, this cost approach focuses on the main cost components: capital costs, fuel costs and operation and maintenance (O&M) costs. Other cost outlays relevant for energy policy analysis such as the externality cost of CO_2 emissions, will be considered in a sensitivity analysis in Section 4.

We use Lazard (2012) as our reference work to obtain average cost data. This study compares the LCOE for different conventional and alternative generation technologies in the US under various operating, technical and economic assumptions. Some of these assumptions are identical for all technologies in order to isolate the effects of key differentiated inputs such as investment cost, capacity factor, fuel costs, etc. All costs considered are before taxes and subsidies, so they better proxy social costs.[9]

Our analysis for electricity generation must be consistent with technologies covering base and peak hours of supply. Among fossil-fuel technologies, we consider Coal and Combined Cycle Gas (CC Gas) for base load. Nuclear is another technology for base load, and the gas peak technology is considered to cover peak hours. We also consider three alternative renewables: Wind (on-shore), Photovoltaics (PV) and Solar-Thermal. While Wind and PV suffer from intermittency costs, the Solar-Thermal does not, but the latter is currently the most expensive among the three alternatives.

We must consider reasonable assumptions regarding technical constraints of the different technologies in the energy system. In the MVPT analysis, these restrictions show up in the lower and upper limits imposed to the shares in the mix of each technology. Consistently with the existing literature, the main technical restrictions are: maximum 7% share of PV, 10% of Solar-Thermal and 25% share

[7] The IEA only updates the information on electricity generating costs at the worldwide level every five years. Therefore, we consider data for 2012 superior to other years available for the measurement of average costs. As indicated in the report by Lazard (2012), most of these technologies have not yet reached a maturity state, and in some of the cases, the levelized cost of electricity (LCOE) from wind and solar sources in America has fallen almost 40% between 2008–2012. Although, we only use 2012 data to calculate the average costs, the whole set of data from 2008, which might be useful for comparative purposes instead, are available upon request.

[8] Awerbuch and Berger (2003) and Marrero and Ramos-Real (2010) presents a detailed description of this methodology. See also any Lazard report for the evaluation of the LCOE.

[9] Lazard (2012) describes all relevant assumption to calculate the LCOE. We do not aim here to give a detailed energy and technology description.

Table 1.A
LCOE (average) and technical restrictions for electric generation.

	Coal[1]	Gas CC	Nuclear	Gas peak	Wind (on-shore)	PV (utility-scale)	Solar-Thermal
Average LCOE cost (US$/MWh)	85.7	75	95.5	215.5	80.9	125	173.5
Lower bound (%)	0	0	0	10	0	0	0
Upper bound (%)	90	90	90	100	25	7	10
Net cap. MW (average)	600	152/34	1100	350	100	10	100–120
Load factor (%), average	93%	10%	90%	70/40%	48/30%	27/21%	30/50%
CO_2 emissions. Lb/MMBtu	211	117	–	117	–	–	–

Source: Lazard (2012) and IEA (2010).
[1] It does not include CO_2 capture and storage.

of Wind (their minimum are zero); also, assuming that peak demand hours are covered by Gas Peaking, a minimum share in the mix of 10% of this technology is assumed.[10] Finally, since Nuclear, Gas CC and Coal can only be used as base technologies, we impose an upper limit of 90% for each; we also set a minimum of 60% as the sum of these three technologies. Based on IEA (2010) and Lazard (2012), Table 1.A reports the average cost values by plant used in the MVPT analysis of Section 4, their lower and upper limits in the mix, the average net capacity and load factor associated to the average costs, and the average CO_2 emission level for each technology.[11] As we show in detail in Section 4.2 we implement sensitivity analysis of LCOE costs that involves three elements: the intermittency costs of Renewables, the decommissioning cost of nuclear plants and the social costs of CO_2 emissions.

3.1.2. Road transport fuels

For the input data needed in the basic implementation of the MVPT over the fuel mix we follow Guerrero-Lemus et al. (2012). Average production costs for the alternative fuels considered are obtained from the IEA and expressed in real terms (over US GDP deflator) once measured in USD_{2009} per kilometer. To calculate the gasoline and diesel costs, we only consider the crude oil and refining costs. On the other hand, to estimate the production costs of first generation biofuels, we just collect feedstock prices taken from the IEA and IMF. All these costs are reported in Table 1.B. We abstract from 2G and 3G biofuels since the required prices for the CAPM analysis, a key issue in this paper, are not readily available. Finally, for the average values of electricity in the transport sector to be used in this work, first we consider the range of 2009 electricity prices for the household sector in the G7 countries, as reported in the 2010 IEA Key World Energy Statistics. The values range from 0.1155 USD_{2009}/kWh in the US to 0.2842 USD_{2009}/kWh in Italy.

On the other hand, in terms of the costs per kilometer, we have used as a reference value the fuel consumption characteristics of the most efficient midsize car models (Toyota Prius for gasoline car, Chevrolet Malibu for flexible fuel car and Volkswagen Golf for diesel car) published in the 2012 Fuel Economy Guide of the US Department of Energy and the US Environmental Protection Agency (EPA), as reported in Table 1.B. The same source has been used to define the electricity consumption characteristics of the most efficient middle size electric car model (Nissan Leaf).[12]

As far as flexible vehicles can use bioethanol blended with gasoline up to 85% (E85), we will consider the E85 blend in our model. On the other hand, as diesel-vehicle manufacturers listed in the Fuel Economy Guide (US Department of Energy & US Environmental Protection Agency, 2011) currently approve the use of biodiesel blends of up to 5% (B5) in their vehicles, and state that vehicle damage caused by using higher blends will not be covered under their manufacturer's warranty, the biodiesel blend considered is B5. It can be seen from Table 1.B that electricity has a higher price than sugar cane ethanol but lower than rapeseed biodiesel.

Compared to Guerrero-Lemus et al. (2012), and to illustrate more on the potentials of the methodology, here we allow more flexibility in the upper and lower limits imposed to the different fuels. Thus, gasoline–diesel goes from a minimum of 50% to a maximum of 100%, while for the other three alternatives considered: rapeseed biofuel, sugar cane ethanol, and electricity, there is no lower limit and their upper bounds are set to 25%.

3.2. Individual risks: systematic versus non-systematic

From the specification of the Capital Asset Pricing Model (CAPM) in Eq. (2) above, it is easy to obtain a reduced form econometric model for each commodity or feedstock price i:

$$\begin{aligned}\Delta p_{it} &= \alpha_i + \beta_i \cdot \Delta p_{mt} + \varepsilon_{it}, t = 1, \ldots, T;\\ \alpha_i &= \Delta p_f(1-\beta_i), \varepsilon_{it} \sim N\left(0, \sigma_i^2\right), \forall t.\end{aligned} \tag{3}$$

[10] See Awerbuch and Berger (2003), Awerbuch and Yang (2007) or Marrero and Ramos-Real (2010) for a more detailed discussion about the technical reasons behind these restrictions.

[11] An important issue in energy planning is the cost structure of each technology. We summarize this aspect, but do not elaborate on it. The economics of nuclear energy and Solar–Thermal are largely dependent on investment costs (80%–90% of total), which are determined by both construction costs and the discount rate. The LCOE of electricity with PV and Wind on-shore exhibits a very high sensitivity to load factor variations, and to a lesser extent to construction costs (on average, 90% and 75% of total, respectively). In contrast, variable costs coming from fuel use are the main determinant of the cost for fossil-fired plants (as high as 50% in CCGT plants.). See Lazard (2012) or the related literature for additional details about these shares for each technology and type of cost.

[12] A midsize car is defined with a limited passenger and cargo volume of 3.11–3.37 m^3. A combined estimate, city and highway kilometers per liter (km/l), is used, which assumes driving 55% in the city and 45% in the highway (Fuel Economy Guide, US Department of Energy & US Environmental Protection Agency, 2011).

Table 1.B
Average cost and technical restrictions for road transport fuel.

	Gasoline–diesel	Sugar cane ethanol	Rapeseed biodiesel	Electricity
Average cost (USD2009/Km.)	0.07427	0.04917	0.09566	0.05883
Lower bound (%)	50	0	0	0
Upper bound (%)	100	25	25	25
CO_2 emissions (grams/Km.)	172	106.25	40.03	103.9

Source: IEA. US Department of Energy and US Environmental Protection Agency.
Fuel Economy Guide (2011). Based on Guerrero-Lemus et al. (2012).

This model can be estimated by OLS, assuming constant parameters and homoscedastic errors, and then used to test the CAPM model and to decompose, for each, i total risk between systematic and non-systematic risk.[13] Since OLS residuals and $E(\Delta p_m)$ are orthogonal, it is easy to obtain the standard variance (risk) decomposition:

$$Var(\Delta p_i) = \beta_i^2 \cdot Var(\Delta p_m) + \sigma_{\varepsilon_i}^2,$$

where $\beta_i^2 \cdot Var(\Delta p_m)$ would be the systematic component and $\sigma_{\varepsilon_i}^2$ the non-systematic one. The R^2 gives the importance of systematic risk over total risk. Using time series of Δp_{it} and OLS estimations of $\beta_i \cdot \Delta p_{mt}$ and ε_{it}, we can estimate the complete variance–covariance matrix for the different commodity prices, distinguishing between overall, systematic and non-systematic risks:

$$\Sigma_{total} = \begin{pmatrix} Var(\Delta p_1) & \text{cov}(\Delta p_1, \Delta p_2) & \dots & \text{cov}(\Delta p_1, \Delta p_k) \\ & Var(\Delta p_2) & \dots & \text{cov}(\Delta p_2, \Delta p_k) \\ & & \dots & \dots \\ & & & Var(\Delta p_k) \end{pmatrix}$$

$$\Sigma_{sys} = Var(\Delta p_m) \cdot \begin{pmatrix} \beta_1^2 & \beta_1 \cdot \beta_2 & \dots & \beta_1 \cdot \beta_k \\ & \beta_2^2 & \dots & \beta_2 \cdot \beta_k \\ & & \dots & \dots \\ & & & \beta_k^2 \end{pmatrix} \qquad \Sigma_{no-sys} = \begin{pmatrix} \sigma_{\varepsilon_1}^2 & \sigma_{\varepsilon_1,\varepsilon_2} & \dots & \sigma_{\varepsilon_1,\varepsilon_k} \\ & \sigma_{\varepsilon_2}^2 & \dots & \sigma_{\varepsilon_1,\varepsilon_k} \\ & & \dots & \dots \\ & & & \sigma_{\varepsilon_k}^2 \end{pmatrix}.$$

For the matrix of systematic risk, the corresponding correlation is equal to zero when any of the β (β_i, β_j or both) is not significantly different from zero. In any other case (when both β_i and β_j are different from zero), the associated cross-correlations are equal to one, hence no reduction of systematic risk though diversification is feasible, by definition.[14] Thus, diversification can only reduce global risk through the non-systematic risk component.

In this framework, we implement Eq. (3) over energy and feedstock prices that are in general taken from the World Bank Commodity Price Data (Pink Sheet), annual time series in real 2005 US$ and available from 1960 to present. Alternatively, data from uranium and rapeseed real prices are from the IMF Commodities Unit Research Department. As commodity prices that are related to electricity generation, we consider crude petroleum real prices (average of Brent and Dubai), coal from Australia and South Africa, natural gas from US and Europe (pipeline) and Japan (liquefied), and the international price of uranium. For the case of fuel in road transport, we select again crude oil as the main commodity for diesel and gasoline, several time series of sugar cane (for US, Europe and the international market) and average corn prices as main feedstock to generate ethanol, and rapeseed and soybean oil prices as feedstock to produce biodiesel.[15] Finally, we use the Energy global commodity index (base 2005) as the baseline market index, Δp_{mt} in Eq. (3).

The contribution of identifying systematic risk over these energy data is twofold. First, it opens up the interaction between the complementarities among technologies and the characterization of each and every market risk. Consider for instance that only gasoline and diesel were available to analyze the risks associated to the energy mix of the road transport. On the one hand, as gasoline and diesel are highly correlated (out of public policy intervention), a market portfolio based on these two energy sources would result that nearly all risk in each fuel is systematic. However, feedstock prices associated to biofuels and electricity prices would present a lower systematic risk (specially the former), and with such a risk measure, an even lower correlation with gasoline and diesel. Thus, under rising prices of fossil fuels, the finding that the way to diversify the energy mix for the road transport is increasing the penetration of both biofuel compatible (*flex* engines) and electric vehicles turns out to be reinforced once systematic risk is accounted for. This kind of result that is well known in finance, seems rarely implemented for the management of non-financial portfolios, and in particular in what refers to as energy portfolios.

[13] Deaton and Laroque (1992), Deaton (1999) or Cashin and McDermott (2002) find evidence on strong commodity price fluctuations (i.e., overall risk), however they do not distinguish between systematic and non-systematic fluctuations. Recently, Chen (2010) emphasizes the importance of this distinction and applies the CAPM regression to metal commodities.

[14] The correlation between the i and j term is given by: $corr(i,j) = \frac{\text{cov}(i,j)}{\sigma_i \sigma_j} = \frac{\beta_i \cdot \beta_j \cdot Var(\Delta p_m)}{\beta_i \cdot Std(\Delta p_m) \cdot \beta_j \cdot Std(\Delta p_m)} = 1$, if $\beta_i, \beta_j > 0$.

[15] For MVPT analyses below, we disregard corn and the soybean because of the superiority in terms of average cost and emissions of sugar and rapeseed, respectively. See Guerrero-Lemus et al. (2012) for a more detailed discussion on this point. Moreover, we consider gasoline and diesel as a single type of fuel, since both are subject to the fluctuations of crude petroleum.

The second contribution of combining the CAPM and the Mean-Variance approaches is better understood within the electricity sector face to face with the energy mix for the road transport sector. The reason is that the electricity portfolio is more diversifiable so that systematic risk is less stringent over the portfolio: it affects oil and natural gas input sources in a context with several more alternative inputs.

Therefore, next we focus on these two contributions of the methodological approach rather than highlighting particular results. In particular, Appendix B shows the estimates for the CAPM, and a set of diagnostic tests for the residuals, using the energy and non-energy commodity indexes as market reference.[16]

Using the energy commodity index, Tables B.1–B.2 show estimated results and the variance decomposition of model (3) for the electricity and fuel road transport examples, respectively. On the other hand, Tables B.3–B.4 show equivalent results when using the non–energy index as the market reference. Consistently with the intuition on CAPM regressions, the estimated model when using the energy index as the market portfolio illustrates how crude oil prices overly contribute to the volatility of both the electricity and the fuel transport portfolios (see column 1 in Tables B.1 and B.2). Beyond that result, we do not find substantial differences in volatility rewarded by the market through input prices among the various input sources of electric power (Table B.1). On the contrary, there are more differences (despite lower significance) in volatility measured by systematic risk in commodity prices for the input sources in the road transport sector (Table B.2). These findings bring about the consideration of non-energy market risk in pricing the portfolio. In this second case (Tables B.3–B.4), the divergences do not seem to be present in oil, but they do appear in coal (more) and natural gas prices possibly reflecting the composition of both energy supply and hedging effects. Such a divergence in the price of risk, face to face either energy market risk or non-energy market risk, is particularly strong when looking to those *assets* that act as inputs for biofuels where the composition between the food and the energy input purposes interacts.

Finally, according to diagnostic tests shown in Tables B.1–B.4, we do not find significant evidence supporting the existence of ARCH structure in the residuals of model (3) for most commodities and feedstock prices, though this finding can be due to the annual frequency of data; the exception is the price of sugar cane and uranium, which shows periods of high volatility in the 70s and since 2007, respectively. ARCH and other diagnostic tests are discussed along Appendix B.

All in all, any diversification of technologies in the mix would reduce both total and non-systematic risk. Again, cross-correlations for systematic risk are equal to $+1$ among those commodities showing systematic risk significantly different from zero. Hence, by definition, systematic risk cannot be reduced by diversifying among those technologies. In our case that occurs when combining any fossil fuels (Coal, Gas and Oil) for electricity generation, or when combining gasoline, diesel or electricity for road transport fuel. Thus, systematic risk can only be reduced by using technologies with low risk of that type, and by combining them with technologies showing null systematic risk (their correlation is zero in that case). That would occur when combining any fossil fuel with Nuclear or any renewable for electricity generation, or when combining gasoline and diesel with certain low energy-correlated biofuels (e.g. rapeseed biodiesel) for road transport fuel.

3.3. Individual time-varying risk

Applied to high-frequency data on financial asset returns, exchange rates or interest rates, most empirical studies concur that market betas display significant time varying properties.[17] Thus, estimating model (3) by OLS would produce biased and inefficient beta estimates. Although in our case we focus on commodity prices at low-frequency data so time-varying estimates are less precise, it turns out that accommodating time variation draws some lessons. First, for energy technologies with low betas (electricity, renewables) the fixed CAPM beta estimate is roughly the average of the time varying estimates. Second, for energy technologies that highly covariate with the market (fossil fuels), the time varying betas mostly reflect the trends of substitution between a shrinking oil share and an expanding gas share in the energy mix during the last decades. These findings are taken into consideration for the subsequent analysis focusing on total and systematic risks obtained from constant betas.

We proceed as follows. We estimate model (3) both by rolling-OLS [cf. Fama and French (1997)] and by implementing state space Kalman Filter methods. The rolling-OLS results confirm but lag the Kalman Filter estimates, for which we face accuracy problems due to the low frequency of the data. This later circumstance makes the application of conditional variance M-GARCH methods difficult [Bollerslev (1990)].[18] The state space alternative is not free from estimation problems due to the limited availability of data, but we consider that it provides a check for parameter stability in our energy commodity and feedstock model. Following Black, Fraser, and Power (1992) and Wells (1994), we estimate a time-varying coefficient specification where α and β evolve according to a

[16] Another extension can combine simultaneously the two market portfolios in a specification where movements in the energy price indexes are controlled for variation in the non-energy index which is left unexplained by variation in the energy index. With that approach, the measure of systematic risks combines risk terms coming from energy and non-energy market price shocks. Preliminary exploration of such a specification points out to diversification opportunities coming from energy use, food use, and hedging purposes. The econometrics of this extension is not free of problems so we leave this approach for further research.

[17] See for instance Beckmann and Czudaj (2013), Huang and Wang (2013), Saleem and Vaihekoski (2010) and Tsai, Chen, and Yang (2014), and the references therein.

[18] The easiest approach is to estimate (3) using rolling-OLS (or recursive) regressions over a fixed interval period of time. Traditionally, this approach has two major drawbacks: there is no means of estimating an optimal size of the window for the rolling regression (a problem exacerbated for annual data and small sample size) and the technique is highly sensitive to outliers. The second approach is based on M-GARCH model, which consists of estimating conditional variances between returns on market portfolio and an asset (commodity) under consideration. Once the conditional variance–covariance is estimated, the time varying beta can be easily calculated using its definition: $\beta_{it} = \sigma_{imt}/\sigma^2_{mt}$, with σ^2_{mt} the time series of the market portfolio and σ_{imt} the covariance between the market and the specific commodity. This approach has also several drawbacks: first, the α_{it} cannot be directly recovered; second, resulting time series contain a large amount of noise, hence the resulting estimated beta does; third, all the estimation problems that a M-GARCH model has when applied to annual data with small sample size (at most, we deal with 50 annual observations).

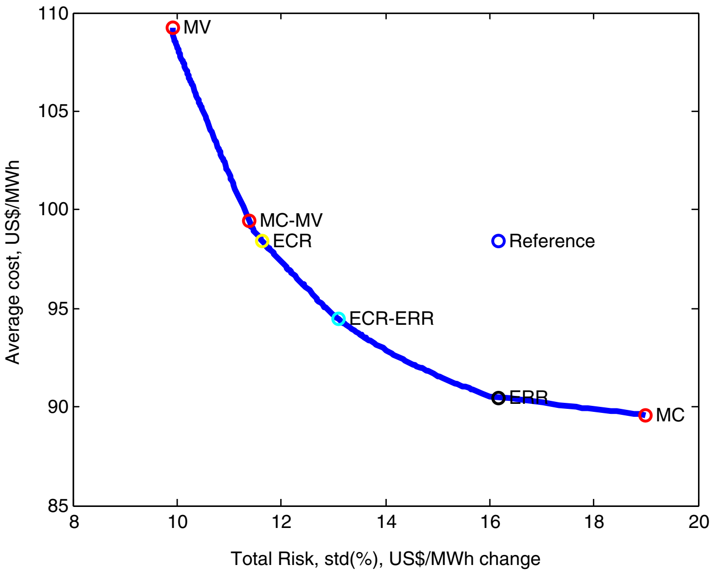

Fig. 2A. Electricity Generation Efficient Frontier: Baseline.

mean reverting first order autoregressive model,

$$\begin{aligned} \Delta p_{it} &= \alpha_{it} + \beta_{it} \cdot \Delta p_m + \varepsilon_{it}, \\ \alpha_{it} - \alpha_i &= \phi_1 (\alpha_{it-1} - \alpha_i) + v_{it}, \\ \beta_{it} - \beta_i &= \phi_2 (\beta_{it-1} - \beta_i) + w_{it}, \end{aligned} \tag{4}$$

with the errors e, v and w following independent gaussian white noise processes with constant variances, denoted by σ_ε^2, σ_v^2 and σ_w^2, respectively. This general specification captures the most common models used in the literature: the random walk (i.e., $\phi_1 = \phi_2 = 1$) and the random coefficient ($\phi_1 = \phi_2 = 0$).

Eq. (4) can be rewritten in terms of parameters in deviation with respect to their constant terms, and the entire system in state-space representation,

$$\Delta p_{it} = \overline{\alpha}_i + \overline{\beta}_i \cdot \Delta p_m + \widetilde{\alpha}_{it} + \widetilde{\beta}_{it} \cdot \Delta p_m + \varepsilon_{it}, \tag{5}$$

$$\begin{aligned} \begin{pmatrix} \widetilde{\alpha}_{it} \\ \widetilde{\beta}_{it} \end{pmatrix} &= \begin{pmatrix} \phi_1 & 0 \\ 0 & \phi_2 \end{pmatrix} \begin{pmatrix} \widetilde{\alpha}_{it-1} \\ \widetilde{\beta}_{it-1} \end{pmatrix} + \begin{pmatrix} v_{it} \\ w_{it} \end{pmatrix}, \\ \widetilde{\alpha}_{it} &= \alpha_{it} - \overline{\alpha}_i; \ \widetilde{\beta}_{it} = \beta_{it} - \overline{\beta}_i \end{aligned} \tag{6}$$

where Eq. (5) is the measurement equation, which relates the observed variables (commodity prices) with time-varying coefficients (state, unobserved variables), and Eq. (6) is the state or transition equation, which governs the time-path of the unobserved coefficients. From an initial set of priors for the parameters and the variances in the transition system, we estimate Eqs. (5)–(6) by maximum likelihood and then use the Kalman and the Fixed Interval Smoothing filters to recover the time evolution of the conditional α and β. In Appendix C we report the main findings, which are in line with the discussion at the beginning of this section.[19] These findings can be summarized as follows. There is evidence of changing betas in fossil fuels and corn, although their ranking remains unchanged. These changes might reflect decreasing share of oil in the energy mix, increasing share of gas, and increasing role of biofuels, and biodiesel (corn) in particular. That fossil fuel betas are converging to one reflects the limited opportunities for diversification in fossil fuels so as to reduce systematic risk. Similar occurs for the case of corn against alternatives. Nuclear as well as most renewable betas remain low and stable so that the measures of risk and the qualitative results for the efficient portfolio do not change beyond the fact of reinforcing the risk free nature of economic costs of the nuclear technology. The changing beta in coal reflects the world wide industrial cycle during the past decade. All in all, the qualitative results are quite robust to both estimation methods incorporating time-varying risk and reinforce the findings obtained with constant betas.

[19] The state space model (5)–(6) is estimated with the E4 algorithm (Casals, Jerez, & Sotoca, 2002). It could also be combined with a heteroskedastic model for the variance of the error term [Fisher and Kamin (1985)]. Such a model would estimate the beta as an unobserved component, allowing for time-varying variance of the σ_ε^2. Thus, we could estimate in the same model non-constant systematic and non-systematic risk, as well as the α_{it} related with the risk premium of commodity i. However, using annual data and a small sample size as in our case (maximum of 50 years) it is difficult to obtain estimates of the nested model.

Table 2.A
MVPT analysis of electricity generation portfolios: Baseline.

	Reference	MC	MV	MC-MV	ECR	ERR	ECR–ERR
Cost, US$/MWh	98.41	89.59	109.20	99.40	98.41	90.48	94.45
Risk (total), std, %	16.18	19.00	9.91	11.39	11.63	16.17	13.10
CO_2, TM/MWh	0.1704	0.1645	0.1048	0.1254	0.1280	0.1372	0.1434
Coal	30.00	0.00	19.57	20.59	18.18	0.00	17.59
Gas CC	30.00	80.84	12.60	22.10	27.92	65.75	37.47
Nuclear	30.00	0.00	15.84	15.26	11.90	0.00	9.94
Gas peak	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Wind	0.00	9.16	25.00	25.00	25.00	24.25	25.00
PV	0.00	0.00	7.00	7.00	7.00	0.00	0.00
Solar-Thermal	0.00	0.00	10.00	0.05	0.00	0.00	0.00

4. Portfolio analysis and results

In this section we analyze the results of the two estimated efficient frontiers for electric generation and transport fuel portfolios. We could estimate a Vector-GARCH model [Bollerslev, Engle, and Wooldridge (1988)] for every commodity considered, so as to obtain a variance–covariance matrix of commodity prices for each period *t*. However, there are several circumstances that such a strategy is difficult in our setting. First, we would need time variation in the average costs of the different energy technologies at the relevant frequencies analogous to those we have for input commodity prices. However, average cost data are generally published over long waves,[20] and given the type of changes in energy technologies over those time spans, typically the costs data are hardly comparable among waves. Second, our strategy in this paper aims at energy planning and it is not intended for financial management. This is particularly so as far as energy portfolios at the economy wide level cannot be reassigned at high frequencies. Finally, multivariate GARCH models are not adequate to implement with annual data.

Notwithstanding, an evaluation of how the variance–covariance matrix of energy commodity prices varies in low and high volatility periods is overly relevant. Our preliminary explorations indicate that in turbulence periods there is compression in energy input prices mostly due to the complementarities between technologies and imperfect completion, and this compression reduces the opportunities to diversify during high volatility periods. Clearly though, our goal here is to obtain an efficient frontier that reflects either current or medium-run values of the costs associated to the different technologies. Thus, more than a time-varying portfolio analysis we focus on counterfactuals associated to alternative scenarios, and we leave the extension to incorporate time-varying total risks for further research.

Consequently, and as emphasized in the Introduction, we specially focus on the methodological contribution of the approach rather than in the seldom energy results. We start by analyzing the baseline energy mix vis à vis the various energy portfolios that are in the cost-risk efficiency frontier for electricity generation. We focus more on the electricity mix due to the greater amount of data available for this portfolio, in particular to carry out next some sensitivity analysis of special interest. The sensitivity analysis covers alternative assumptions over the available technologies as well as changes in the costs associated to those technologies. Finally, we show and comment the results for fuel road transport mostly with the aim of illustrating the tension between total and systematic risk by comparison with a different but related portfolio.

4.1. Electricity

A key feature of the potential of the MVPT approach becomes apparent by opening up the possibility of renewables in a reference electricity generation mix in which that technology is absent. Thus, the baseline electricity mix is represented by 30% for Nuclear, CC Gas, and Coal, whereas 10% is for Gas Peaking (its lower bound) and a zero % share is for renewables. This counterfactual mix, which is uniform among conventional technologies, is not far from the actual mix in many OECD countries.[21] As indicated above, the baseline case for electricity excludes CO2 costs, decommissioning costs for Nuclear, and intermittency of renewable energy, and considers total risk (standard deviation of annual changes) under the reference $30 + 30 + 30 + 10$ mix above.

The reference energy mix (see Fig. 2.A) is inefficient since it is located to the north east of the Energy Efficient Frontier (EEF). Even in the baseline setting, the primary finding is the strong trade-off between average costs and total risk, i.e.: there are a lot of options to improve along both dimensions when starting from the baseline. For instance (see Table 2.A), keeping the reference cost (Equal Cost than Reference, ECR, mix), 28.1% risk can be reduced (from 16.18 to 11.63), whereas keeping total risk (Equal Risk than Reference, ERR), cost can decrease 8.1% (from 98.41 to 90.48).

Also, the concavity of the frontier suggests here a substantial margin to combine technologies to reduce costs, since it is the case in energy applications that we basically deal with technologies showing non-negative correlations. Linearity of the frontier implies instead that correlations among technologies are close to one, and therefore, that any reduction in costs is only obtained through switching from one technology to another, with little possibilities of combining them to reduce risk.

An important additional finding is that moving from reference to, for instance, the average ECR–ERR, then not only both average cost and risk fall, but also CO_2 emissions fall nearly 19%. Actually, CO_2 emissions fall in general except for the minimum cost (MC)

[20] Annually for U.S. since 2008 (Lazard, 2012), but every 5 years at the Worldwide level (IEA, 2010).

[21] Excluding renewable energies, the OECD average is about 60% of fossil energies (Coal and Gas mostly) and the set of Hydro and Nuclear represents approximately 30%.

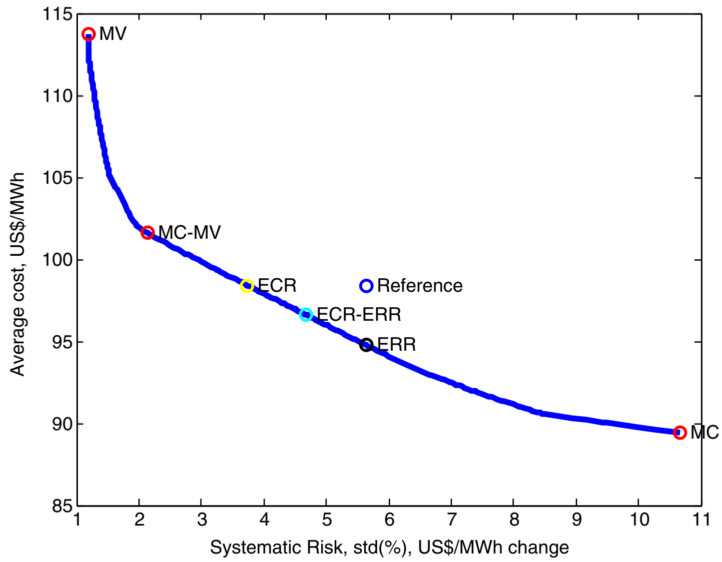

Fig. 2B. Electricity Generation Efficient Frontier: Systematic risk.

portfolio, which is concentrated in CC Gas. More specifically, efficiency gains imply moving away from Nuclear (which is uranium price driven) and Coal (higher cost than CC Gas). On the contrary, CC Gas increases its share except when risk reduction is key. Gas Peaking is always in its lower bound, because its average cost is the highest, but also because it is strongly correlated with conventional technologies (it is natural gas fueled).

Regarding the role of renewables in the efficient mix, let us start noticing that, as Gas Peaking, PV and Solar-Thermal are high-cost technologies. However, differently from Gas Peaking, PV strongly enters the mix (it is set in its upper limit), except when cost reduction is key. This is because of its relatively low individual risk, and fundamentally because of its low correlation with conventional technologies: Coal, Gas and Nuclear. Despite its high stand-alone individual cost, its consideration in the energy portfolio and posterior reallocation of the different technologies allow to reduce not only overall risk but also average cost (and CO_2 emissions) with respect to the reference and many other feasible though inefficient electricity portfolios. Such an intuitive result for energy policy highlights the kind of key feature of the MVPT in this setting.

In terms of risk, wind technologies show similar advantages than PV. However, Wind (on-shore) exhibits a plus, since this technology is nowadays among the most competitive ones in terms of average cost. Thus, the current limits of wind energy correspond to its intermittency problems and its integration to the grid with all other technologies (Wind shares are set to its upper bound in most cases). The case of Solar-Thermal is just the opposite because its cost is higher than Wind and PV. Therefore, in the baseline analysis, it only participates in the MV portfolio which basically weighs the risk reduction.

The first departure from the benchmark, still under the electricity mix, refers to the consideration of systematic rather than total risk, which is a relevant contribution of our analysis. For ease of exposition, we focus on the systematic risk coming from the energy market portfolio. It turns out, in particular, that the distinction between systematic risk which is energy market based (market portfolio consists of energy commodities) versus the one which is non-energy market based (market portfolio consists of non-energy commodities), matters more for the efficient fuel transport as far as biofuels have both an energy and non-energy commodity nature.

When considering only the systematic risk, the first important consequence is that combining conventional technologies is not an efficient way to reduce the risk. This is because, regarding systematic risk, cross-correlations among fossil technologies are equal to one, as indicated above. This is apparent from the lesser concavity of the frontier in Fig. 2.B, that often exhibits piecewise linear segments. However, with higher costs, more space is open for the penetration of all Renewables (PV and Solar Thermal, in addition to Wind), and that

Table 2.B
MVPT analysis of electricity generation portfolios: Systematic risk.

	Reference	MC	MV	MC–MV	ECR	ERR	ECR–ERR
Cost, US$/MWh	98.41	89.46	113.70	101.60	98.41	94.76	96.59
Risk (systematic), std, %	5.65	10.67	1.20	2.14	3.74	5.65	4.69
CO_2, grams/Km	0.1704	0.1687	0.0181	0.0570	0.1098	0.1703	0.1400
Coal	30.00	0.00	0.00	7.88	18.17	29.98	24.08
Gas CC	30.00	83.13	0.00	7.28	17.85	29.99	23.92
Nuclear	30.00	0.00	48.00	49.84	28.98	5.03	17.01
Gas peak	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Wind	0.00	6.87	25.00	25.00	25.00	25.00	25.00
PV	0.00	0.00	7.00	0.00	0.00	0.00	0.00
Solar-Thermal	0.00	0.00	10.00	0.00	0.00	0.00	0.00

frontier becomes less linear even when defined over CAPM systematic risk. This fact is because Renewables, and to a lesser extent Nuclear, show zero – or very low – individual systematic risks and zero cross-correlation with conventional technologies. We consider this novel finding for the MVPT of the energy mix a relevant contribution when the objective is energy risk management.

Thus, when the efficiency frontier is defined over total risk, the minimum variance (MV) portfolio is overly diversified (see column 3 in Table 2.A). However, when MV is defined only over systematic risk, both Nuclear and renewable energies are reaching their technical upper bound (see column 3 in Table 2.B). This result is justified by a relatively low correlation between uranium price and oil price, so that the systematic risk of the former is relatively low. On the contrary, CC Gas shrinks in all portfolios since its systematic risk is relatively higher. Wind power still remains in its technical upper bound, whereas PV and Solar-Thermal only enter in the MV portfolio. The superiority of Nuclear and Wind with respect to PV and Solar Thermal is clear in this case. Thus, combining Nuclear and Renewables with fossil technologies is the only way we have to reduce systematic risk through diversification.

4.2. Further sensitivity analysis

Sensitivity analysis of the results over the aforementioned methodological dimensions can be implemented by further exploring the determinant of costs. From the point of view of energy policy analysis there is in particular the very important consideration of the intermittency cost of renewable energies, the decommissioning cost of nuclear plants, and the costs of CO_2 emissions mainly for thermal technologies. To calculate these augmented costs we follow the most common approach in the literature.

First, the intermittency cost of renewable energies might generate important grid-level system costs.[22] We use values for MWh reported by NEA (2012) for penetration levels between 10% and 30%.[23] Second, the average cost of nuclear plants is augmented with decommissioning costs. Decommissioning costs are about 15% of capital costs according to NEA (2010). Last, but not the least, we have CO_2 emission costs, which attempt to internalize the social costs of emissions within the private costs. This cost is calculated as the price of the tons emitted multiplied by the emission factor resulting from the generation (Tm CO_2/KWh). This cost would only affect fossil fuel technologies (see Table 1.A).

Appendix D.1 reports the results that can be summarized as follows. Adding these additional costs imply that Nuclear decreases in favor of CC Gas while Coal remains the same. Moreover, Wind moves to its upper bound due to its large complementarity with fossil fuels and as a way to reduce average cost and risk. With these additional cost constraints, reduction in CO_2 emissions is much more limited, for instance only 8% when moving from reference to ECR–ERR. If adding the CO_2 cost to conventional energies while assuming a high price of CO_2 of about 70 US$/TM$CO_2$, a strong reduction of CO2 emissions even beyond the baseline case is found (from 19% to 32%). PV gains space and it is even part of the mix under the ECR–ERR portfolio. Coal specially shrinks in this case, and CC Gas augments only slightly. Another important insight is that the MV portfolio remains the same.

It is also interesting to consider how the results with augmented costs change when the volatility measure is systematic rather than total risk (see Appendix D.1). The intuition goes again through the linearity of the efficiency frontier. As it occurs when considering total risk versus systematic risk in the baseline case, but now incorporating decommissioning and external costs, the results further illustrate on the possibilities for the different technologies to act as complements while reducing average cost and risk. Targeting systematic risk, the option for Nuclear is stronger relative to CC Gas since it allows to hedge against such a risk. Then, because of that extra switch for Nuclear when considering systematic risk, CO_2 emissions decrease more if total risk were the policy target instead.

There are several other counterfactuals that illustrate on the relevant trade-offs. For instance, another clear cut case is the one excluding Nuclear (see Appendix D.2). Looking to total risk opens the mix even for Solar-Termal, while PV and CC Gas go up, and Coal stays positive. Under systematic risk instead, and with all costs, excluding nuclear power forces to keep CC Gas, but interestingly opens up the space for PV that even moves close to its upper-bound under the current calibration. Notice that excluding Nuclear, the reference mix becomes 45% CC Gas + 45% Coal + 10% Gas Peak.

One could also explore the trade-offs between Renewables. For instance, it might be the case that an alternative renewable technology like the Solar-Thermal nearly ever enters in the mix, mostly due to the existence of more efficient, uncorrelated with conventional energies, and subject to less systematic risk, wind power (see again Appendix D.2). We show that in a case in which wind power is not available (the counterfactual excludes it from the mix), PV strongly enters up to its upper-bound in most portfolios despite its medium to high average costs, and then Solar-Thermal enters in most of the efficient portfolios even at current relatively high cost. The remaining 25% of wind power excluded goes to the rest of conventional energies. Finally, under total risk, and excluding both Nuclear and wind power, extra space is covered by CC Gas and PV. The precise figures for all these methodologically and policy relevant counterfactuals are reported in Appendix D.

4.3. Fuel road transport

Fig. 3.A and .B depicts the Energy Efficient Frontier (EEF) estimated for fuel in the road transport (the *Fuel Efficient Frontier*) when considering either total or systematic risk, respectively. The reference mix is highly inefficient (clearly a lot more inefficient than for electricity) as it is far to the north east of the frontier in both cases. Since the reference mix is extremely inefficient in both cases, the

[22] We follow the assumptions in NEA (2012). Grid-level system costs can be divided into three categories: a) day-to-day cost of balancing scheduled and unscheduled drops in output (balancing costs), b) back-up costs or necessary investments in complementary flexible capacity required to cover peak, and c) investment in additional transmission to connect the resource to and reinforce networks.

[23] We consider intermittency costs in a broad sense (grid-level) under the high costs for adequacy and grid connection. Thus, these costs can reach up to 40$/MWh for onshore wind and up to 80$/MWh for solar (in the worst case about a 40% of LCOE). These values are lower when intermittency costs include only balancing costs.

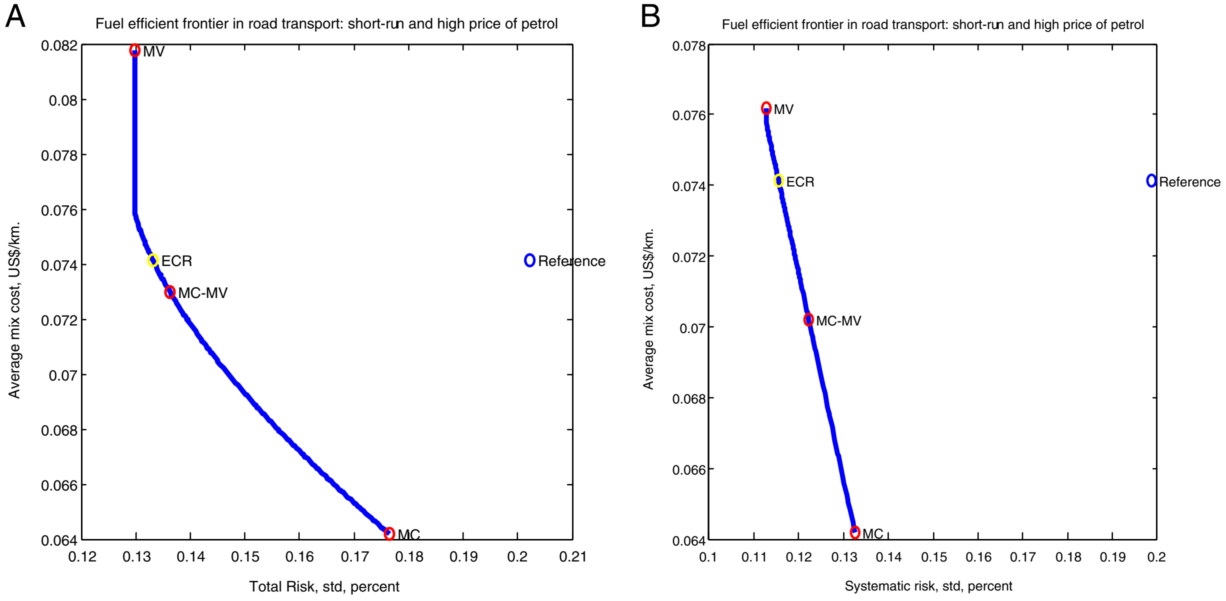

Fig. 3. A (left) and B (right). Road Transport Fuel Efficient Frontier: Total (left) and systematic risk (right).

ERR portfolio and the ERR–ECR average are not well defined. Thus, for illustrative purposes and following the strategy in Guerrero-Lemus et al. (2012), we focus on the MC, MV and the MC–MV average. We further show that inefficiency (the distance of the reference mix to the frontier) increases when considering systematic risk (compare the reference mix in Fig. 3.A and .B). It is also worth noting the reduced chances to reduce risk over the EEF that we have in the case for fuel road transport. This finding is consistent with the results in Section 3.2 regarding CAPM estimations for this sector.

Tables 3.A and 3.B report the distribution of the portfolios under either total or systematic risk. The first result to highlight is that the distribution in both portfolios is nearly the same. This is mostly due to the overall stability of the risk rankings across fuels. The gasoline–diesel basket is always the more risky asset. On top of that, since we are considering a high oil price scenario (the most likely one), the average cost of such a basket is also high, and therefore this fuel combination is at its lower bound in the portfolio. Second position in the risk ranking is for the sugar cane ethanol, which is the more risky alternative to gaso–diesel, as well as the more correlated alternative. Notwithstanding, its low generation cost makes it enter in its upper-bound whenever average cost is a priority: the MC portfolio, and less, the MC–MV portfolio.

The major change is for rapeseed biodiesel, but not enough so as to change its importance in the different portfolios. Whereas its total risk is the third in the ranking, its systematic risk is almost zero, below the one of electricity. Under these circumstances, and even though its correlation with gaso–diesel is low, it only enters whenever risk is a priority: the MV portfolio, and less, the MC–MV portfolio, because it is more costly than electricity and sugar cane ethanol.

Finally, even though electricity (for the road transport) exhibits a positive systematic risk, as far as its price follows closely the general energy index, its share in the efficient mix remains low. Also, given its low cost compared to rapeseed biodiesel, it always enters in the mix at its upper bound. A precise assessment of the scope for electricity would require a deep inquire on the overly technical determinants of the use of electricity as a fuel.

5. Concluding remarks

In this paper we use the Mean-Variance Portfolio Theory (MVPT) to compute the efficiency frontier for two different energy portfolios: i) an electric generating technology mix, and ii) a road transport fuel mix. The use of the MVPT methodology contributes to characterize a finance framework for energy risk management. Moreover, we use the CAPM methodology to consider, in each case, the

Table 3.A
MVPT analysis: alternative fuel road transport portfolios (total risk).

	Reference	MC	MV	MC–MV	ECR
Cost, US$/Km.	0.0741	0.0641	0.0780	0.0711	0.0741
Risk (total), std, %	0.2032	0.1770	0.1339	0.1454	0.1368
CO_2, grams/Km	165.1	138.6	122	128.7	124.3
Gaso–diesel	93.0	50.0	50.0	50.0	50.0
Sugar cane ethanol (1G)	3.5	25.0	0.0	10.1	3.5
Rapeseed biodiesel (1G)	3.5	0.0	25.0	15.0	21.5
Electricity	0.0	25.0	25.0	25.0	25.0

Table 3.B
MVPT analysis: alternative fuel road transport portfolios (systematic risk).

	Reference	MC	MV	MC–MV	ECR
Cost, US$/MWh	0.0741	0.0642	0.0762	0.0702	0.0741
Risk (systematic), std, %	0.1987	0.1326	0.1127	0.1223	0.1155
CO_2, grams/Km	165.1	138.5	122	129.9	124.3
Gaso–diesel	93.0	50.0	50.0	50.0	50.0
Sugar cane ethanol (1G)	3.5	25.0	0.0	12.0	3.5
Rapeseed biodiesel (1G)	3.5	0.0	25.0	13.0	21.5
Electricity	0.0	25.0	25.0	25.0	25.0

important issue of total risk versus systematic risk only, in a setting with energy technologies that exhibit complementarities. We further check the stability of parameters by extending the CAPM model to incorporate time varying systematic and non-systematic risks. The former refers to market risk, common to all technologies and hence with no possibilities to reduce it by technology diversification, while the second is a technology-specific risk and hence susceptible to be diversified in the own generation process. This type of analysis that is well known in finance, seems rarely implemented for the management of non-financial portfolios, and in particular in what refers to as energy portfolios. We leave for further research the very important issues of the measurement of risk sequentially over energy and non-energy market portfolios, and the extension to time varying total risk that would possibly enhance our empirical results.

For energy policy regarding electricity, we can draw some important conclusions. The primary finding is the existence of strong trade-off between average cost and total risk. Thus, the concavity of the frontier suggests a substantial margin to combine technologies. The share of Renewables increases in most of the efficient portfolios when reducing the risk is important (MV portfolio) and particularly for wind energy. On the other hand, an important additional finding is that moving from the reference to other mix, not only implies that average cost and risk fall but also the CO_2 emissions. When considering the systematic risk instead, the most important finding is that combining conventional technologies is not an efficient way to reduce the risk. The sensitivity analysis accounts for the intermittency costs of Renewables, the decommissioning costs of nuclear plants and the costs of CO_2 emissions. Adding these costs when considering total risk implies that nuclear energy tend to shrink in favor of CC Gas, while wind energy remains in its upper bound and the reduction in CO_2 emissions is much more limited. When moving to systematic risk instead, CO_2 emissions decrease more because nuclear energy is better than gas to hedge such a risk. Policy recommendations relying in counterfactuals such as trade-offs between Renewables can be overly useful as well.

Regarding the fuel mix of road transport comparison with the mean-variance results for electricity draws also important lessons for energy policy. First, the reference mixes are highly inefficient compared to the case with electricity and the distribution of the portfolios under either total or systematic risk is nearly the same. Thus, on the one hand, compared to electricity, there is more room to move away from fossil fuels when a reduction of risk is important, while in the other hand, there are more limited opportunities to diversify systematic risk over the EEF for the road transport than for electricity. Secondly, and related, the gasoline–diesel mix is always the more risky, followed by the sugar cane ethanol and by rapeseed biodiesel. Finally, electricity for the road transport, taking into account its low cost compared to rapeseed biodiesel, always enters in the mix at its upper bound.

Beyond the specific results, we conclude that there are several reasons why our approach to energy risk management is useful when designing energy policy. We retain what can be labeled as energy planning approach to energy risk management by checking the stability of parameters. We argue that the theory provides a guide on how to proceed to identify an optimal energy portfolio. Also, the approach requires plausible figures for expected average costs and its volatilities and correlations relevant for alternative scenarios faced in energy planning. Finally, the computed efficient frontier and the technical constraints help to characterize the energy policy maker risk tolerance.

A natural extension should account for the fact that economies are facing a larger menu of energy technologies, in very much the same way emerging economies have access to more international assets with globalization [cf. Devereux (2009)]. Another line of research is to pursue an integrated approach to energy planning of a joint primary energy mix for an entire energy system. There are two major difficulties to analyze the entire energy system in an integrated way. First, information to build up the efficient frontier of primary energy requires data from all energy sources and their end uses, which is complex and unavailable for the economy as a whole. Second, the construction of any primary energy mix requires also considering technical assumptions about energy intermediate consumptions as well as general equilibrium considerations in terms of economic interrelations among activities. A partial equilibrium approximation and reduced form risk management theoretical framework as the one adopted here may limit the scope of the policy results [despite Levy (2010)]. Rather, dynamic stochastic general-equilibrium energy use models [cf. Díaz and Puch (2013)] or non-renewable resource models [cf. Golosov, Hassler, Krusell, and Tsyvinski (2014)] are the adequate tools to characterize optimal policy. However, we argue that the combined MVPT–CAPM approach in this paper is a relevant step towards organizing the evidence and identifying the relevant trade-offs on optimal energy risk management policy and related applications.

Appendix A. Commodity and feedstock prices

This Appendix describes the units of the commodity and feedstock prices used in Section 3.2. Data are taken from the World Bank Commodity Price Data (Pink Sheet) and the IMF Commodities Unit Research Department.

- Coal (Australia), thermal GAR, International Coal Report, World Bank. Source: Bloomberg; IHS McCloskey Coal Report.
- Coal (South Africa), thermal NAR, International Coal Report, World Bank. Source: Bloomberg.

- Crude oil, average spot price of Brent, Dubai and West Texas Intermediate (equally weighed), World Bank. Brent, Dubai and West Texas oil are from Bloomberg, Energy Intelligence Group (EIG) and OPEC.
- Natural Gas (Europe), average import border price and a spot price component, World Gas Intelligence, World Bank.
- Natural Gas (US), spot price at Henry Hub, Louisiana, Thomson Reuters Datastream and The Wall Street Journal; World Bank.
- Natural Gas LNG (Japan), import price, c.i.f, recent two months' averages are estimates, World Gas Intelligence; World Bank.
- Sugar (EU), EU negotiated import price for raw unpackaged sugar from African, Caribbean and Pacific (ACP) under Lome Conventions, c.i.f. European ports, International Monetary Fund; World Bank.
- Sugar (US), nearby futures contract, c.i.f., Bloomberg, World Bank.
- Sugar (world), International Sugar Agreement (ISA) daily price, raw, f.o.b. and stowed at greater Caribbean ports, International Sugar Organization; Thomson Reuters Datastream; World Bank.
- Soybean oil (Any origin), crude, f.o.b. ex-mill Netherlands, ISTA Mielke GmbH, Oil World; US Department of Agriculture; World Bank.
- Maize (US), no. 2, yellow, f.o.b. US Gulf ports, US Department of Agriculture; World Bank.
- Uranium U3O8 Swap Futures End of Day Settlement Price, IMF Commodities Unit Research Department, IMF.

Appendix B. CAPM regressions

Tables B.1–B.2 show estimated results of model (3) and its variance decomposition for electricity and fuel road transport when using the energy index as the market reference. Tables B.3–B.4 show the equivalent results when the non-energy index as the market reference is used. The tables also include widely used diagnostic tests for normality, autocorrelation and heteroskedasticity. In this respect, most of the cases show no evidence of non-normality in the residuals, except maybe for the case of the price of sugar that exhibits excess volatility in the 70s. On the other hand, outliers occur only in the 70s, but outlier corrections do not affect the estimates while substantially improving the JB tests. Coal and electricity price models exhibit autocorrelation, which is not rejected in general.

Table B.1
CAPM electricity portfolio + Market = Energy index. Risk analysis for electricity portfolio: CAPM model using energy global index from WB as market index.

	Crude oil average (Brent, Dubai)	Coal (South Africa)	Coal (Australia)	Natural gas, US (pipeline)	Natural gas, EU (pipeline)	Natural gas, Japan (Liquefied)	Uranio (International)
α	−0.0058	0.0042	0.0068	0.0041	0.0050	0.0100	0.0217
std(α)	0.0050	0.0190	0.0213	0.0331	0.0133	0.0176	0.0603
β	1.1276***	0.5335**	0.2833**	0.4388**	0.5688***	0.5188***	0.1576
std(β)	0.0293	0.2215	0.1336	0.1710	0.1013	0.1108	0.2172
Risk decomposition: total = systematic (energy market index) + non-systematic							
Std(endogenous variable), total	0.2758	0.2362	0.2204	0.2277	0.2000	0.1732	0.2862
Std(residual): non-systematic	0.0522	0.2054	0.2099	0.2039	0.1475	0.1251	0.2852
Abs(β) · Std(market), systematic	0.2708	0.1165	0.0672	0.1014	0.1351	0.1198	0.0234
R2 (% systematic)	96.49	27.15	11.48	21.43	46.70	49.41	1.60

Note: std(Energy global index, annual changes) = 0.2403 for the whole sample (1960–2012).
OLS estimates, Newey–West Standard Errors Variance–Covariance. For each case, sample depends on data availability. For crude oil, a big outlier is corrected in 1970 (results suffer from minor changes, but the JB test after correction does not reject normality). Although some outliers exist for other commodities, we do not correct them because results do not vary significantly when correcting them.
The F-test refers to the joint significance of the regressors in the estimated equation. The Box–Pierce Q-test for residual autocorrelation establishes under the null the lack of autocorrelation of the residuals, and it follows a chi-squared with degrees of freedom equal to the number of lags used (we use 8, but results are quite robust to changes in this number of lags). The ARCH-LM statistics is based on the F-statistic from the auxiliary regression of squared standardized residuals on their lags (assume 2-lags). The JB test statistics of Normality of residuals have a chi-2 asymptotic distribution under the null of Normality.
*** 1% significant.

Table B.2
CAPM Transport portfolio + Market = Energy index. Risk analysis for transport portfolio: CAPM model using energy global index from WB as market index.

	Gasoline (US, average)	Electricity (US, average)	Sugar cane (EU, import)	Sugar cane (US)	Sugar cane (international)	Corn (US)	Rapeseed (international)	Soybean oil (international)
α	0.0140	0.0401***	−0.0127	−0.0150	−0.0127	−0.0064	0.0360	0.0012
std(α)	0.0128	0.0120	0.0135	0.0233	0.0521	0.0188	0.0314	0.0161
β	0.9653***	0.0873***	0.0862	0.2910	0.3846	0.2243***	0.0071	0.0491
std(β)	0.0533	0.0317	0.0574	0.2177	0.2683	0.0810	0.2653	0.0869
Risk decomposition: std(Energy global index, annual changes) = 0.2403 for the whole sample (1960–2012)								
Std(endogenous variable), total	0.2190	0.0556	0.0911	0.2076	0.3964	0.1633	0.2041	0.1569
Std(residual): non-systematic	0.0598	0.0510	0.0896	0.1975	0.3894	0.1557	0.2039	0.1565

(continued on next page)

Table B.2 *(continued)*

	Gasoline (US, average)	Electricity (US, average)	Sugar cane (EU, import)	Sugar cane (US)	Sugar cane (international)	Corn (US)	Rapeseed (international)	Soybean oil (international)
Risk decomposition: std(Energy global index, annual changes) = 0.2403 for the whole sample (1960–2012)								
Abs(β) · Std(market), systematic	0.2107	0.0221	0.0165	0.0641	0.0743	0.0492	0.0089	0.0118
R2 (% systematic)	92.78	18.21	5.18	11.34	5.44	10.90	0.01	0.58

Note: std(Energy global index, annual changes) = 0.2403 for the whole sample (1960–2012).
See note in Table B.1. For soybean oil, a big outlier is corrected in 1973 (results suffer from minor changes, but the JB test now does not reject normality).
*** 1% significant.

Table B.3
CAPM Electricity portfolio + Market = Non-energy index. Risk analysis for electricity portfolio: CAPM model using non-energy index (not including precious metals) as market index.

	Crude oil average (Brent, Dubai)	Coal (South Africa)	Coal (Australia)	Natural gas, US (pipeline)	Natural gas, EU (pipeline)	Natural gas, Japan (liquefied)	Uranio (international)
α	0.0455	0.0057	0.0234	0.0246	0.0310	0.0268	0.0152
std(α)	0.0347	0.0194	0.0244	0.0357	0.0249	0.0295	0.0498
β	1.0128***	1.2393***	0.3330	0.1541	0.4566**	0.6253**	0.9263
std(β)	0.2324	0.4217	0.4222	0.3262	0.1949	0.2599	0.5718
Risk decomposition: total = systematic (non-energy market index) + non-systematic							
Std(endogenous variable), total	0.2758	0.2362	0.2204	0.2296	0.2000	0.1732	0.2862
Std(residual): non-systematic	0.2542	0.2005	0.2192	0.2294	0.1953	0.1625	0.2704
Abs(β) · Std(market), systematic	0.1070	0.1248	0.0227	0.0107	0.0429	0.0598	0.0938
R2 (% systematic)	16.75	30.59	3.45	0.57	6.48	14.54	11.57

Note: std(non-energy global index, anNual changes) = 0.1115 for the whole sample (1960–2012).
See note in Table B.1.
*** 1% significant.
** 5% significant.

Table B.4
CAPM Transport portfolio + Market = Non-energy index. Risk analysis for transport portfolio: CAPM model using non-energy index (not including precious metals) as market index.

	Gasoline (US, average)	Electricity (US, average)	Sugar cane (EU, import)	Sugar cane (US)	Sugar cane (international)	Corn (US)	Rapeseed (international)	Soybean oil (international)
α	0.0246	0.0451***	−0.0082	−0.0023	0.0032	0.0020	0.0157	0.0013
std(α)	0.0305	0.0144	0.0139	0.0196	0.0452	0.0139	0.0196	0.0096
β	0.8886**	−0.0315	−0.1704	0.4979**	1.0362***	1.0054***	1.3859***	0.9666***
std(β)	0.3320	0.0658	0.1362	0.2432	0.3822	0.1515	0.3369	0.1436
Risk decomposition: total = systematic (non-energy market index) + non-systematic								
Std(endogenous variable), total	0.2190	0.0564	0.0911	0.2076	0.3964	0.1633	0.2004	0.1554
Std(residual): non-systematic	0.2010	0.0563	0.0900	0.2021	0.3830	0.1200	0.1419	0.1130
Abs(β) · Std(market), systematic	0.0871	0.0039	0.0142	0.0475	0.1021	0.1108	0.1415	0.1066
R2 (% systematic)	18.61	0.48	4.35	7.14	8.49	47.09	51.54	48.10

Note: std(non-energy global index, annual changes) = 0.1115 for the whole sample (1960–2012).
See note in Table B.1.
*** 1% significant.
** 5% significant.

Appendix C. Time-varying betas

In this appendix we just report the time-varying betas of main commodity and feedstock prices so as to illustrate on the findings discussed at the end of Section 3.3. The reported rolling-OLS (dashed line) is over a window of 15 years (robust to 10–20 years), so the sample is truncated. The reported state space from Kalman filter and Fixed Interval Smoothing (solid line) leads the rolling-OLS estimate and is more robust to outliers.

Table C.1 shows estimated results of the time varying model (4) and Fig. C.1 shows the time-varying betas of main commodities and feedstock prices. We can distinguish two types of results. First, estimated ϕ (ϕ_1 for the α equation and ϕ_2 for the β equation) are small (non-significantly different from zero), which tends to be accompanied by large variance in the error terms of the coefficients (especially for that of the α process). This situation would indicate lack of persistence of the parameters, which fluctuate randomly around their constants, α_i and β_i. In this situation, these constants would be good mid-term estimations of the parameters for our purpose. Focusing on the β, and according to results in the table, this is the case for uranium, sugar, rapeseed, soybean oil AND electricity to a lesser extent. Second, the other possibility is that the associated ϕ is statistically different than zero (the closer is ϕ to one, the more persistent is the time path of the parameter). This situation tends to be accompanied by a small variance of the error term of the transition equation, hence the time path becomes smoother. Focusing on the β, this situation is related to crude oil, natural gas, coal and corn to a lesser extent.

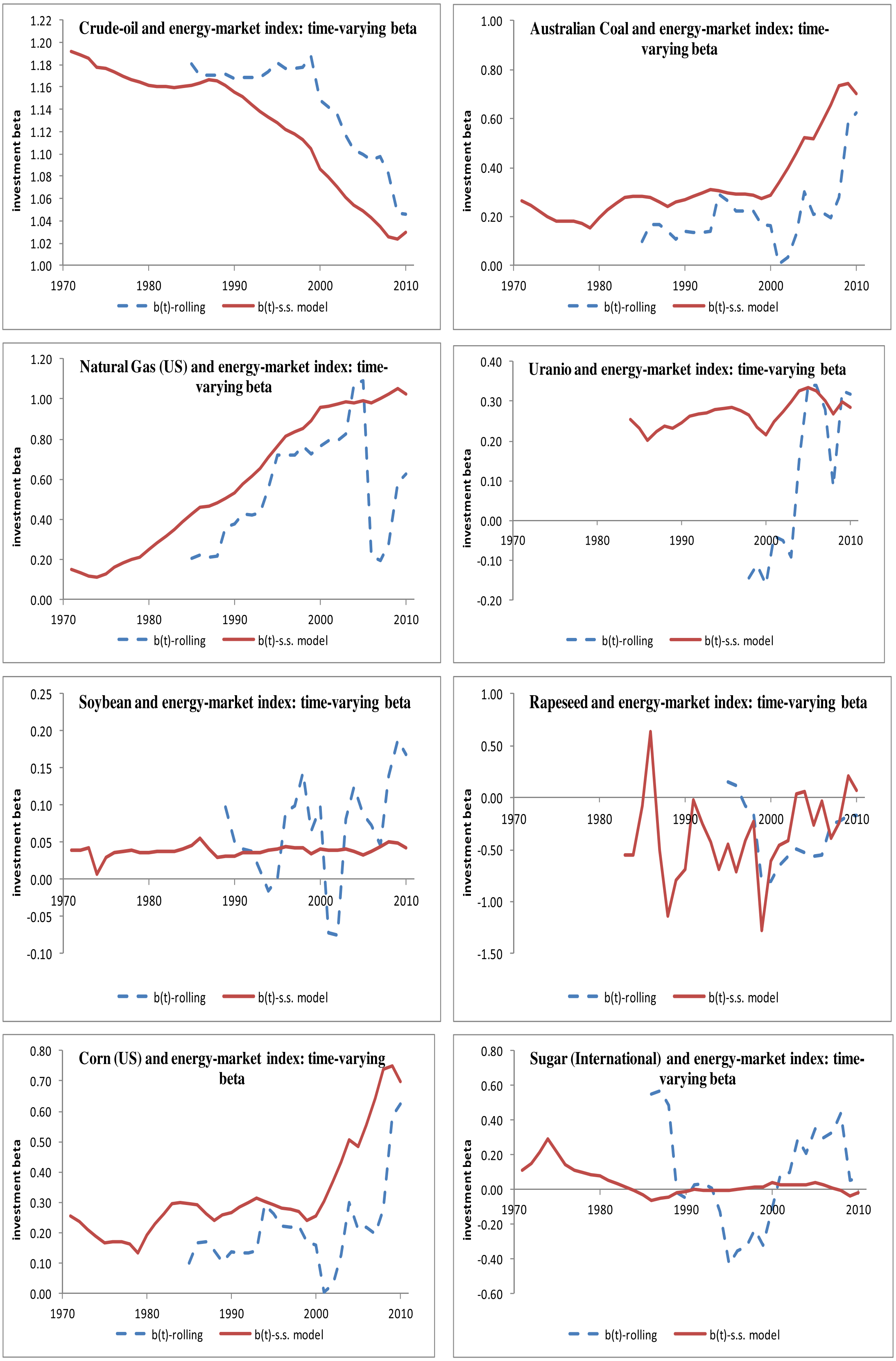

Fig. C.1. Time-varying betas of main commodities and feedstock prices.

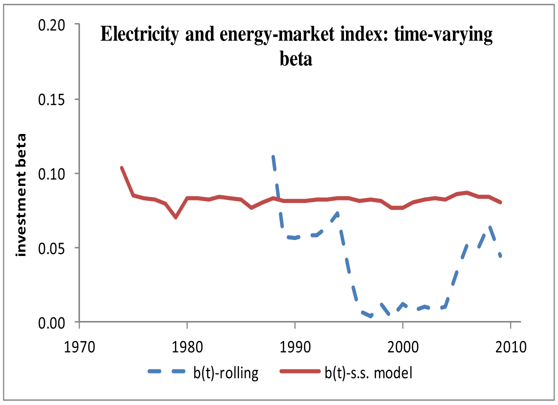

Fig. C.1. (*continued*).

Table C.1
Estimation of state-space model (time-varying parameters) of main commodities and feedstock prices.

	Crude oil average (Brent, Dubai)	Coal (Australia)	Natural Gas, US (pipeline)	Uranio (international)	Electricity (US, average)	Sugar cane (international)	Corn (US)	Rapeseed (international)	Soybean oil (international)
ϕ_1	−0.2069***	−0.3377	0.7483*	0.8249	0.9014***	0.5537	−0.2408	0.0237	0.8933
std(ϕ_1)	0.0049	8.4731	0.4703	0.553	0.1621	5.2114	7.4227	4.822	0.8225
ϕ_2	0.9494***	0.8453***	0.9540***	0.6506	0.2515	0.701	0.8153***	0.0738	0.4357
std(ϕ_2)	0.0779	0.3368	0.0796	2.099	9.3942	2.4505	0.3962	0.521	13.9593
α	0.1002	−0.0100***	1.0386	8.1023	1.2233	−1.1674	1.2101	7.6822***	−0.0595
std(α)	0.4459	0.0001	4.5299	5.6392	2.2421	5.9009	3.2555	2.4789	3.2150
β	1.1190***	0.3632***	0.5890*	0.2826	0.0833**	−0.0025	0.3504**	−0.4065***	0.0382
std(β)	0.0563	0.1920	0.3476	0.2321	0.0375	0.2369	0.1893	0.1797	0.1049
σ^2_ε	0.0007	0.0379	0.0287	0.0643	0.0028	0.125	0.0375	0.0109	0.028
σ^2_v	0.0001	0.1651	34.2968	7.4768	2.0557	10.3116	0.5831	0.3428	1.6699
σ^2_w	0.0005	0.0241	0.0174	0.0172	0.0013	0.027	0.0297	0.2002	0.0039

*** 1% significant.
** 5% significant.
* 10% significant.

Appendix D. Sensitivity analysis

D.1. Sensitivity analysis over augmented costs

Augmented costs include intermittency cost of renewables, decommissioning cost of nuclear plants, and CO_2 emissions costs mainly for thermal technologies. Fig. D.1 and Table D.1 show results for EEF of electricity generation when considering these augmented costs. We show results over total risk (left panel) and systematic risk (right panel in the Table). Tables do not contain results for the ECR and ERR portfolios.

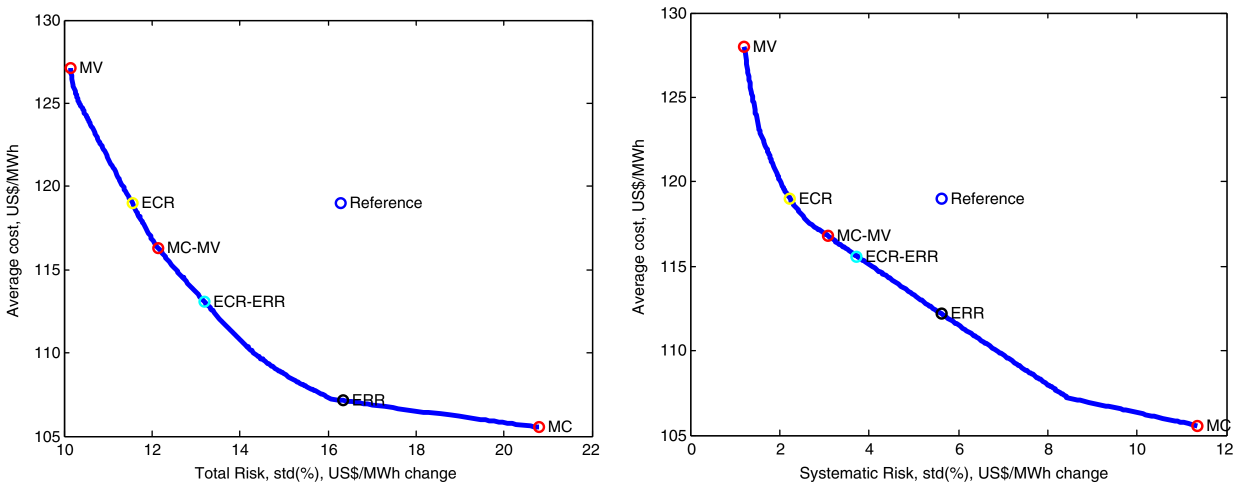

Fig. D.1. Electricity Generation Efficient Frontier including intermittency, decommissioning and CO_2 costs: Total (left) and systematic (right) risk.

Table D.1
MVPT analysis of electricity generation portfolios including intermittency, decommissioning and CO_2 costs: Total (left) and Systematic (right).

	Total risk					Systematic				
	Reference	MC	MV	MC–MV	ECR–ERR	Reference	MC	MV	MC–MV	ECR–ERR
Cost, US$/MWh	119.00	105.50	127.10	116.30	113.10	119.00	105.60	128.00	116.80	115.60
Risk (total), std, %	16.30	20.80	10.16	12.13	13.20	5.62	11.35	1.21	3.07	3.73
CO_2, TM/MWh	0.1704	0.1811	0.1051	0.1099	0.1130	0.1704	0.1799	0.0183	0.0529	0.0634
Coal	30.00	0.00	19.35	9.22	5.68	30.00	0.00	0.06	0.00	0.00
Gas CC	30.00	89.98	13.13	34.07	42.15	30.00	89.36	0.00	19.21	24.99
Nuclear	30.00	0.00	15.52	14.71	14.56	30.00	0.00	50.00	45.79	40.01
Gas peak	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Wind	0.00	0.02	25.00	25.00	25.00	0.00	0.64	25.00	25.00	25.00
PV	0.00	0.00	7.00	7.00	2.61	0.00	0.00	7.00	0.00	0.00
Solar-Thermal	0.00	0.00	10.00	0.00	0.00	0.00	0.00	7.94	0.00	0.00

D.2. Sensitivity analysis over renewable energies when excluding Nuclear and Wind

Counterfactuals illustrate the changes in expensive renewables (PV and Solar Thermal) when excluding only Nuclear (left pannel in Table D.2. and left Graphic in Fig. D.2.) or when excluding both Nuclear and Wind (right pannel in Table D.2. and right Graphic in Fig. D.2.) technologies from the mix. Not considering these technologies from the mix might be feasible due to legislatory and geographical reasons. To simplify the exposition, this counterfactual focuses only on total risk.

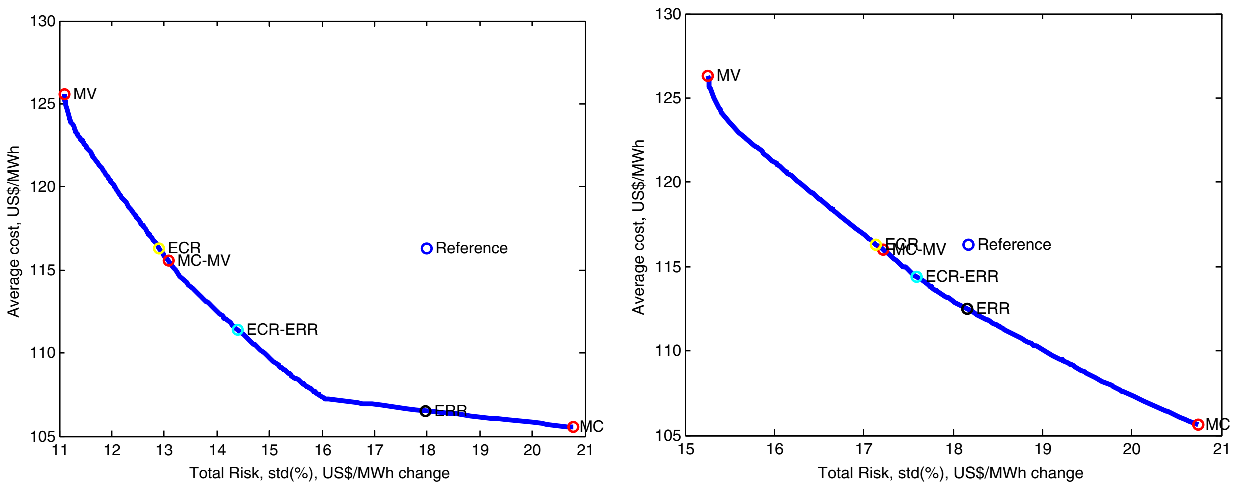

Fig. D.2. Electricity Generation Efficient Frontier when excluding Nuclear (left) and both Wind and Nuclear (right) under total risk.

Table D.2
MVPT analysis of electricity generation portfolios when excluding Nuclear (left) and both Wind and Nuclear (right) under total risk.

	Exclude Nuclear (total risk)					Exclude Nuclear and Wind (total risk)				
	Reference	MC	MV	MC–MV	ECR–ERR	Reference	MC	MV	MC–MV	ECR–ERR
Cost, US$/MWh	116.30	105.50	125.60	115.60	111.40	116.30	105.60	126.30	116.00	114.40
Risk (total), std, %	18.00	20.77	11.11	13.08	14.39	18.17	20.75	15.26	17.22	17.60
CO_2, TM/MWh	0.2466	0.1809	0.1434	0.1482	0.1465	0.2466	0.1816	0.2035	0.1970	0.1990
Coal	45.00	0.00	26.37	17.65	10.91	45.00	0.38	36.54	21.82	21.04
Gas CC	45.00	89.89	21.63	40.02	51.22	45.00	89.62	36.45	59.47	61.96
Nuclear	–	–	–	–	–	–	–	–	–	–
Gas peak	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Wind	0.00	0.11	25.00	25.00	25.00	–	–	–	–	–
PV	0.00	0.00	7.00	7.00	2.88	0.00	0.00	7.00	7.00	7.00
Solar-Thermal	0.00	0.00	10.00	0.34	0.00	0.00	0.00	10.00	1.72	0.00

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