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The role of economic and policy variables in energy-efficient retrofitting assessment. A stochastic Life Cycle Costing methodology

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ABSTRACT

Energy saving is a major policy objective worldwide and in the EU in particular. Evaluating the convenience of energy-efficient investments, however, is complex. This paper aims to apply stochastic Life Cycle Costing to assess the economic value of energy-efficient building retrofitting investments. The proposed approach investigates how macroeconomic variables affect such an evaluation by explicitly taking into account their interdependent stochastic nature. Consequently, the economic evaluation of an investment is itself stochastic thus expressing both its expected value and its inherent uncertainty and risk. On this basis, an illustrative case-study is presented, where alternative designs of the energy-saving intervention are compared and a sensitivity analysis performed to identify the determinants of the LCC outcome and of its variability. In terms of policy implications, a tool providing a sounder evaluation of the convenience of such investments can suggest when and to what extent incentives may be appropriate to facilitate these investments and what possible financial instruments could be put forward in order to reduce the associated risk.

1. Introduction: policy challenges and motivations

Major economic and environmental concerns are driving nations towards reducing energy consumption (Ouyang et al., 2009). In this respect, improving energy efficiency can definitely provide a key contribution to strengthening energy security worldwide. Globally, between 2000 and 2016, energy efficiency improved by just 13% and the International Energy Agency warns that governments are not designing new policies as fast as it would be needed (IEA, 2017). In fact, eight of the ten countries showing the largest efficiency improvement since 2000 are European countries and the European Union (EU) has definitely given a very strong policy impulse to energy efficiency over the last decade.

In February 2015, the European Commission (EC) presented the Framework Strategy for Energy Union as one of the ten priorities of the Juncker Commission (EC, 2015). Energy efficiency is a crucial part of this strategy in order to lower energy demand and polluting emissions, but also to promote jobs and growth through research, innovation and greater competitiveness.

In pursuing higher energy efficiency, buildings represent a critical issue in Europe, where they account for around 40% of EU energy consumption and around 75% of the building stock is inefficient (EC, 2016a). The Energy Efficiency Financial Institutions Group (EEFIG), established in 2013 by the EC and the United Nations Environment Program, indicates that the EU's investment need in building's energy efficiency for the 2014–2030 period is huge: 1,300 billion US dollars (EEFIG, 2015). In order to make buildings, both new and existing ones, meet minimum energy requirements, several EU-level and country-level initiatives and regulations have been recently put forward (Petersdorff et al., 2006; Itard et al., 2008; Burman et al., 2014).

In April 2018, the European Parliament approved an update to the 2012 Energy Efficiency Directive (2012/27/EU) including the new 30% energy efficiency target for 2030 and reinforcing measures and policies that must ensure major energy savings (EC, 2016b). Fiscal incentives are among these measures and have been introduced by several EU, as well as non-EU, countries (IEA, 2017).

Nonetheless, discussions have also arisen about the actual effectiveness of these regulations and incentives. On the one hand, they might be unnecessary, as the external conditions are such to make these private investments already convenient. On the other hand, and more importantly, they could be insufficient to really promote private investments to the desired level. In practice, one of the main problems in achieving the ambitious energy efficiency objective, is the lack of private investors' convenience to make such long-term investments

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especially in existing buildings. In fact, retrofit interventions have proven to be very effective in improving the energy performance of existing buildings, but its perceived convenience still represents a major challenge (Kibert, 2008).

This mostly depends on the high uncertainty associated to these long-term and high-cost (thus, low returns) investments and to the investors' risk aversion. This latter may have been strengthened by negative macroeconomic climate and expectations, especially in the post-2008 years and in some low-growing EU countries. In such conditions, these investment decisions may have been postponed or given up.

The lack of evidence on the performance of energy efficiency investments, and of corresponding commonly agreed procedures and standards, makes the benefits and the financial risk harder to assess (EEFIG, 2015). This explains some recent initiatives of the European institutions aimed to change the risk perception of financiers and investors in this field, i.e. to de-risk these investments by providing better and wider information, new evaluations tools and financial instruments. The Smart Finance for Smart Buildings initiative of the European Investment Bank is exemplary in this respect (EC, 2018). The recent EU Directive 2018/844, amending Directive 2010/31/EU on the energy performance of buildings and Directive 2012/27/EU on energy efficiency, further stresses the point: Member States are expected to facilitate the access to appropriate mechanisms for (among others): "the reduction of the perceived risk of energy efficiency operations for investors and the private sector" by also providing "accessible and transparent advisory tools on relevant energy efficiency renovations and financing instruments" (OJEU, 2018).

Life Cycle Costing (LCC) analysis is a widely used method to properly determine the whole costs associated to such investments during a specific time period and, consequently, to assess its convenience. Numerous national and EU regulations explicitly acknowledge LCC as a proper assessment tool (EC, 2011). Nonetheless, standard LCC does not fully capture the logic and the determinants of investors decision implied by the uncertainty and, thus, the risk associated to the investment. Several assumptions and simplifications usually made in the application of the standard LCC disregard the relevance of the specific macroeconomic climate (i.e. macroeconomic variables) in which investment decisions are made and of the consequent long-term uncertainty. Indeed, not only the decision on whether to invest depends on uncertainty and expectations, but also the choice among alternative options is made over a mean-variance space (Bodie et al., 2018) and this aspect is not properly considered by conventional LCC studies.

This paper aims to contribute to the recent literature on the so-called probabilistic LCC analysis that puts forward significant methodological improvements to take uncertainty and expectations into account within LCC calculations. While these recent contributions still use major simplifications on the actual probabilistic nature of the economic data, here some major novelties in the LCC approach are introduced in this direction. In particular, the probabilistic processes generating the macroeconomic variables entering the LCC are assumed time-dependent and interdependent. In this sense, the proposed approach is a "multivariate stochastic" rather than a "univariate probabilistic" LCC analysis. Consequently, LCC simulations are not based on some distributional assumption for any macroeconomic variable involved, but on the multivariate time-dependent distributions estimated within a Vector AutoRegressive (VAR) model using the respective observed time series.

The rest of the paper is structured as follows. Section 2 shortly overviews the literature on LCC and on probabilistic approaches to LCC in the field of buildings, especially in energy-efficient building retrofitting, and overviews its main methodological challenges. Section 3 presents the novelties of the stochastic LCC methodology here developed. Section 4 details the specific characterisation of the macroeconomic scenario within which the multivariate data generation process is estimated. Although the proposed stochastic LCC approach can be applied to any building renovation interventions, in section 5 it is applied to an exemplary case study to illustrate the potential of the methodology. Section 6 presents and discusses the main results by also assessing their robustness and illustrating some validation exercises of the stochastic approach compared to the conventional deterministic LCC calculations. Policy conclusions are finally drawn in section 7.

2. Literature review and main methodological challenges

2.1. LCC of energy efficiency measures for buildings

In the last two decades, LCC has become an important decision method, part of the whole design process of a building construction or renovation project (Ferreira et al., 2013). It allows to compare the total expected costs and savings (expressed in monetary terms) due to the application of alternative design options during a specific time period and choose the most profitable one. A considerable amount of research refers to standardized methods to assess the economic impacts of Energy Efficiency Measures for building design and renovation, as those reported in the International Standard ISO 15686–5:2008 (ISO, 2008) and the European Standards EN 15459-1:2017 (CEN, 2017). In Europe, the Directive 2010/31/EU established that Member States shall calculate "cost-optimal levels" of their minimum buildings energy performance requirements using a specific framework methodology (OJEU, 2012a,b) based on EN 15459. Recent Directive 2018/844 again encourages "[…] in relation to buildings undergoing major renovation, high-efficiency alternative systems, in so far as this is technically, functionally and economically feasible" (OJEU, 2018). LCC assessments of buildings design options have thus become familiar to designers, investors and practitioners.

Several authors apply economic analysis methods to assess the affordability of different design options or establish the cost-optimal solution for a specific building case or for typical national reference buildings, as required by the EU obligation. In several studies, multi-objective optimization models are proposed to assess technology choices and find compromise solutions for a building case study. For instance, Asadi et al. (2012) considered energy savings and costs as possible conflicting objective functions in retrofitting a family house in Portugal, while Ascione et al. (2015) focused on energy demand, thermal comfort and costs for a refurbishment project in Italy. Both analyses are limited to the assessment of the investment costs of design options, disregarding other cost categories.

Hamdy et al. (2013) developed a simulation-based optimization method to find the cost-optimal and nearly zero energy performance levels for a single-family house in Finland, including all the investment and operating costs for building and service systems, over a specified calculation period. However, they assumed constant real interest and energy price escalation rates. Han et al. (2014) also applied a LCC analysis framework including all the phases of a building life cycle: construction, annual operation, maintenance and demolition, in terms of financial cost. They analysed the affordability of solutions for an office building case study, also considering two alternative energy pricing scenarios. Also, Delmastro et al. (2016) propose an approach to identify the cost-optimal mix of successful renovation packages for the building stock at urban scale. The global cost evaluation is based on standard EN 15459. Furthermore, a "feasibility index" for the retrofit action is proposed, taking into account the socio-economic conditions of buildings occupants.

Further exemplary studies are reported in the recent comprehensive review of Ferrara et al. (2018), which presents 88 scientific works on cost-optimal analysis applications in Europe since the Directive 2010/31/EU entered into force. As argued by the authors, the cost-optimal results are strongly influenced by the calculation assumptions and the scenarios in which the optimization study is performed. Standardized LCC methods usually imply a certain degree of simplification about the cost items and macroeconomic scenarios identification and quantification.[1] Nevertheless, only in few studies uncertainty is taken into account through sensitivity analyses, mainly focusing on financial parameters and thus highlighting that the variation of such parameters may lead to substantial changes in optimal levels and related technologies over time (Basinska et al., 2015; Thalfeldt et al., 2017; Hamdy et al., 2017; Copiello et al., 2017). Ferrara et al. (2018) concluded that future research work should concern the robustness of cost-optimal design solutions to the variation of boundary conditions, such as climate and economic scenarios.

LCC is significantly influenced by assumptions on key parameters, such as discount rates, investment costs, prices of components and energy, building lifespans and components service lives (Moore and Morrissey, 2014). As recently stated by Ilg et al. (2016), the variety of sources and types of uncertainty in LCC makes it difficult even to provide a meaningful and simple categorization. The possible inconsistency of LCC approaches not properly taking uncertainty into account, therefore, has been already emphasized within this literature (Goh et al., 2010; Menassa, 2011; Sesana and Salvalai, 2013; Das et al., 2015). It has been demonstrated that poor availability and reliability of input data, or inaccurate assumptions on macroeconomic variables, may jeopardize results reliability and lead to improper decisions (Burhenne et al., 2013; Di Giuseppe et al., 2017a), *de facto* limiting the LCC application (Gluch and Baumann, 2004).

Disregarding uncertainty neglects that, according to economic theory, investment decisions depend on both the expected net returns and their variance, as the larger the variance the riskier the investment (Bodie et al., 2018). This affects investment decisions according to investor risk aversion and to the availability of financial instruments taking care of this risk. Moreover, investment decisions do not just concern the “to do or not to do” dilemma but, more frequently, the choice among alternative investments (or the optimal combination of different investments), as well as the choice of the proper timing of the investment itself. In this respect, the uncertainty about investments' returns (thus, the variance) may become a key criterion, since it may significantly differ across alternatives and in moments in time depending on varying external economic conditions. As a consequence, taking uncertainty properly into account is not only important to assess and predict investors’ decisions, but also to properly design policies aimed to affect them.

2.2. The main methodological challenges and the proposed approach

In order to contribute to the recent literature on LCC under uncertainty, this paper proposes a Monte Carlo-based stochastic approach to LCC of energy efficiency measures and a model to characterise the macro-economic scenario for the assessment. First of all, this approach provides a realistic decision support during the design phase by delivering evidence about design robustness and possible ranges of performance indicators (economic returns) of a specific design option. Secondly, it compares the economic performance of different design options both in terms of expected returns and of its variance, thus possibly identifying the dominant/dominated alternatives (i.e. those with a higher/lower expected return and a lower/higher variance). Therefore, it also suggests a sort of portfolio of alternatives to be optimized by combining different expected values and different risks. Thirdly, through sensitivity analysis it provides evidence about the magnitude of LCC input parameters' and variables’ uncertainty and about their impact on the results.

Although the proposed methodology is partially based on previous works (Wang et al., 2012; Burhenne et al., 2013; Di Giuseppe et al., 2017a,b), it substantially improves the existing approach on several aspects to better capture the economic rationale underlying the “probabilistic” nature of some of the key variables included in the LCC calculations.

The first novelty consists in that the probabilistic nature of LCC input variables now takes their time dependency explicitly into account. In practice, these economic variables behave like random variables whose distribution at a given time *t* is conditional on their realization at previous times *t-s*. Under stationarity (thus the initial conditions do not influence the variable values after a long-enough period), the probabilistic LCC calculations over a time span T are no more obtained as a sequence of T independent draws but as a draw of an interdependent sequence over T. This implies that the “probabilistic LCC” should be more properly called a “stochastic LCC” and this term will be used henceforth.[2]

The second and major novelty of the present approach is that not only LCC macroeconomic variables are time dependent, but they are also interdependent. In practice, they are time-interdependent. This means that any variable's distribution is conditional on the distribution of the other variables and, therefore, due to time dependency, on the lagged distributions of the other economic variables.[3] Rather that NxT independent draws (where N is the number of variables), the approach thus draws a sequence of T values of a Nx1 vector.

A third major novelty is the consequence of the abovementioned time interdependence among economic variables entering the LCC. As economic theory and empirical evidence highlight, this interdependence depends (in intensity and direction) on the macroeconomic “climate” or “scenario” in which it occurs. “High growth-low inflation” and “low grow-high inflation” are two quite diverse macroeconomic conditions whose difference is, in fact, reflected into a different interdependence between the macroeconomic variables involved: Gross Domestic Product (GDP) growth rate, inflation rate, interest rate. There is already a significant amount of studies where the LCC exercise has been repeated and results compared, across alternative scenarios (see, for instance, Di Giuseppe et al., 2017a,b).[4] In all those cases, however, scenarios are defined upon some more or less arbitrary or *ad hoc* conjectures about the future. Here, scenarios are defined on the basis of actual historical experiences, that expressed a different linkage and interdependence among macroeconomic variables (see section 4).

The consequent forth major novelty is that no distributional assumption is needed (actually, normality is maintained for simplicity), as the Monte Carlo simulations are based on the estimated distributions of the macroeconomic variables and this estimation is made on observed time series. Therefore, the typical concern about the reliability of the distributional assumption in probabilistic LCC calculations is here substantially downscaled: not only these distributions are estimated from real data, but also alternative distributions can be obtained by looking at different time series as expressions of different medium-long term macroeconomic conditions.

3. The LCC calculation model

The proposed LCC method for assessing the convenience (or affordability) of building retrofit interventions is based on the procedure of European Standards EN 15459–1:2017 (CEN, 2017). This procedure

[1] For instance, in the methodology framework established by Directive 2010/31/EU, the practice of using constant market interest rates and inflation rates ignores the possibility of variations over the life cycle resulting from changes in monetary and fiscal policies (Morrisey et al., 2013).

[2] In fact, this is not the first attempt to adopt a stochastic instead of a probabilistic LCC approach by taking time dependence into account. For instance, some recent studies have already put forward similar methodological improvements (see Pittenger et al., 2012; Burhenne et al., 2013).

[3] For a deeper discussion on the economic rationale of this interdependence see section 4.

[4] The same can be noticed in homologous Life Cycle Assessment (LCA) studies (Roux et al., 2016).

leads to two possible economic indicators of this convenience: the Global Cost (GC), and the Payback Period (PP). As these indicators are directly linked to the length of the LCC calculation period (CP), results can be compared on different time horizons.

Retrofit interventions can be performed according to alternative design options. The cost categories included in this calculation are: (1) the initial investment costs; (2) the energy costs; (3) the maintenance costs; (4) the replacement costs. The GC of the j-th option at the end of the CP, but referred to the starting year (t = 0) (i.e., $GC_{j,0}$), is calculated following the method described in equation (7) of the Standard EN 15459-1:2017. As suggested by the standard itself, the formula is here adapted to propose annual variations of the discount rate and of price development rates, as follows[5]:

$$GC_{j,0} = CI_j + \sum_{t=1}^{CP} [(CM_j + CS_{j,\,t})R_t^{disc}\, R_t^{L} + CE_j\, R_t^{disc}\, R_t^{E}] - Val_{j,\,CP} \tag{1}$$

where CI_j are the initial investment costs, CM_j the annual maintenance costs assumed constant, CE_j the annual energy costs assumed constant, R_t^{disc} the discount factor, R_t^L and R_t^E the price development rates (respectively for human operation and for energy), $CS_{j,\,t}$ the replacement costs assumed equal to the discounted investment costs whose frequency depends on the service life SL_j of the design option as follows:

$$CS_{j,\,t} = \begin{cases} 0 & \text{if } \; t \notin (SL_j + 1{,}2SL_j + 1, \ldots), \quad t \le CP \\ CI_j & \text{if } \; t \in (SL_j + 1{,}2SL_j + 1, \ldots), \quad t \le CP \end{cases} \tag{2}$$

$Val_{j,\,CP}$ is the residual value of the j-th investment design option at the end of the CP. Its calculation is based on a straight-line depreciation of the initial investment or replacement cost of the option until the end of the calculation, discounted at the beginning of the evaluation period, as follows:

$$Val_{j,\,CP} = CI_j \left(\frac{r_j}{SL_j} \right) R_{CP}^{disc}\, R_{CP}^{L} \tag{3}$$

where r_j represents the remaining lifetime at the end of the CP of the last replacement:

$$r_j = \left\{ SL_j \left[int\left(\frac{CP-1}{SL_j} \right) + 1 \right] \right\} - CP \tag{4}$$

The discount factor R_t^{disc} depends on the discount rate. Following the EN 15459-1, the LCC equation is specified in real terms. The discount rate d_t thus expresses the real interest rate as $d_t = \frac{i_t^N - \pi_t}{1+\pi_t}$ where the π_t indicates the inflation rate and i_t^N the nominal interest rate. The LCC calculation here performed is "dynamic" in the sense that π_t (inflation rate) and i_t^N (nominal interest rate) vary over time. Therefore, the discount factor R_T^{disc} is itself time variant as it is computed as $R_t^{disc} = \prod_{s=1}^{t} \frac{1}{1+d_s} = \frac{1}{1+d_1}\, \frac{1}{1+d_2} \cdots \frac{1}{1+d_t}$.

Accordingly, price development rates R_t^L and R_t^E, applied to all cost components of the LCC equation (i.e. energy costs, periodic or replacement costs, maintenance costs),vary over time as follows: $R_t^L = \prod_{t=1}^{T} (1+e_t^L) = (1+e_1^L)\,(1+e_2^L) \ldots (1+e_T^L)$ and $R_t^E = \prod_{t=1}^{T} (1+e_t^E) = (1+e_1^E)\,(1+e_2^E) \ldots (1+e_T^E)$. R_t^L expresses the price development rate of labour (L) (i.e., the wage development rate) and, as clear in (1), applies to maintenance and replacement costs. R_t^E expresses the price development rate of energy (E) and applies to energy costs. Consequently, the respective escalation factors e_t^L and e_t^E are defined as $e_t^L = \frac{w_t - \pi_t}{1+\pi_t}$ and $e_t^E = \frac{o_t - \pi_t}{1+\pi_t}$ where w_t and o_t indicates the nominal wage and oil price growth rates at time t, respectively.

The payback period (PP) can be very helpful to compare different design options. It can be calculated as the minimum number of years (S) making the cumulative energy savings equalizing the total investment costs (i.e., the initial investment plus the maintenance and the replacement costs). As a discounted PP is computed, the present value of these savings and costs are here defined as follows:

$$\begin{aligned} Savings_j &= \sum_{t=1}^{S} [(PE_H^{pre} - PE_{Hj}^{post})EnT]R_t^{disc}\, R_t^{E} \\ Costs_j &= CI_j + \sum_{t=1}^{S} [(CM_j + CS_{j,\,t})R_t^{disc}\, R_t^{L}] \end{aligned} \tag{5}$$

where PE_H indicates the heating energy consumption expressed as $PE_H = (Q_H/\eta_H)$. Q_H^{pre} is the building pre-renovation energy need, Q_{Hj}^{post} is the building post-renovation energy need, associated to the j-th design option; η_H is the building equipment overall efficiency for heating; EnT is the energy tariff. η_H depends on the quality of the building heating equipment while EnT depends on the energy carrier. The remaining cost categories and economic parameters in (5) are expressed as in (1).[6]

Equations (3) and (4) are adapted from equation (6) of EN 15459-1:2017, while equation (5) is adapted from equation (8) of EN 15459-1:2017 to ease the implementation of the calculation procedure in the software environment R.[7]

4. The stochastic approach to LCC

The analysis of the retrofitting investment GC and PP is here performed through Monte-Carlo simulations fed with draws of the LCC uncertain (i.e., stochastic) parameters. This requires defining the stochastic nature (the Probability Density Functions, PDFs) of all LCC variables and parameters (the inputs of the GC and the PP calculation). They can be grouped in 3 major categories: the parameters related to the design option characteristics (investment cost, service life, maintenance costs); the parameters related to the building energy performance and the energy carrier (building energy need; building overall efficiency for heating, energy source national tariff); the macroeconomic variables (inflation rate, market interest rate, price development rates). The former two categories here defined "technical variables", express the specific technical characteristics of the intervention under study (interior insulation solutions in historic buildings, in the present analysis). They will be presented and discussed in detail in section 5 with regard to an exemplary case.

The way macroeconomic variables enter the adopted LCC approach represents one of the main contributions of the present study and, thus, is described in detail in this section.

4.1. VAR modelling in macroeconomics

The adopted LCC calculation includes four macroeconomic variables: the inflation rate, the real interest rate, the real GDP growth rate (proxying the growth rate of wages in real terms), the oil price growth rate. The dynamics of these variables is the main source of uncertainty within the stochastic LCC. In the proposed method, the macroeconomic variables are drawn from a parametric model, estimated on observed time series. Out-of-sample projections of this estimated model are then generated to have projections of the individual macroeconomic variables entering the LCC.

The main challenge in generating such projections, in fact, consists in properly specifying this parametric model eventually expressing the actual stochastic processes generating these series (Sims, 1980). Macroeconomic theory suggests that these variables are the expression of

[5] It is worth reminding that the costs associated to greenhouse gas emissions are neglected because LCC is here performed in a "financial" perspective, that is the perspective of a building designer or owner.

[6] It is worth noticing that, unlike the GC, the PP ignores all costs and savings that occur after payback has been reached.

[7] https://www.r-project.org/.

the formation of macroeconomic equilibria. These equilibria make these variables endogenous and interdependent, while their dynamics arises from the timing of the adjustment to new equilibria. Macroeconomic models representing the formation of these equilibria are extremely complex (dozens if not hundreds of equations and unknowns) and may strongly differ across theoretical traditions (Christiano et al., 2018; Lutz and Lütkepohl, 2017). Nonetheless, since the seminal work of Sims (1980) the empirical investigation of these equilibria has progressively overcome the complexity (and the controversies) of the macroeconomic theoretical models, by specifying and estimating systems of simultaneous dynamic reduced-form equations, where any endogenous macroeconomic variable is determined by its lagged values and by the lagged values of all other macroeconomic variables of interest. These are called Vector AutoRegression (VAR) models (Christiano et al., 2006, 2018).

By empirically expressing the formation of the underlying macroeconomic equilibria, VAR models are also able to capture the specificity of these equilibria in time and space, thus adapting to the specific macroeconomic context and environment under investigation. Indeed, different specific macroeconomic contexts, may find significantly different equilibria among the endogenous variables, also due to the specific dependence of these equilibria on external shocks transmitted through exogenous variables. Among these variables, of more interest here, is the possible role of the oil price as an exogenous variable and a source of shock. [8]

Even though the four variables under consideration here (i.e.: interest rate, GDP, inflation and oil price) are typically included in macroeconomic VAR models (Sims, 1980; Smets and Wouters, 2003), it is not possible to formulate univocal ex-ante expectations on the linkages among them. *Ceteris paribus* (i.e., if other shocks are excluded), the prevalent theoretical expectations in terms of their short-term relationship are the following. A positive demand-side shock on growth, induces a positive adjustment of both inflation and real interest rates; a positive monetary shock on the interest rate, negatively affects growth and thus the inflation rate; a positive supply-side shock on inflation rate (like, for instance, an oil price shock), depresses growth and thus the interest rate. Nonetheless, by activating complex re-equilibrating feedbacks, all these shocks induce a dynamic adjustment that may eventually downsize, and even revert, the shorter-term response to these shocks.

In practice this complex dynamic relationship, of which the VAR model is the reduced form, prevents from anticipating a general correlation among the macroeconomic variables under consideration. The magnitude and direction of this correlation are time and country-specific and the VAR model estimation allows to recover them from the past, that is, looking at real time series. Simultaneous projections of macroeconomic variables can be thus generated from multivariate relationships estimated on these observed time series, rather than relying on individual and static statistical distributions assumed *ex ante*.

4.2. The adopted VAR model

The modelling approach here adopted to generate macroeconomic projections is a Vector AutoRegression model with exogenous variables (VARX). A VARX model assumes that the behaviour of N economic series can be represented by a discrete multivariate stochastic process as follows (Lütkepohl, 2005):

$$\Pi(L)\mathrm{Y}_t = \mathrm{c} + \beta'\mathrm{X}_t + \mathrm{u}_t, \quad t = 1, \ldots, T \tag{6}$$

$\Pi(L) = \mathrm{I}_N - \Pi_1 L - \ldots - \Pi_p L^p$ is the lag polynomial where Π_p are NxN coefficient matrices. Y_t is the Nx1 vector of the endogenous economic series observed at time t, c is the Nx1 vector of constant terms, X_t is the Mx1 vector of the exogenous variables observed at time t, β is the MxN matrix of unknown coefficients, u_t is the Nx1 vector of i.i.d. disturbance terms distributed as N(0,Ω) with Ω indicating the variance-covariance. Provided that the N series in Y and the M series in X are stationary (i.e., I(0)), the unknown coefficients in (6), included the terms in Ω, can be consistently estimated and the respective relationship among the variables can be thus projected outside the observed sample. Given the normality assumption on the disturbance terms, estimation is here performed via Maximum Likelihood estimation.

In the present work, the variables included in Y are: the inflation rate (π), the interest rate (i^R) and the GDP growth rate (g^R) both expressed in real terms. The only exogenous variable included in X is the oil price (O). Moreover, it is assumed that oil price directly influences only the inflation rate while the other two variables in Y are affected only indirectly via $\Pi(L)$. Consequently, the only non-zero terms admitted in β are those concerning the inflation rate. Unit root tests clearly indicate that all variables in Y behave like I(0) series while the oil price is I(1). Therefore, this latter variable enters (6) as first difference (i.e., the change of oil price from t-1 to t).[9] π and i^R enter the LCC calculation as described in Section 3. g^R, combined with π, defines the price development rate, specifically accounting for the dynamics of labour costs (i.e., wages).[10] Finally, O is used to express the price development rate of energy. According to (1), all economic variables enter the LCC calculation in nominal terms, in order to make explicit the influence of inflation rate on global costs. Therefore, the projections of the real interest rates and real GDP growth obtained from the VAR model estimation are transformed into nominal variables using the corresponding projections of inflation rates.

The VAR model is estimated on the basis of real data, i.e. observed time series. As different historical experiences might be considered in this respect possibly leading to different VAR estimates, a choice has to be made on which time series to adopt. In practice, the approach can be performed on alternative macroeconomic climates or scenarios. The macroeconomic scenario here considered aims to express a sort of regular (or baseline) case, a balanced growth path of the economy with an inflation rate around 2% and mild GDP growth and long-term real interest rates. The evolution of the Western European countries during the 1980–2005 period is here assumed as the reference for this regular (or baseline) scenario. By Western European countries here we intend the EU-19 aggregate. For this aggregate, however, data are not available prior to 1990. Therefore, for the period 1980–1989, EU19 data have been replaced with West Germany data.[11]

Following an iterative procedure based on the Akaike Information Criterion, the best fitting VAR is selected among all the possible ones. The model that best fits the data is a VARX(4,1). This is a dynamic system with four lags ($p = 4$) for the endogenous variables and only one lag for the exogenous variable.

[8] The inclusion of oil price (or oil shocks) within macroeconomic VAR models has become popular since late '70s and early '80s particularly to capture the different response to oil shocks (Bernanke et al., 1997; Hamilton and Herrera, 2004; Kilian, 2009). Although for some peculiar country oil price is more correctly assumed as an endogenous variable (see Ito, 2008, for Russia), it is typically assumed that the macroeconomic equilibrium under analysis is affected by the oil price but doesn't affect it (Small Open Country assumption) (Vu and Nakata, 2018). This assumption is here maintained and, therefore, oil price enters the adopted VAR model as an exogenous variable.

[9] Unit-root test specifications and results are available upon request.

[10] Labor cost is assumed to be a major component of maintenance and substitution costs. Neoclassical long-run economic growth models predict that wages grow following labor productivity growth which, in turn, equals the per capita real GDP growth rate (Solow, 1956).

[11] The data source of the macroeconomic variables is the OECD database (http://stats.oecd.org/; accessed 02.11.2017). In the case of the oil price, the series adopted for the 1980–2005 period are taken from the Energy Information Administration (EIA). Data have been dowloaded from https://www.eia.gov (accessed on 02.11.2017).

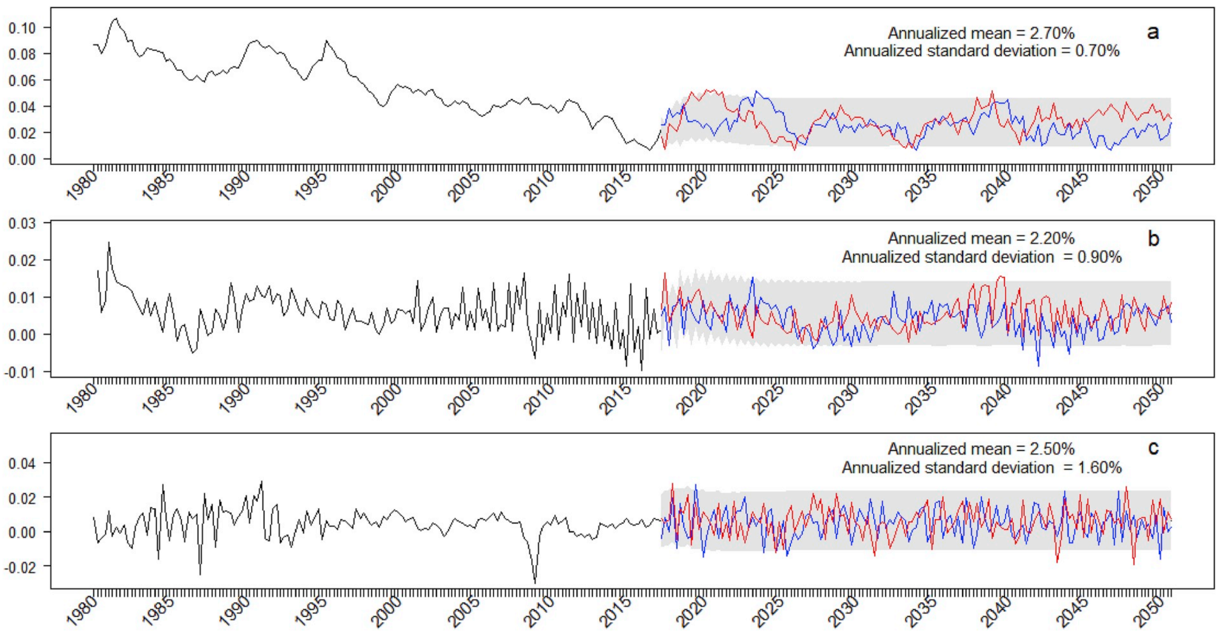

Fig. 1. Quarterly observed macroeconomic series (in black), 2 exemplary 30-years projections (red and blue lines) and sample mean, standard deviation ad the 95% confidence interval computed on 5632 simulation runs: interest rate (real) (a), inflation rate (b), GDP growth (real) (c). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4.3. Macroeconomic projections and sensitivity analysis

Once the VARX(4,1) model is estimated on the basis of historical data, it can be used to generate 30-years predictions of the three endogenous economic variables (inflation rate, interest rate and GDP growth). To generate these predictions, the VAR model must be firstly fed with a projection of the exogenous variable. Here, the first difference of the EIA oil price 2017–2050 forecast is used. Then, a Monte Carlo simulation approach is adopted to generate *K* draws of shocks on the three macroeconomic variables. *K* 30-years simultaneous projections of these variables are finally generated from the estimated VARX (4,1) model.

Fig. 1 is aimed to illustrate this modelling exercise on macroeconomic variables. For the three endogenous variables, it reports the observed time series (from 1980 to 2017) then followed by the respective 30-years VAR predictions generated with the Monte Carlo simulation discussed above. 5632 simulation runs are performed, and theFig. 1 reports and depicts the respective annualized sample means, standard deviations and confidence intervals.[12] For the sake of understanding, for any endogenous variable Fig. 1 only exhibits two exemplary projections out of the 5632 obtained.

Together with the Monte-Carlo draws of the other LCC parameters identified by proper PDFs (see section 5), these projections of the macroeconomic variables propagate the stochastic nature of the LCC calculation into a statistical distribution of its output variables (*GC* or *PP*). Such distribution can be thus used to assess the economic performance of a design option in the mean-variance space, that is, in terms of expected value (the mean) and risk as expressed by its variability (the variance). On this basis, different design options can be compared to find the cost-optimal solution according to the European framework based on Energy Performance of Buildings Directive (EPBD) Recast 2010/31/EU (OJEU, 2012a,b).

As described in Di Giuseppe et al. (2017a), on this stochastic nature of the LCC outcome a Sensitivity Analysis (SA) can be finally performed through variance-based decomposition (Sobol method; Sobol, 2001). The Sobol method is used to calculate, for any stochastic input of the LCC calculation, *total order sensitivity index* (STi).[13] STi measures the contribution to the output variance due to each input, including all variance caused by its interactions with any other input variables (Saltelli et al., 2008; Saltelli et al., 2010). The higher the value of the sensitivity indices, the most influential the respective input on the LCC outcome.

5. Case-study application

The stochastic LCC approach presented above is here illustrated through a case-study: the application of alternative interior insulation solutions (the *design options*) in a historic building. Historic buildings represent about the 30% of the EU stock (EC, 2010) and any renovation action aimed to improve their energy performance must preserve the external façades due to their architectural quality. Therefore, results here obtained are representative for this whole class of buildings and interventions. Under the same baseline macroeconomic scenario, alternative energy scenarios (alternative building heating equipment and related energy carriers) are also considered. For this case-study application, the inputs of the LCC calculation, beside the macroeconomic variables, are the technical variables detailed in Table 1. The respective stochastic characterisation is also summarized in the last two columns of Table 1 and will be detailed in sections 5.1 and 5.2.

The initial *Investment Costs* include all the purchase, construction and installation costs of the insulation system considered. The *Energy Costs* are the annual costs of the building heating system obtained multiplying the annual heating energy (PE_H) by the tariff for the energy

[12] Monte Carlo simulations are derived at quarterly frequency but are then annualized before entering the LCC calculation. As all these variable behave as I (0) series mean value and standard deviation projections evidently become constant already after few quarters.

[13] The Sobol method also allows the calculation of another index called *first-order sensitivity index* that indicates the main contribution of each input factor to the variance of the output. Due to space limitations, though the adopted approach also computes this further index, respective results are not reported here and are available upon request.

Table 1
List and groups of parameters entering LCC calculation and their proposed stochastic characterisation.

LCC parameter		Proposed PDF	Reference for the stochastic characterisation
Design option characteristics	*Investment cost* [€]	Normal	Data fitting on available cost data
	Service life [years]	Normal	Probabilistic Factorial Method (ISO 15686-8)
	Replacement costs [€]	Normal	As investment costs
	Annual maintenance costs [€]	Normal	Data fitting on available cost data
Building energy performance and energy carrier	*Building energy need* [kWh/y]	Normal	Data fitting on calculated wall heat loss, considering a variation on wall thickness and on Heating Degree Days (HDD) data
	Energy source national tariff [€/kWh/y]	Uniform	Data fitting on available tariffs data
	Building overall efficiency for heating	Normal	Author judgement

carrier considered as already specified in (5). The *Maintenance Costs* concern the need of periodic maintenance of the internal finishing material, i.e. the rendering or the painting over the insulation, which depends on the estimated service life of these specific materials. Estimated periodic maintenance costs are here "yearly distributed" in order to obtain annual maintenance costs. Finally, the *Replacement Costs* of the design options are recurrent costs, with a frequency depending on the service life of the insulation system concerned. The replacement costs are considered equal to the initial investment costs needed to replace the whole design option.

5.1. Design options

The case study under investigation refers to the internal thermal insulation typically used for historic building renovation in Italy. In particular, the intervention concerns a plastered brick masonry with a variable thickness (from 16 to 29 cm) of a historic building that is supposed to be in the region Emilia-Romagna, climatic zone "E". This case is representative of many buildings needing renovation in the EU, as brick masonry is the dominating wall typology for historical buildings in EU countries.[14] Three alternative design options are considered (Table 2):

1. Insulation system A: 10 cm Expanded Polystyrene insulating material (EPS) coupled with plasterboard, without vapour barrier, directly fixed to the wall through a specific mortar.
2. Insulation system B: 12 cm Cork, finished with a specific mortar as surface rendering (similar to ETICS used in building facades) and directly fixed to the wall through a mortar.
3. Insulation system C: 10 cm Rockwool coupled with plasterboard, with vapour barrier, fixed to the wall through a metallic frame.

All internal insulations reach almost the same U-value (i.e., the overall heat transfer coefficient) for the wall based on the actual Italian law requirements (0.33 W/m^{2}K for the insulation system B and 0.34 W/m^{2}K for the insulation systems A and C). The slight difference depends on the commercial insulation thicknesses available in the market.

The statistical distributions of the investment costs are assumed normal and are obtained through a data-fitting procedure on the following available costs data: prices of the materials composing the insulation system; labour cost for the insulation system installation; overheads (including safety costs); enterprise profits; discounts; Value Added Tax (VAT). Data about these costs are obtained from the pricing lists available in the web or at retailers, from national data on labour costs published by Italian Labour Ministry,[15] from discounting data provided by the Regional Administrations. A VAT of 10% (as for private user) was considered according to national legislation.

Table 2
Technical characteristics of the design options under analysis.

Layer:	Standard thickness [m]	Density [kg/m^3]	Thermal conductivity [W/mK]
Insulation system A			
Adhesive mortar	0.006	1400.00	0.540
EPS	0.100	18.00	0.035
Adhesive mortar	0.006	1400.00	0.540
Plasterboard	0.013	680.00	0.200
Skimcoat	0.004	1200.00	–
Primer + paint	0.0002	1670.00	–
Insulation system B			
Adhesive mortar	0.007	950.00	0.310
Cork	0.120	120.00	0.040
Surface rendering	0.007	950.00	0.310
Primer + paint	0.0002	1670.00	–
Insulation system C			
Rock Wool	0.1	70.00	0.035
Vapour barrier	0.0002	2700.00	–
Plasterboard	0.013	680.00	0.200
Skimcoat	0.004	1200.00	–
Primer + paint	0.0002	1670.00	–

For the probabilistic characterisation of the service life, a reference service life of 30 years is assumed and a Probabilistic Factorial Method (ISO, 2008) is then applied where all factors matter, except for Factor E (outdoor environment), and a uniform distribution (0.9; 1.1) is assigned (Re Cecconi, 2011). For the replacement costs, the same cost items and normal distribution of the investment costs are considered. For maintenance costs, the only item taken into account is the wall internal painting with a specific frequency for all the insulation systems. Painting material costs data come from a regional pricelist. Consistently with standard EN 15459, maintenance costs are then yearly distributed, based on an internal panting service life established at 15 years. For the calculation of the e*nergy need* (Q_h) the U-value follows a uniform distribution according to the wall thickness variation. On this basis, Q_h calculation has been performed based on the annual HDD method[16] and a normal distribution is adopted considering the HDD annual variations (years from 2000 to 2009). The heating hours per day have been fixed at 24.

[14] See the report on historical building types and combinations of structural solutions produced within the RIBuild H2020 project (https://www.ribuild.eu/sites/default/files/RIBuild_D1.1_2.0.pdf).

[15] D.D. n. 23/2017, 3rd April 2017 on the average hourly labor cost in Italy for employees of construction companies (original in Italian). Available from: http://www.lavoro.gov.it/temi-e-priorita/rapporti-di-lavoro-e-relazioni-industriali/focus-on/Analisi-economiche-costo-lavoro/Documents/Operai-maggio-2016.pdf [accessed on 14.06.2018].

[16] The HDD of Emilia Romagna Region, climatic zone E (Italy), were extracted from Eurostat database (http://ec.europa.eu/eurostat/web/products-datasets/-/nrg_chddr2_a [accessed on 14.06.2018]) and calculated by the Joint Research Centre (Institute for Environment and Sustainability - IES/MARS Unit).

5.2. Energy scenarios

Beside energy needs, energy costs are computed under three alternative building equipment solutions for heating with respective energy sources: natural gas (GAS), electricity (ELE), oil (OIL). The statistical distributions of the energy tariffs are assumed uniform. For gas and electricity, the mean value is given by the real actual tariff in the regulated market, while the tariff's variability is that observed in the free market in Italy. The empirical mean and variability of tariff of the oil for heating are derived from the Italian union of oil companies and are based on monthly oil price data provided by the Ministry of Economic Development.[17] All tariffs include taxes. Finally, the following uniform distributions are assumed for the heating equipment efficiency considering typical ranges in Italy: 0.6–1 for natural gas, 2.5–4 for electricity and 0.4–0.8 for oil.

6. Results and discussion

The Monte-Carlo stochastic LCC analysis is applied to the three design options under the three alternative energy scenarios. A study period of 30 years is assumed[18] and 5632 simulation runs are performed. The empirical statistical distributions of the resulting LCC output (*GC* and *PP*) are obtained (sections 6.1 and 6.2) and the SA is performed on these results (section 6.3). Section 6.4 reports a comparison of the LCC stochastic results to those obtained through the standardized "deterministic" calculation, considering typical values assumed for the macro-economic variables, to validate the proposed approach.

6.1. Comparing design options

Fig. 2 suggests that results present considerable variability, thus uncertainty. For any design option, the box plots represent only the 50% probability that Global Costs are contained within those ranges. GC vary (interquartile range) from 110 to 130 €/m^2 for solution A, from 147 to 170 €/m^2 for solution B and from 124 to 140 €/m^2 for solution C. It is also worth noticing that the median GC significantly differs across options. It varies from 119 €/m^2 for the insulation system A (EPS) to 158 €/m^2 for the insulation system B (Cork), while it is 132 €/m^2 for the insulation system C (Rock Wool). The same is observed for the median PP varying from a minimum of 4.7 years (A) to a maximum of 8.3 (B). In general, it emerges that option A ensures the lower GC and PP, followed by options C and B.

The ranking of options based on the mean or median performance is confirmed by the respective variability. Fig. 3 reports the Cumulative Distribution Function (CDF) of the two performance indicators (GC and PP) and of the three options. This representation is useful to compare the probability that a certain solution reaches a global cost target. For instance, by fixing a GC of 160 €/m^2, there is a higher than 90% probability that solutions A and C reaches the target, while this probability falls at 60% for solution B. As the comparison across options are made on the same energy scenario (GAS in the present case), this difference among the three insulation measures is mainly due to the different initial investment costs (above all, insulation materials and labour cost) while, in practice, maintenance costs are the same and energy costs are very similar.

6.2. Comparison across alternative energy scenarios

An even larger variability of the investment performance emerges whenever alternative energy scenarios are admitted. Figs. 4 and 5 display the median and the CDF of the six possible combinations of options and energy scenarios. Results confirm a clear univocal ranking of the alternatives: under any energy scenario, option A is the best performing while option B is the worst. At the same time, for any design option, the ELE scenario is the best case while OIL is, by large, the worst.

Such ordering can be further appreciated by displaying the six cases on a mean-variance space (Fig. 6). This allows the ordering of cases using the following conventional utility score (U_j) (Bodie et al., 2018): $U_j = -E(GC_j) - \rho VAR(GC_j)$, where $E(GC_j)$ and $VAR(GC_j)$ indicates the mean and the variance of the GC of the j-th option, respectively, $\rho > 0$ is a risk aversion coefficient, with $\rho = 0$ under risk neutrality. Therefore, for a given value of ρ, it is possible to draw an indifference curve in the mean-variance space expressing all the mean-variance combinations on which the investor is indifferent as they grant the same utility. At the same time, if for cases j and i it is $E(GC_j) < E(GC_i)$ and $VAR(GC_j) < VAR(GC_i)$ it can be concluded that the j-th option is always preferred to the i-th one, regardless the value of ρ (case *j* dominates *i*). According to Fig. 6, it clearly emerges that option A and the ELE scenario always dominate, thus provide a univocal ranking of cases. In only one pair of cases (C-Gas and B-Ele) indifference possibly occurs with a mild risk aversion coefficient of $\rho = 0.72$.

6.3. Sensitivity analysis and robustness check

The actual validity of the proposed stochastic LCC approach depends on the reliability of the conclusions being drawn. This reliability, in turn, consists in the robustness of the results and in the accuracy of these results with respect to the real system the model aims to reproduce. The present and the following sections thus aim to assess the robustness of results produced by the approach and to validate it. The stochastic nature of the proposed approach seems particularly informative for both these efforts.

On the first aspect, in particular, the approach not only generates stochastic LCC outcomes, thus it allows assessing the variability of this outcome given the dataset entering the LCC calculation. More importantly, it enables evaluating the main determinants of this variability. As anticipated, this assessment of the robustness of the results produced and, therefore, of the reliability of the conclusions being drawn, is here performed with a SA, based on the Sobol method. The SA is preliminary to any validation exercise as it indicates which input uncertainty is more influencing the output variance and if this result is still valid assuming several design options and energy scenarios.

Fig. 7 displays the total order sensitivity indices (STi) of the LCC input data for the three insulation solutions under the three energy scenarios. The SA eventually suggests that the main source of results' uncertainty are the initial investment costs and the interest rate. The main difference among the insulation systems STi is that solution B entail higher values for the Investment Costs (CI) and the Service Life (SL), being the most expensive solution. Consequently, the variation of the investment costs STi is quite notable among the different energy scenarios. Insulation Systems A and C investment costs uncertainty influences for less than 17% the output variance, in the gas and oil scenarios. Considering the electricity scenario (which implies the lower energy costs), their impact increases to about 27%. The Investment Cost STi for the Insulation System B impact for less than 30% the output variance in the gas and oil scenarios, reaching 41% in the electricity scenario.

The uninfluential inputs on the output variance (STi < 0.1) are the maintenance costs, due to their relatively low cost, and the inflation rate. This latter result is, in fact, quite predictable. In the LCC calculation the analysis is performed in real terms. The GDP growth rate and interest rate enter in nominal terms, but the inflation rate is used to obtain real values and make its influence on global costs explicit. A similar conclusion can be drawn also for the GDP growth rate whose STi remains quite low in all energy scenarios and, in particular, its

[17] http://www.unionepetrolifera.it/?page_id=948.

[18] Longer periods of 40, 50 and 60 years have also been considered and results are available upon request.

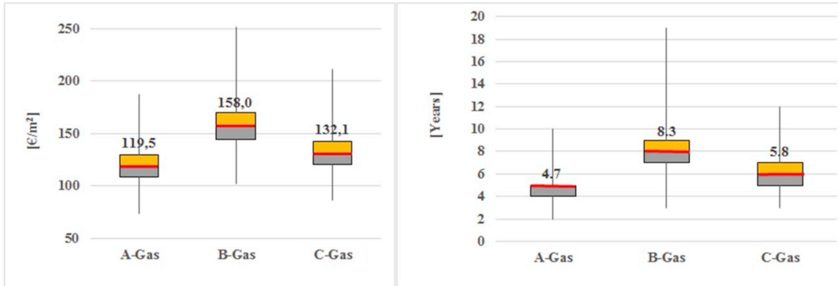

Fig. 2. Box-whiskers plots of the Global Cost (left) and Payback Period (right) for design options A, B, C, with natural gas as energy scenario (calculation period = 30 years).

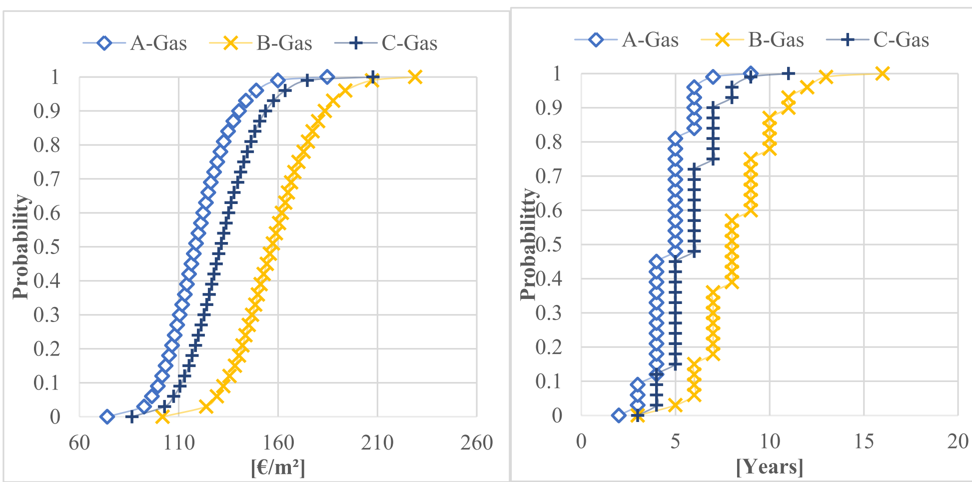

Fig. 3. Cumulative distribution of the Global Cost (left) and Payback Period (right) for design options A, B, C, with natural gas as energy scenario (calculation period = 30 years).

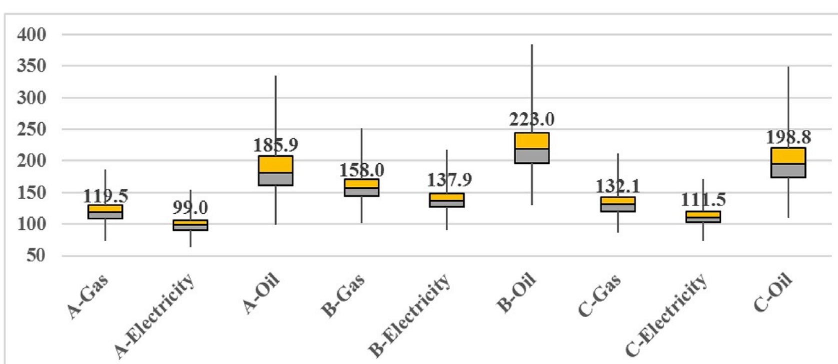

Fig. 4. Box-whiskers plots of the Global Cost for design options A, B and C under electricity, gas and oil scenarios (calculation period = 30 years).

influence is almost negligible in the oil energy scenario.

Among the macroeconomic variables, interest rate is the most influential input parameter in all energy scenarios as it is responsible for about 34–52% of the overall outcome variability. This result is consistent with previous results (Burhenne et al., 2013; Di Giuseppe et al., 2017a,b) and confirms the well-known "*tyranny of discounting*" particularly stressed by the literature on climate change (Portney and Weyant, 1999; Pearce et al., 2003). Not only the interest rate decides about the present value of costs and benefits taking place in the distant future. More importantly, it can deeply influence the overall investment decision as it brings about higher overall outcome variability.

6.4. Model validation

It is worth reminding that the main objective of the present study is to put forward a methodological improvement in LCC calculations compared to the conventional approach adopted in most of the literature and suggested by international regulations and standards. Given this methodological focus, the proposed approach wants to model the conventional LCC practice, while incorporating all possible variants and variability for a given case (i.e., building) under analysis. Therefore, the idea is that the method has to be validated for its capacity to reproduce and contain standard LCC calculations, not on alternative cases but on

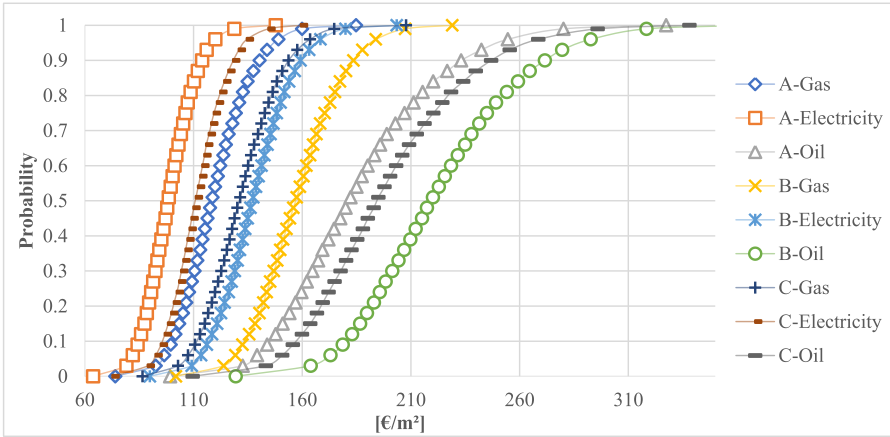

Fig. 5. Cumulative distribution of the Global Cost for design options A, B and C under electricity, gas and oil scenarios (calculation period = 30 years).

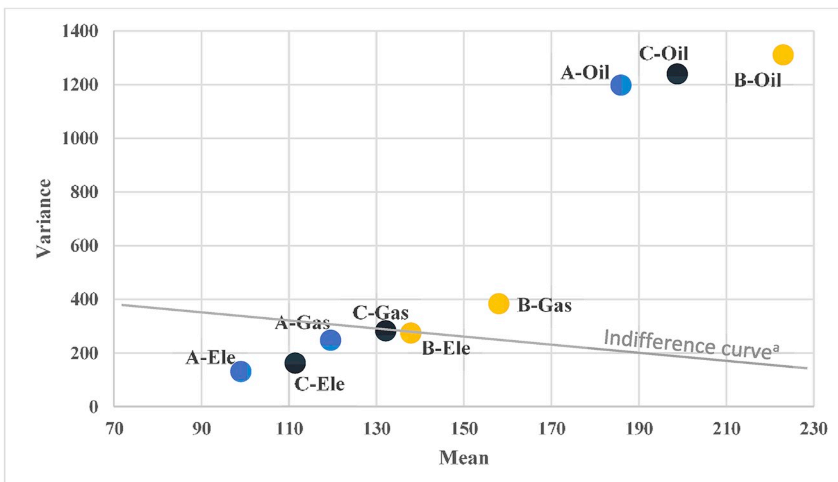

Fig. 6. Comparison of design options and energy scenarios combinations in the GC mean-variance space. [a] All points on the *Indifference curve* have the same Utility = (Mean + 0.72Variance).

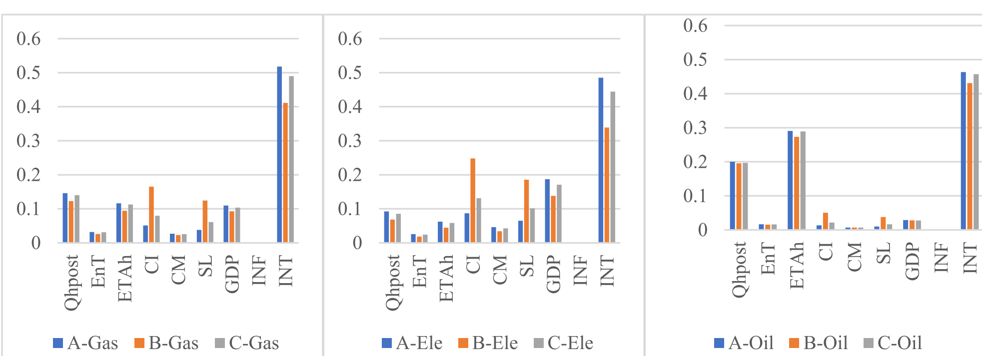

Fig. 7. STi of design options A, B, and C for gas (left), electricity (centre) and oil (right) scenario (calculation period = 30 years). Legend of the LCC input data included in the analysis, Qhpost = heat transmission losses through the wall after renovation; EnT = Energy tariff of the energy source considered; ETAh = overall system efficiency for heating; CI = insulation system initial investment cost; CM = insulation system maintenance cost; SL = insulation system service life; GDP = nominal growth rate of GDP; INF = inflation rate; INT = nominal interest rate.

alternative standard applications on a given building. Hence by validation we mean to assess the performance of the proposed approach by applying the stochastic LCC method to alternative datasets defined as a sequence of *deterministic experiments*. The rationale of this exercise is to verify if the PDFs results obtained through the stochastic LCC (as those presented in sections 6.1 and 6.2) are able to embed those obtained with standard deterministic LCC assessments. A sequence of two complementary deterministic experiments are performed.

Firstly, deterministic LCC is performed by fixing the technical variables at the mean value of their PDFs (see Table 1). For the macro-economic variables, three alternative deterministic scenarios are considered, based on data coming from EU reports and policies:

- "Det 3%" scenario, characterised by a discount rate of 3% and an energy price escalation factor of 2.8%, as suggest by Guidelines accompanying Commission Delegated Regulation (EU) No 244/2012 on the methodology framework for calculating cost-optimal levels of minimum energy performance requirements for buildings (European Parliament, 2012);
- "Det 3% + EIA" scenario, characterised by a discount rate of 3%

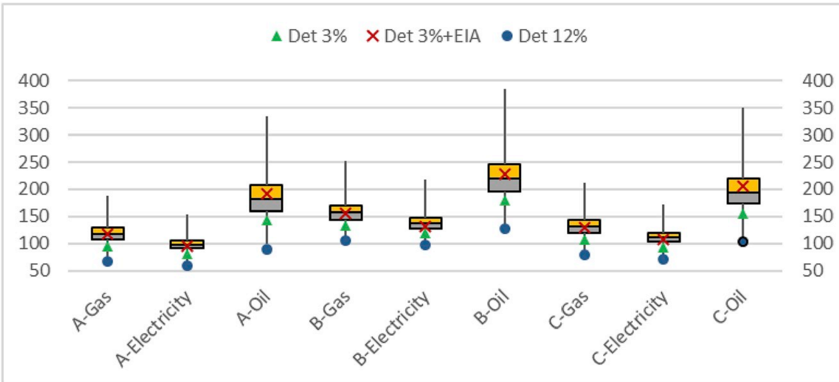

Fig. 8. Box-whiskers plots of the Global Cost for design options A, B and C under electricity, gas and oil scenarios. Coloured dots represent the GC results of the deterministic assessments performed in the scenarios Det 3%, Det 3% + EIA, Det 12% under mean values of the technical parameters (calculation period = 30 years).

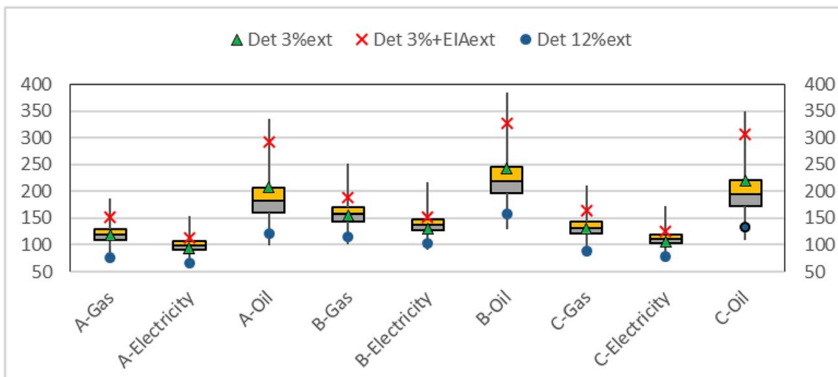

Fig. 9. Box-whiskers plots of the Global Cost for design options A, B and C under electricity, gas and oil scenarios. Coloured dots represent the GC results of the deterministic assessments performed in the scenarios Det 3%, Det 3% + EIA, Det 12% with extreme superior values for the technical parameters Q_H^{post} and η_H (calculation period = 30 years).

and energy price escalation factors according to EIA 2017–2050 forecast[19];

- "Det 12%" scenario, characterised by a discount rate of 12% and a labour escalation factor of 1,5% (as estimated in the EU Report on energy trends to 2050 (EC, 2016c).

The second deterministic experiment fixes the most influential technical inputs according to the SA above, that are Q_H^{post} and η_H , at the superior extreme value of their PDFs. Then, the deterministic LCC is performed again under the three deterministic economic scenarios ("Det 3%ext", "Det 3% + EIAext" and "Det 12%ext" scenarios, respectively).

Results of these validation exercises are presented in Figs. 8 and 9, respectively. They allow appreciating three major strengths of the proposed approach.

First, the outcome of the stochastic LCC calculation is able to contain the outcome of all the deterministic experiments here performed, even considering extreme values of the technical characteristics and extreme economic scenarios (i.e., Det 12%ext). The stochastic LCC calculation here proposed produces results and rankings that maintain their validity under very different applications of the deterministic LCC. In practice, the proposed approach significantly downsizes the typical criticality of the assumption to be made on the conventional LCC input variables.

Secondly, the two validation exercises also make clear another important improvement implied by the proposed stochastic approach. Deterministic experiments, thus the conventional LCC exercises, often fix values of the technical and economic variables independently, thus disregarding that, for instance, if the discount rate is assumed at a very extreme value, the interdependence occurring with the other macroeconomic variables inevitably implies that they also have to be adjusted accordingly. The practical consequence is that deterministic LCC calculation improperly, and often inadvertently, shift the outcome towards extreme values, namely, the tails of the distributions generated by the stochastic LCC approach.

Finally, the deterministic LCC calculations can generate rankings across options and scenarios only on the basis of the computed deterministic global cost. The reliability of these rankings is questionable any time the outcome is very close, and uncertainty is high. For instance, in all the deterministic experiments the performance of the Gas and Electrictiy scenarios for all options (A, B and C) tend to be very close. The stochastic LCC, on the contrary, is able to compare and rank these options and scenarios according to the whole PDF of their performance thus allowing for a more reliable judgment (see Fig. 6).

7. Conclusions and policy implications

The present paper proposes an original stochastic LCC approach to the assessment of building renovation investments. The approach contributes to the investigation on the role of LCC input data uncertainty, especially that of macroeconomic variables, in determining expected returns and riskiness of these investments. Though the main focus of the paper concerns the methodological novelty of the approach used for the characterisation of a macro-economic scenario for a stochastic LCC, it also maintains policy relevance due to the lack of such evaluation tools as emphasized by the recent EU policy initiatives in this field.

On the one hand, public EU funding to improve energy efficiency has remarkably increased over the years. On the other hand, however, there is still the need of further unlocking private financing for energy

[19] https://www.eia.gov [accessed on 01.04.2018].

efficiency investments in order to meet the ambitious environmental targets set up by recent policy commitments (EC, 2018). The building sector, in particular, is expected to represent a critical one in chasing higher energy efficiency (EC, 2016a). A huge amount of investments in building's energy efficiency (i.e.1,300 billion US dollars, according to Energy Efficiency Financial Institutions Group; EEFIG, 2015) is thus estimated to be needed up to 2030.

One of the main problems in achieving the ambitious energy efficiency objective is the apparent lack of private investors' convenience to make such long-term and high-cost investments in buildings, due to this perceived uncertainty. In fact, a growing evidence has been produced that the risks associated with energy efficiency investments are lower than perceived. Therefore, one major challenge to de-risk these investments consists in providing private investors with better and accessible information as well as appropriate evaluations tools and financial instruments.

This policy objective has been recently reinforced by the EU Directive 2018/844 on energy efficiency of buildings, that encourages Member States to support the mobilisation of investments by providing access both to appropriate mechanisms for the reduction of the perceived risk of energy efficiency operations and to "accessible and transparent advisory tools on relevant energy efficiency renovations and financing instruments" (OJEU, 2018). In November 2016, the De-risking Energy Efficiency Platform of the Energy Efficiency Financial Institutions Group (EEFIG) was launched to improve the sharing and transparent analysis of existing energy efficiency projects and to assist financial institutions with appropriate tools for value and risk appraisal (EEFIG, 2017).

However, advisory tools currently used for the evaluation of the (global) cost and expected returns of an energy efficiency retrofitting investment, like the conventional Life Cycle Costing (LCC) methodology, often understate the role of economic variables in determining both the expected returns of the investment and its uncertainty, thus the associated risk. Therefore, the relevance of this study is that the proposed evaluation method can become itself a policy tool available to private and public investors.

Results obtained for an exemplary case-study make explicit how macroeconomic variables and policies eventually affecting these variables - and in particular the interest rate - remain critical in determining private agents' attitude towards these investments. The key role of the interest rate suggests collecting additional evidence on alternative macroeconomic scenarios compared to the "normal" environment here considered. In particular, "extreme" macroeconomic conditions like periods of deflation or stagflation could be analysed. In these peculiar circumstances the relationship among the macroeconomic variables significantly changes and this may substantially affect the LCC outcome. Therefore, this kind of evidence could be helpful to confirm the results here obtained and, in particular, the tyranny of the interest rate.

Nonetheless, with very limited exceptions, results here obtained confirm a clear univocal ranking among alternatives: under any energy scenario there is a "dominant option" that is the best performing, while there is an option that is always the worst. At the same time, for any design option, the electricity scenario is the best case while oil is, by large, the worst. This result indicates a unidirectional private investors choice regardless their risk aversion. In the class of building renovation investments represented by this case study, the main implication of this evidence is that any policy aiming to de-risk these investments through financial risk coverage instruments is not expected to introduce a bias across energy sources and design options.

Sensitivity analysis and validation exercises highlight strengths and potentials of the proposed stochastic approach on which future research is expected to contribute further. The stochastic approach seems more suitable than the conventional deterministic LCC calculations in taking possible extreme values of technical characteristics and economic conditions into account, by maintaining its results and rankings valid over a large set of different values. More importantly, it also reveals that, under these extreme values, the conventional deterministic LCC calculations might fail to capture the interdependency across variables thus generating systematically biased outcomes.

Acknowledgements

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References

Asadi, E., Da Silva, M.G., Antunes, C.H., Dias, L., 2012. Multi-objective optimization for building retrofit strategies: a model and an application. Energy Build. 44 (1), 81–87.
Ascione, F., Bianco, N., De Stasio, C., Mauro, G.M., Vanoli, G.P., 2015. A new methodology for cost-optimal analysis by means of the multi-objective optimization of building energy performance. Energy Build. 88, 78–90.
Basinska, M., Koczyk, H., Szczechowiak, E., 2015. Sensitivity analysis in determining the optimum energy for residential buildings in Polish conditions. Energy Build. 107 (15), 307–318.
Bernanke, B.S., Gertler, M., Watson, M., 1997. Systematic monetary policy and the effects of oil price shocks. Brook. Pap. Econ. Act. 1, 91–142.
Bodie, Z., Kane, A., Marcus, A., 2018. Investments, eleventh ed. McGraw-Hill Education, New York.
Burhenne, S., Tsvetkova, O., Jacob, D., Henze, G.P., Wagner, A., 2013. Uncertainty quantification for combined building performance and cost-benefit analyses. Build. Environ. 62, 143–154.
Burman, E., Mumovic, D., Kimpian, J., 2014. Towards measurement and verification of energy performance under the framework of the European directive for energy performance of buildings. Energy 77, 153–163.
CEN, 2017. EN 15459-1:2017. Energy performance of buildings - Economic evaluation procedure for energy systems in buildings - Part 1: Calculation procedures. Module M1-14, 2017-05-31.
Christiano, L.J., Eichenbaum, M., Trabandt, M., 2018. On DSGE models. J. Econ. Perspect. 32, 113–140.
Christiano, L.J., Eichenbaum, M., Vigfusson, R., 2006. Assessing structural VARs. NBER Macroecon. Annu. 21, 1–106.
Copiello, S., Gabrielli, L., Bonifaci, P., 2017. Evaluation of energy retrofit in buildings under conditions of uncertainty: the prominence of the discount rate. Energy 137, 104–117.
Das, P., Van Gelder, L., Janssen, H., Roels, S., 2015. Designing uncertain optimization schemes for the economic assessment of stock energy-efficiency measures. J. Build. Perform. Simulat. 1493, 1–14.
Delmastro, C., Mutani, G., Corgnati, S.P., 2016. A supporting method for selecting cost-optimal energy retrofit policies for residential buildings at the urban scale. Energy Policy 99 (1), 42–56.
Di Giuseppe, E., Iannaccone, M., Telloni, M., D'Orazio, M., Di Perna, C., 2017a. Probabilistic life cycle costing of existing buildings retrofit interventions towards nZE target: methodology and application example. Energy Build. 144, 416–432.
Di Giuseppe, E., Massi, A., D'Orazio, M., 2017b. Probabilistic life cycle cost analysis of building energy efficiency measures: selection and characterization of the stochastic inputs through a case study. Procedia Eng. 180, 491–501.
EC, 2010. Energy-efficient Buildings PPP. Multi-Annual Roadmap and Longer-Term Strategy. Directorate-General for Research and Innovation (European Commission) 978-92-79-15228-3.
EC, 2011. Proposal for a Directive of the European Parliament and the Council on Public Procurement. EC, Directorate-General for Internal Market and Services. COM, Brussels (2011)896 final.
EC, 2015. Energy Union Package. A Framework Strategy for a Resilient Energy Union with a Forward-Looking Climate Change Policy. EC, COM, Brussels (2015) 80 final.
EC, 2016a. Annex Accelerating Clean Energy in Buildings to the Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank Clean Energy for All Europeans. 30.11.2016 COM. (2016) 860 final ANNEX 1, Brussels.
EC, 2016b. Proposal for a Directive of the European Parliament and of the Council Amending Directive 2012/27/EU on Energy Efficiency. Brussels, 30.11.2016. COM (2016) 761 final.
EC, 2016c. EU Reference Scenario 2016 - Energy, Transport and GHG Emissions-Trends to 2050. European Commission, Directorate-General for Energy, Directorate-General for Climate Action and the Directorate-General for Mobility and Transport, Brussels. https://doi.org/10.2833/9127.
EC, 2018. EU Invests in the Planet: Ten Initiatives for a Modern and Clean Economy. The

Juncker Commission's Contribution to the "One Planet Summit". Paris, 12 December 2017.
EEFIG, 2015. Energy Efficiency – the First Fuel for the EU Economy: How to Drive New Finance for Energy Efficiency Investments. Energy Efficiency Financial Institutions Group, Brussels.
EEFIG, 2017. EEFIG Underwriting Toolkit. Value and Risk Appraisal for Energy Efficiency Financing. Energy Efficiency Financial Institutions Group, European Commission, Brussels.
European Parliament, 2012. Guidelines accompanying commission delegated regulation (EU) No 244/2012 of 16 January 2012. Offic. J. Eur. Union 55, 1–28. https://doi.org/10.3000/19770677.L_2012.081.eng.
Ferrara, M., Monetti, V., Fabrizio, E., 2018. Cost-optimal analysis for nearly zero energy buildings design and optimization: a critical review. Energies 11 (6), 1478. https://doi.org/10.3390/en11061478.
Ferreira, J., Duarte Pinheiro, M., de Brito, J., 2013. Refurbishment decision support tools review-Energy and life cycle as key aspects to sustainable refurbishment projects. Energy Policy 62, 1453–1460. https://doi.org/10.1016/j.enpol.2013.06.082.
Gluch, P., Baumann, H., 2004. The life cycle costing (LCC) approach: a conceptual discussion of its usefulness for environmental decision-making. Build. Environ. 39 (5), 571–580.
Goh, Y.M., Newnes, L.B., Mileham, A.R., McMahon, C.A., Saravi, M.E., 2010. Uncertainty in through-life costing-review and perspectives. IEEE Trans. Eng. Manag. 57 (4), 689–701.
Hamdy, M., Hasan, A., Siren, K., 2013. A multi-stage optimization method for cost-optimal and nearly-zero-energy building solutions in line with the EPBD-recast 2010. Energy Build. 56, 189–203 Elsevier B.V.
Hamdy, M., Sirén, K., Attia, S., 2017. Impact of financial assumptions on the cost optimality towards nearly zero energy buildings – a case study. Energy Build. 153 (15), 421–438.
Hamilton, J.D., Herrera, A.M., 2004. Oil shocks and aggregate macroeconomic behavior: the role of monetary policy. J. Money Credit Bank. 36, 265–286.
Han, G., Srebric, J., Enache-Pommer, E., 2014. Variability of optimal solutions for building components based on comprehensive life cycle cost analysis. Energy Build. 79, 223–231 Elsevier B.V.
IEA, 2017. Energy Efficiency 2017. © OECD/IEA 2017. https://doi.org/10.1787/9789264284234-en.
Ilg, P., Scope, C., Muench, S., Guenther, E., 2016. Uncertainty in life cycle costing for long-range infrastructure. Part I: leveling the playing field to address uncertainties. Int. J. Life Cycle Assess. 5, 1–16 Springer Berlin Heidelberg.
ISO, 2008. ISO 15686-8:2008. Buildings and Constructed Assets - Service Life Planning - Part 7: Reference Service Life and Service-Life Estimation. International Organization for Standardization.
Itard, L., Meijer, F., Vrins, E., Hoiting, H., 2008. Building Renovation and Modernisation in Europe: State of the Art Review. OTB Research Institute for Housing, Urban and Mobility Studies, Delft University of Technology, Delft.
Ito, K., 2008. Oil prices and macro-economy in Russia. The Co-integrated VAR model approach. Int. Appl. Econ. Manag. Lett. 1, 37–40.
Kibert, C.J., 2008. Sustainable Construction: Green Building Design and Delivery, second ed. John Wiley and Sons, Inc., Hoboken.
Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am. Econ. Rev. 99 (3), 1053–1069.
Lütkepohl, H., 2005. New Introduction to Multiple Time Series Analysis. Springer, Berlin3540262393 u.a.
Lutz, K., Lütkepohl, H., 2017. Structural Vector Autoregressive Analysis. Cambridge University Press, Cambridge (UK).
Menassa, C.C., 2011. Evaluating sustainable retrofits in existing buildings under uncertainty. Energy Build. 43 (12), 3576–3583.
Moore, T., Morrissey, J., 2014. Lifecycle costing sensitivities for zero energy housing in Melbourne, Australia. Energy Build. 79, 1–11 Elsevier B.V.
Morrisey, J., Meyrick, B., Sivaraman, D., Home, R.E., Berry, M., 2013. Cost-Benefit assessment of energy efficiency investments: accounting for future resources, savings and risks in the Australian residential sector. Energy Policy 54, 148–159.
OJEU, 2012a. Commission delegated regulation (EU) No 244/2012 of 16 January 2012 supplementing directive 2010/31/EU of the European Parliament and of the council. Offic. J. Eur. Union 18–36.
OJEU, 2012b. Guidelines accompanying commission delegated regulation (EU) No 244/2012 of 16 January 2012 supplementing directive 2010/31/EU of the European Parliament and of the council. Offic. J. Eur. Union 55, 1–28.
OJEU, 2018. Directive (EU) 2018/844 of the European Parliament and of the council of 30 may 2018 amending directive 2010/31/EU on the energy performance of buildings and directive 2012/27/EU on energy efficiency 2018/844. Offic. J. Eur. Union 75–91.
Ouyang, J., Ge, J., Hokao, K., 2009. Economic analysis of energy-saving renovation measures for urban existing residential buildings in China based on thermal simulation and site investigation. Energy Policy 37, 140–149. https://doi.org/10.1016/j.enpol.2008.07.041.
Pearce, D., Groom, B., Hepburn, C., Koundouri, P., 2003. Valuing the future. World Econ. 4 (2), 121–141.
Petersdorff, C., Boermans, T., Harnisch, J., 2006. Mitigation of CO_2 emissions from the EU-15 building stock. Beyond the EU directive on the energy performance of buildings. Environ. Sci. Pollut. Res. 13 (5), 350–358.
Pittenger, D., Gransberg, D., Zaman, M., Riemer, C., 2012. Stochastic life-cycle cost analysis for pavement preservation treatments. Transport. Res. Rec.: J. Transport. Res. Board 2292, 45–51.
Portney, P.R., Weyant, J.P. (Eds.), 1999. Discounting and Intergenera-Tional Equity. Resources for the Future, Washington, D.C.
Re Cecconi, F., 2011. Epistemic uncertainty propagation in service life prediction using the factor method. In: International Conference on Durability of Building Materials and Components, pp. 1–9 Porto, Portugal.
Roux, C., Schalbart, P., Assoumou, E., Peuportier, B., 2016. Integrating climate change and energy mix scenarios in LCA of buildings and districts. Applied Energy 184, 619–629.
Saltelli, A., Ratto, M., Andres, T., 2008. In: Wiley, J. (Ed.), Global Sensitivity Analysis: the Primer. WILEY-VCH Verlag, Chichester.
Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., Tarantola, S., 2010. Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Comput. Phys. Commun. 181 (2), 259–270 Elsevier B.V.
Sesana, M.M., Salvalai, G., 2013. In: Overview on Life Cycle Methodologies and Economic Feasibility for nZEBs. Building and Environment, vol. 67. Elsevier Ltd, pp. 211–216.
Sims, C.A., 1980. Macroeconomics and reality. Econometrica 48, 1–48.
Smets, F., Wouters, R., 2003. An estimated dynamic stochastic general equilibrium model of the Euro area. J. Eur. Econ. Assoc. 1 (5), 1123–1175.
Sobol, I.M., 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. Math. Comput. Simulat. 55 (1–3), 271–280.
Solow, R.M., 1956. A contribution to the theory of economic growth. Q. J. Econ. 70 (1), 65–94.
Thalfeldt, M., Pikas, E., Kurnitski, J., Voll, H., 2017. Window model and 5 year price data sensitivity to cost-effective façade solutions for office buildings in Estonia. Energy 135 (15), 685–697.
Vu, T.K., Nakata, H., 2018. Oil price fluctuations and the small open economies of Southeast Asia: an analysis using vector autoregression with block exogeneity. J. Asian Econ. 54, 1–21.
Wang, N., Chang, Y.-C., El-Sheikh, A., 2012. Monte Carlo simulation approach to life cycle cost management. Struct. Infrastruct. Eng. 8 (8), 739–746.