real value of energy efficiency

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REFEREE: Real Value of Energy Efficiency

The state of art of the existing models and tools to support policy makers in the analysis of the real effects of the energy efficiency measures

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1 Introduction and summary

The REFEREE (Real ValuE oF EneRgy EfficiEncy) project aims to bring the multiple benefits of energy related measures to the attention of experts in other fields than energy. The inclusion of the multiple impacts of energy efficiency could significantly alter the result of cost-benefit evaluations (Thema, et al., 2019); substantially contributing to the economic viability of energy efficiency measures. The REFEREE project will focus on two general objectives. First, it seeks to analyse and quantify direct and indirect non-energy impacts of energy efficiency investment as well as their cost effectiveness. Secondly, the resulting analysis will be developed into an easy-to-use tool which can support policy makers, household, business, financial institutions, and other relevant stakeholders. More specifically, state-of-the-art modelling techniques will be used to have a better treatment of the multiple benefits of energy efficiency technologies, which will be fed into the policy decision-support tool.

This deliverable is split into two parts. The first part (Part A) of the report presents the state-of-the-art approaches and methods used to model energy-efficiency and estimate the multiple benefits associated with the deployment of such measures. An extensive range of literature sources were reviewed, including academic articles, reports from international organisations, and evidence from previous European research projects, to identify the most common methods adopted to quantify and monetise the benefits of energy efficiency.

Energy efficiency measures have been traditionally associated with benefits from reduced energy demand and lower greenhouse gas (GHG) emissions. However, the evidence shows that there are numerous other co-benefits linked to improved energy efficiency, that can potentially affect various stakeholders and address a range of social, economic, environmental, and health-related issues (IEA, 2014). The multiple benefits of increased energy efficiency include energy security, job creation, increases in disposable income, productivity gains, increased comfort from better insulation and a reduction in environmental damages. The assessment of the multiple benefits is key to the development of economically sound energy efficiency policy, and to aiding understanding of how these measures are contributing to decarbonizing the economy. To date, the monetary value of these benefits has been scarcely quantified (Kamal et al., 2019), partly due to data availability and to the absence of mature methodologies that could comprehensively account for multiple benefits (Ürge-Vorsatz et al., 2016). As a result, the beneficial impacts of energy efficiency policy are yet not well understood. The absence of systematic valuation methods for the multiple benefits of energy efficiency is a major problem in designing good policy, and existing methods tend to overlook and underestimate the true value of energy efficiency measures.

Thus, the purpose of this review is two-fold: to expand the understanding of the available methodologies for the quantification of the various co-benefits of energy efficiency and their related challenges and limitations; and to highlight a range of potential approaches to use for future valuation of energy efficiency benefits. For this purpose, multiple benefits are grouped into four main macro areas: industrial productivity, socio-economic development, health & well-being, environment & climate. A review of methods used in the literature for quantification is presented in detail for each macro area. The key findings of this review will be used to develop a suitable methodology for the quantification and monetisation of the multiple benefits of energy efficiency within the REFEREE project. Ultimately, the quantification of the aggregate benefits will be integrated into a policy-decision making tool to be used by policymakers.

The second part (Part B) of the report is dedicated to the evidence review of technology diffusion models. This evidence review explores and compares different modelling frameworks used for estimating the evolution of new technologies. The contents of this report will ultimately inform the development of new tools for modelling the take-up of energy efficiency measures across a range of sectors in response to relevant policy. A vast range of literature surrounding diffusion models was reviewed, placing a focus on well-established models as well as new state of the art modelling approaches.

A key component in estimating the benefits of energy efficiency policies is to understand the cascading effects between policy and behavioural changes. This means considering both the supply and the demand of sectors as well as including policy makers as a central force. Most importantly, the model needs to be able to accurately simulate how changes in policy and behaviours affects the adoption and uptake of new and mature technologies. Thereby, it is not only important to consider technologies which are viable today, but to model the evolution and adoption of new technologies in the future.

PART A ASSESSING THE METHODS USED TO MODEL ENERGY EFFICIENCY CO-BENEFITS

2 Review of methodologies used for the assessment of multiple benefits

This chapter provides an overview of the approaches identified in the literature to quantify the multiple benefits associated with energy efficiency. Different types of co-benefits require different quantification approaches. Based on the conceptual framework presented by the IEA (IEA, 2014), this review covers four main macro areas: industrial productivity, socio-economic development, health & well-being, environment and climate. Within each macro area, specific methods for quantification are presented for the related benefits.

2.1 Industrial productivity

Energy efficiency improvements can deliver multiple benefits to industry. These include cost reductions, increased value through innovation, improved competitiveness and labour productivity, which ultimately lead to better outcomes for businesses and the economy at large. Quantification and monetisation of these benefits is crucial to assess the cost-effectiveness of energy efficiency policy.

2.1.1 Labour productivity

Alongside the commonly known impacts on carbon emissions and energy savings, energy efficiency policy can potentially have a positive effect on labour productivity. The linkages between energy efficiency and labour productivity are relatively understudied; there is no standard metric to quantify these benefits. Workers' productivity is closely linked to the indoor work environment. A recent study, carried out within the COMBI project, used two indicators to measure the impacts on labour productivity in Europe; active days (or hours) of work and workforce performance (Chatterjee & Ürge-Vorsatz, 2018). The active days (or hours) indicator reports information on absences from work, years gained from healthy lifestyle and time saved from road congestion associated with energy efficiency interventions. The workforce performance indicator, defined as the labour input by the entire workforce per unit of time, allows the measurement of the impact of indoor air quality and thermal comfort in commercial buildings on mental wellbeing, concentration ability and ultimately work performance and profits. The study showed that an average 4.5 active workdays per person can be gained each year as a result of deep retrofitting of buildings, and the construction of Passivhaus[1]

1 Passivhaus residences are very low energy buildings which require little energy for space heating and cooling. In particular, Passivhaus buildings efficiently exploit sun, internal heat sources, heat recovery, strategic shading, passive cooling techniques, hence rendering conventional heating and cooling systems unnecessary.

residences. The increase in productivity achieved though energy efficiency measures for each EU country was estimated at around 15.7 million Euros per year, while an average of 1,961 healthy life years per million population could be gained every year by avoiding indoor pollution in buildings. However, the study demonstrated that monetising labour productivity impacts is not always possible, due to the non-marketable nature of the benefits. For this reason, qualitative assessments can be a useful instrument to assess productivity benefits and incorporate those into energy efficiency impact assessments. Another study, (Adhvaryu et al., 2020) assessed how replacing less efficient light bulbs with LED lighting in garment factories in India improved the indoor work environment and led to an increase in the productivity of workers. It is well known that thermal stress can affect human beings physically and undermine their task performance (Hancock et al., 2007), and hot days can negatively impact productivity in working environments without air conditioning (Adhvaryu et al., 2020). Productivity was measured as actual quantity produced divided by target quantity, which was derived from an industrial engineering measure ("Standard allowable minute", SAM). Results showed that the introduction of LEDs reduced by 85% the negative impact of hot temperatures on workers' productivity. A European study estimated labour productivity gains by multiplying the total square meters of renovated buildings by the cost saving per m^2 renovated (Cambridge Econometrics, 2016). The extent of renovated non-residential buildings was determined through modelling techniques, while the cost saving per m^2 was based on the literature and estimated to be between €0.60 and €1.00 (Fisk, 2000; Gonand, 2015; Ürge-Vorsatz et al., 2009). However, it is important to highlight that the cost saving from productivity gains can be expected to vary across countries, hence the use of a single EU-wide average value could result in an inaccurate estimation.

2.1.2 Industrial competitiveness

Rapid deployment of energy efficiency measures is likely to lead to competitive advantages in Europe in the sectors that produce energy efficient equipment (i.e., construction, insulation, and flat glass sectors). However, the benefits associated with increased competitiveness are very difficult to quantify, due to confidentiality of information held by private companies. The size of these sectors depends on the demand of their products; therefore it is closely linked to the extent of the energy efficiency policy. A recent study used the E3ME macro-econometric model to estimate the value of insulation and flat glass industries as a measure of industrial competitiveness (Cambridge Econometrics, 2016). Macro-econometric models are particularly useful in assessing productivity benefits, as their results already incorporate measures of value added for different industries.

A similar study estimated indicators for energy intensity and energy cost impacts for industrial sub-sectors in Europe, to measure the effectiveness of production, hence competitiveness of energy intensive sectors (i.e., pulp & paper, basic chemicals & fertilisers, non-metallic minerals, cement, iron & steel, non-ferrous metals) (Cambridge Econometrics, 2017). Energy intensity and energy cost impacts can be derived as the ratios of total energy consumption and total energy costs, respectively, on the value added for each industry. This quantification method is very straightforward, although detailed sectoral data are typically required. Finally, international competitiveness of energy intensity industries can be measured using the aggregated value added of these industries as a share of the worldwide value added. A recent study showed that energy efficiency policy could increase international market competitiveness in European energy intensive sectors by about 5% in 2030 (Cambridge Econometrics, 2017).

2.2 Socio-economic development

Energy efficiency improvements are expected to have a positive impact on socio-economic development, resulting from increased economic activity, either directly or indirectly. Investments in energy efficiency contribute to boost economic output, while creating additional job opportunities. These investments can potentially displace spending in other sectors of the economy, which can offset some of the positive effects on the economy. The beneficial impacts resulting from increased energy efficiency can be measured using indicators such as gross domestic product (GDP), employment, public budget, and energy prices.

2.2.1 Gross Domestic Product (GDP)

Gross domestic product (GDP) is a measure of the total market value of goods and services produced each year, and is therefore considered a measure of economic development. Within the multiple benefits literature, the impact on GDP is typically estimated through modelling exercises and/or econometric analysis at the national or regional level. The most common approach to the quantification of GDP impacts is the use of macroeconomic models, which can capture linkages between investment in energy efficiency and economic activity, while providing sectoral details. A recent study carried out for the European Commission adopted the E3ME macroeconomic model to determine the impact on GDP. The study estimated that large-scale interventions in energy efficiency are likely to increase GDP by more than 4% (Cambridge Econometrics, 2016, 2017). However, different macroeconomic models are based upon different underlying assumptions, and deliver contrasting results. A similar study adopted two different models to determine the impacts on economic output (Cambridge Econometrics, 2015). One of the models, GEM-E3, is a Computable General Equilibrium (CGE) model based on neoclassical economic theory, while the other model, E3ME, is a macro-econometric model based on post-Keynesian theory. Although both models require information on the take-up of energy efficiency measures and on the investments costs as inputs, the GEM-E3 model estimates a negative impact on GDP, while the E3ME model predicts an increase in economic output. These conflicting outcomes can be explained by the different treatment of investments within each model. The CGE model assumes that investments in energy efficiency will crowd out other investments, whereas E3ME allows the investments in energy efficiency to be additional to those already taking place across the economy. The COMBI project estimated the impact on GDP by disentangling the short-run impacts from the long-run impacts. To do this, a CGE model was combined with an Input-Output (I-O) analysis. The study estimated that ambitious energy efficiency programmes could increase EU GDP by 0.9% in the short run, whereas in the long run the estimated impact on GDP could be slightly negative. While in the short-run, energy efficiency investments are expected to boost economic activity, in the long-run energy efficiency result to be more expensive that other carbon mitigation efforts. Moreover, the short-term stimulus is expected to occur in countries with the potential to support further growth (i.e., negative output gap, situation of economic downturn), as for countries with a positive output gap, the investment stimulus effect falls flat and does not materialize in the economy. Another example of a macroeconomic model combined with an Input-Output framework is the ASTRA-D model used in the study by (Hartwig et al., 2017). The authors investigated the long-term macroeconomic effects of an ambitious energy efficiency policy scenario in Germany, finding evidence of significantly positive growth effects for GDP between 0.9% and 3.4% between 2020 and 2050. The policy scenarios were analysed by linking energy demand models with the ASTRA-D macroeconomic model, which goes beyond some of the typical assumptions of CGE models and relies on a dynamic Input-Output framework. Other macroeconomic models have also been used to assess the impact of energy efficiency improvements on GDP in past years. For example, (Bataille & Melton, 2017) relied on the RGEEM (Regional General Equilibrium Energy Model) CGE model to estimate how energy efficiency impacted Canadian GDP from 2002 to 2012. To do so, the authors compared the reference scenario (i.e. observed historical energy efficiency improvements) with a counterfactual scenario with no changes in energy efficiency, and found evidence that energy efficiency improvements led to a 2% increase of Canadian GDP over a decade. The impacts of energy efficiency on economic growth have also been estimated in many developing countries with econometric techniques. (Sinha, 2015) applied an error correction model (ECM) to study the long-run causal association between economic growth and energy waste as a proxy of energy efficiency, considering historical data for India between 1971 and 2010. Results showed the existence of a negative relationship between energy waste with economic growth, implying that GDP growth and energy efficiency are positively correlated. In another study, (Akram et al., 2021) showed that energy efficiency is an important driver of economic growth in BRICS countries, providing evidence that energy efficiency policies can be part of a development strategy to bring not only environmental benefits, but also long-term economic gains.

2.2.2 Employment

Alongside the stimulus in economic output, energy efficiency interventions can support the creation of new job opportunities. However, jobs are also expected to be lost in the energy production sector as a result of the reduction in energy demand. Hence, the assessment of employment impacts usually refers to the number of net jobs that are created or lost through energy efficiency measures. Employment effects are also classified into direct and indirect jobs created. Direct jobs are created in the manufacturing and installation of energy efficient equipment, while indirect jobs are created along the supply chains that are linked to the manufacturing and installation sectors. The effect of energy efficiency measures on employment typically ranges from 9.2 to 17.07 jobs created every year for every million Euros invested (IEA, 2014). Sectoral analyses are typically used to determine net employment impacts. Numerous studies estimated employment effects resulting from energy efficiency measures using I-O analysis at the country level (Garrett-Peltier, 2017; Oliveira et al., 2014; Sergio Tirado Herrero et al., 2011). Input-Output analysis allows an estimation of how increasing spending in energy efficiency affects output and employment in various sectors. A major limitation of I-O models is that these are relatively static, meaning that they do not reflect any changes in the interaction between sectors over time. I-O models are typically incorporated into macro-econometric models to provide a dynamic representation of the interactions across sectors, as in the case of the study on the macroeconomic effects of energy efficiency policy in Germany by (Hartwig, et al. 2017). Within the COMBI project, employment impacts were estimated in the short-run and in the long-run for European countries, using a combination of CGE and I-O models (Sigurd Næss-Schmidt et al., 2018). In the short-run energy efficiency interventions were found to impact the labour market by creating 2.3 million job-years, whereas no significant impact was found in the long-run. A similar study estimated the employment benefits of energy efficiency improvements using the E3ME macroeconomic model, and concluded that, in the most ambitious energy efficiency scenario, employment can potentially increase by 2% in the EU (Cambridge Econometrics, 2017). Finally, there are also examples of studies that did not rely on an I-O framework. (Bataille & Melton, 2017) used the RGEEM CGE model and showed that energy efficiency investments increased employment by 2.5% in Canada between 2002 and 2012, mostly due to the reallocation of scarce productive capital from capital intensive sectors (i.e. energy supply sectors) to labour intensive sectors. Similarly, (Costantini et al., 2018) concluded that energy efficiency improvements have a negative effect on employment growth in energy-intensive industries, but the effect on employment dynamics of industry and services is positive when energy efficiency is improved in the public sector. In this case the authors carried out an econometric analysis using a panel dataset covering 15 European countries between 1995 and 2009. However, the methodologies presented are not designed to provide significant recommendations on the level of skills required for the employment opportunities arising from energy efficiency interventions. Skills constraint could lead to displaced workers being unable to find new jobs and companies facing skills shortages, which could ultimately result in higher unemployment and lower productivity in some sectors. An additional assessment of the level of skills in the labour market requires a qualitative assessment of key sectors (i.e., construction and engineering) as quantitative methods are generally unable to capture this dynamic.

2.2.3 Public budgets

Public budget impacts resulting from energy efficiency policy are closely linked to socioeconomic development. Although energy efficiency measures are likely to impose a cost burden on public budgets, these can also deliver additional tax revenues, provide higher return on investments, and lower the cost of unemployment and social welfare programmes. The impact of energy efficiency policy on public budgets is triggered by two main factors: investments in energy efficiency and energy demand reductions. On one hand, investments that are required to implement energy efficiency measures are taxable and likely to generate additional tax revenues, while contributing to create new employment opportunities. Higher tax revenues can also be expected from increased labour participation and ultimately from increased consumption of taxed goods and services. On the other hand, energy demand reductions could potentially result in cumulative savings for governments in the case of reduced subsidies for energy production and consumption. The full effect on public budgets resulting from energy efficiency policy is rarely estimated, and most of the quantitative assessments focus solely on the cost side of energy efficiency measures, rather than on the positive impacts. Macroeconomic models are typically well suited to estimate the impacts of increased energy efficiency on public budgets, as these usually cover the whole economy and can represent the interactions among sectors. Therefore, I-O analyses, CGE models and macro-econometrics models are all good candidates to infer the potential impacts on public budgets. The main advantage of using macroeconomic modelling is that many factors affecting public finances are already included in the modelling results. A recent study on the macroeconomic impacts of energy efficiency in the European Union showed that the positive effects on public budgets could be on average as high as 2% of GDP (Cambridge Econometrics, 2017). Positive impacts on public budget ranging from 0.06% to 0.56% of GDP were estimated in the COMBI project (Sigurd Næss-Schmidt et al., 2018). The latter, however, adopted budgetary semi-elasticities to determine the effect of energy efficiency measures on public finance. Budgetary semi-elasticities indicate to what extent an increase in GDP results in an increase in the public budget (i.e., a budgetary semi-elasticity of 0.5 for a given country implies that a 1% increase in GDP leads to a 0.5% of GDP increase in the public budget). The estimate does not account for gains from reduced expenditure on social security, the health system and energy tax revenues. Moreover, this approach is highly dependent on the state of the economy, as elasticities vary with the economic cycle and tend to be larger when the economy operates beneath its peak (IEA, 2014). A major challenge in the estimation of impacts on public budgets is that all methodological options struggle to provide results from both impacts associated with energy efficiency investments and impacts from reduced energy demand. Results from modelling exercises most of the time require additional computations and extensions to cover all relevant aspects affecting public budgets.

2.2.4 Energy prices

By reducing final energy demand, energy efficiency interventions can potentially decrease energy prices for final consumers, when energy is supplied from competitive markets. In the literature this effect is commonly known as demand-reduction-induced price effect (DRIPE) (Kamal et al., 2019), which is a measurement of the reduction of wholesale energy prices for final consumers. Lower energy demand due to efficiency improvements leads to the shedding of the most expensive sources of generation and to a reduction in the wholesale price of energy. The reduction in prices is in theory passed on to consumers, and can be estimated for energy-sector goods and services including electricity and natural gas. While numerous studies focused on the relationship between energy demand and energy prices, the literature estimating the energy price reductions from energy efficiency measures is relatively scant. The typically adopted approach involves using electricity and natural gas market models to examine what the market price effects would be from energy consumption reductions. In the United States, (Kushler et al., 2005) showed that energy-efficiency efforts for gas and electricity could generate gas price reductions of about 39% of the direct avoided costs of the energy efficiency programs.

Similarly, (Mosenthal et al., 2006) showed that price reductions in New York from a state-wide gas-efficiency program would be 25% of the direct avoided costs. While this remains an underexplored area, some observed that price reductions are an implicit transfer that benefits consumers at the expense of producers (Chernick & Plunkett, 2014).

2.2.5 The value of buildings

Energy efficiency measures in buildings (i.e., insulation, lighting, ventilation) lead to higher value of residential and commercial real estates. Unlike other socio-economic indicators, the value of buildings is scarcely assessed in the literature. The prevalent approach adopted in previous studies involve qualitative surveys and contingent valuation to infer the willingness to pay a premium for energy cost savings, improved corporate image, worker productivity, improved comfort, and aesthetics (Dalla Mora et al., 2018; Pires Neves et al., 2005; Wobus et al., 2007). A recent analysis extrapolated results from previous studies in order to derive an estimate of the impacts on the value of buildings at the European level (Cambridge Econometrics, 2017). However, the results were not translated into monetary terms.

2.3 Health & well-being

Energy efficiency measures directly affect the health and well-being of both individuals and society as a whole. Improved energy efficiency leads to reduced prevalence of diseases stemming from outdoor and indoor pollution. However, there are many indirect benefits from energy efficiency that are also worth considering. For instance, reduced energy bills could lead to a decrease in the incidence of fuel poverty. Similarly, improved health conditions may lead to savings in public healthcare spending. The potential impacts of improved energy efficiency on health and well-being can be inferred using indicators such as reduced mortality and morbidity, increases in disposable income and savings in healthcare costs.

2.3.1 Mortality and morbidity

Improved energy efficiency in buildings (i.e. insulation, improved heating and cooling systems, lighting and energy using equipment) leads to reduced incidences of diseases related to low indoor thermal quality, poor air quality and dampness. Moreover, energy efficiency policies can contribute to reduce emissions and pollutant concentrations in outdoor settings. Improved air quality has a positive effect on health outcomes, through reducing the risk of respiratory, coronary, and cardiac diseases. The health benefits are expected to outweigh the costs of energy efficiency programmes. Previous studies showed that when accounting for health improvements, overall benefits are estimated to be four time higher than investment costs (IEA, 2014). Numerous techniques have been adopted in the literature to assess the value of health benefits. However, not all studies assessed the full range of health benefits, meaning that commonly used methodologies face limitations when aggregating multiple benefits. As a result, estimates of the health impact of energy efficiency tend to be overlooked in the literature. The prevalent methodology involves qualitative surveys, which infer the willingness to pay (or the willingness to accept) for energy efficiency improvements in buildings (Dalla Mora et al., 2018; Pires Neves et al., 2005; Skumatz & Gardner, 2005; Wobus et al., 2007). The revealed preference approach is typically adopted to infer the value of the health benefits brought about by energy efficiency measures. A major limitation to this method is that results are very sensitive to the answers given by the respondents, who usually struggle to attribute an accurate monetary value to their preferences. The statistical life years approach is used to measure the monetary value of the years of life a person is expected to gain from improved energy efficiency. A recent study at the EU level estimated the health impacts associated with energy efficiency in buildings using the statistical life year approach (Mzavanadze, 2018a), and showed that the value of avoided premature mortality due to indoor cold in 2030 ranges from 323 million Euros to 2.5 billion Euros. Savings of 338 million Euros to 2.9 billion Euros could also be accrued due to avoided asthma morbidity from indoor dampness. However, the statistical life year approach requires information of the number of individuals exposed to potential diseases and on the rate of mortality due to cold and dampness in buildings. This information is usually not publicly available, hence strong assumptions need to be set to quantify the health benefits in terms of number of avoided deaths or years of life gained. Another study, (MacNaughton et al., 2018) estimated the health co-benefits of energy efficiency interventions by using an additional metric, namely the Social Cost of Atmospheric Release (SCAR), to monetize the co-benefits from reduced pollutant emissions. This framework is an extension of the Social Cost of Carbon (SCC) methodology for valuation of the estimated damages associated with an increase in carbon dioxide emissions in a given year (Shindell, 2015). It is however important to highlight that the results provided by these methods should be treated with care as placing a monetary value on life and avoided emissions can be very challenging and prone to criticisms. To address this challenge, proxy measures can be identified to measure the value of health benefits brought by energy efficiency in buildings. Some of the most common proxy measures include the cost of avoided treatment due to improved health and well-being, and the number of days off school/work, which can be translated in monetary terms using estimates of the cost of hiring a caregiver for the sick child and/or the value of lost earning (Chatterjee & Ürge-Vorsatz, 2018; IEA, 2014).

2.3.2 Public health spending

Besides providing health benefits for the individuals, energy efficiency policy is likely to have a positive impact on society as a whole. Energy efficiency measure can generate considerable savings in healthcare costs. Unfortunately, savings in public health spending are not usually quantified within energy efficiency assessments. This is because the impacts on public spending are highly dependent on the specific climate and on the characteristics of the health system in each specific country. Some studies used estimated costs of morbidity and mortality drawn from the literature to approximate the impacts of health care costs at the European level (Cambridge Econometrics, 2016, 2017). This approach, however, does not account for the fact that health costs vary between countries (i.e. due to differences in labour costs). Alternatively, the opportunity cost approach is used to measure the cost of mortality and morbidity due to air pollution. A recent study combined costs of mortality and morbidity with the estimated decrease of pollutants for each EU country across various energy efficiency scenarios (Cambridge Econometrics, 2017). The study showed that energy efficiency could lead to mortality and morbidity cost savings of up to 77 billion Euros each year. Although this method is quite straightforward, it typically requires a modelling exercise to determine the reduction in pollutants concentration due to energy efficiency interventions. Finally, complex modelling exercise can be adopted to determine accurate estimates of the heath cost savings. For instance, the GAINS air pollution and greenhouse gas model is an advanced modelling tool typically used to quantify the avoided premature deaths and the avoided loss of life expectancy due to reduced air pollution (Mzavanadze, 2018b). The modelling results are then combined with estimates of the Value of a Life Year (VOLY), to provide a monetary value for the improved health conditions. The monetisation on these benefits provides a good approximation of the potential savings on public health expenditure. However, this represents a controversial estimation, as it attempts to measure the value of human life instead of using the actual market values of productivity loss, costs of hospitalization, medication, and medical care.

2.3.3 Social impacts

Improved energy efficiency in buildings, through their impact on health, can potentially provide several other benefits, which range from family cohesion, sense of community among residents, healthier lifestyles, improved access to local services, enhanced cognitive ability for children and higher rates of school attendance (IEA, 2014). However, the valuation of social impacts remains difficult, as it is very challenging to quantify the exact contribution of energy efficiency improvements to each of these.

Moreover, the complex nature of social impacts may require a qualitative assessment, as these benefits are rarely associated with a direct market value.

2.4 Environment & climate

Energy efficiency interventions can positively affect the environment and the climate. Improved energy efficiency leads to lower energy consumption of fossil fuels and ultimately to reduced emissions, air pollution and consumption materials. The reduction in energy consumption is also associated to reductions in water demand and land use by the power generation sector.

2.4.1 Air pollution and emissions

The current energy system in Europe mainly relies on fossil fuel combustion, which results in the emission of greenhouse gases (GHG) and air pollutants (i.e., SO_X, NO_X, VOCs, PM_{10}, $PM_{2.5}$), although it is changing rapidly. Energy efficiency measures can contribute to improve air quality through reductions in energy consumption. An important first step to the assessment of the environmental impacts is to quantify the reduction in emissions resulting from improved energy efficiency. This is typically estimated through sophisticated modelling exercises, which allow the linking of investment for energy efficiency to energy consumption and emissions. The GAINS model (Greenhouse Gas – Air Pollution Interactions and Synergies model) is a popular tool, also used in the COMBI project, to quantify the extent of air pollution damages following accelerated energy efficiency interventions (Mzavanadze, 2018b). The study conducted in the COMBI project showed that an accelerated adoption of energy efficiency measures in building, transport and industry sectors would bring 32% reductions in SO_2 emissions by 2030, 42% in NO_X, 23% in $PM_{2.5}$. The GAINS model has also been used in the literature to estimate the reductions in air pollution control costs as a consequence of energy efficiency investments, for example in the study by (Zhang et al., 2014) on the iron and steel industry in China. Another study used the E3ME economic model to assess impacts on final energy consumption, and used these to determine the amount of avoided GHG emissions following the introduction of energy efficiency measures (Cambridge Econometrics, 2016, 2017). To do this, average emission factors were derived from historical data and applied to the reduction in energy consumption. Alternatively, the Life Cycle Assessment (LCA) method is a common tool used in the literature to estimate the carbon emission reductions stemming from energy efficiency improvements. A major advantage of using the LCA approach is that it allows the measurement of impacts across the entire lifetime cycle of the investment. The reduction in emissions is then translated into the associated avoided cost for society. Environmental costs include damage costs and abatement costs, but monetisation of these impacts is rarely considered in impact assessment studies due to double counting concerns. This is because the benefits of energy efficiency manifest in different areas even though they are strictly interrelated. For instance, energy efficiency improvements benefit the environment *per se*, but they also improve human health through their impact on the environment. The monetisation of both the effect on the environment and the effect on human health could rise double counting concerns, as the same impact is quantified twice. Therefore, the monetisation of impacts associated with reduced air pollution is typically interpreted as the value of improved human health.

Besides the human health effects described in section Errore. L'origine riferimento non è stata trovata., reduced air pollution resulting from energy efficiency is expected to positively affect ecosystems. Impacts on ecosystems include the reduction of acidification and eutrophication, which ultimately lead to vegetation growth, clean water bodies and improved agricultural harvest. Results from the GAINS model showed that 4.4 and 13.3 thousand km^2 would be spared from, respectively, acidification and eutrophication thanks to the pollution reductions brought by energy efficiency improvements (Mzavanadze, 2018b).

2.4.2 Natural resources

The reduction in energy consumption resulting from energy efficiency measures ultimately leads to lower raw materials requirements to provide energy services. Previous studies showed that both water consumption and land use for the power sector are expected to decline as a result of reduced energy consumption (Cambridge Econometrics, 2016, 2017). To do this, water withdrawal coefficients (i.e., cubic meter of water required per GWh of energy generated) were derived from previous studies and applied to the amount of energy reduction achieved with energy efficiency measures. However, it is important to highlight that the reduction in natural resources exploitation is highly dependent on the local geography of each country and the technology adopted in the power sector. The literature on energy efficiency presents considerable gaps on the assessment of natural resources impacts.

2.4.3 Material consumption

The impact of energy efficiency on material consumption is relatively underexplored in the literature. It is not clear whether energy consumption has a positive or negative effect on material consumption. Domestic Material Consumption (DMC) is a commonly used measure to represent the material intensity of sectors of the economy. As the demand for materials is defined by various factors (i.e., economic production, prices of inputs, technology), typically modelling exercises are required to estimate the impacts on material consumption. A recent study adopted the E3ME macro-econometric model to estimate the consumption of seven materials in 20 different sectors following the implementation of energy efficiency measures in Europe (Cambridge Econometrics, 2016, 2017). The study showed that demand for materials tended to increase due to higher investments in building renovation, as well as due to the rebound effect from increased economic activity. However, the increase in material consumption was limited to the duration of the investment, and consumption was expected to return to the original level once the investment is completed.

3 Discussion on quantification of multiple benefits

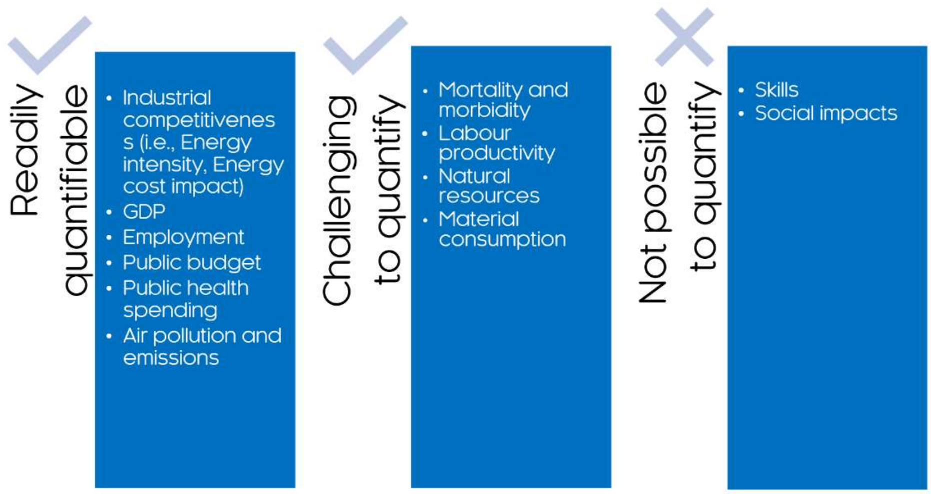
While there is no single method for quantifying the multiple benefits of energy efficiency, evidence from the scientific literature shows that it is crucial to measure and quantify both direct and indirect impacts arising from the deployment of energy efficiency measures. A comprehensive assessment of the multiple benefits can provide clearer insights to policymakers, and inform the design of effective energy efficiency policies. Where a monetary value clearly exists, adequate methodologies should be adopted to calculate the value of such benefits. The IEA's guidance on capturing the multiple benefits of energy efficiency suggests that even a rough estimate of a benefit's value is more accurate than assuming a value of zero (IEA, 2014). However, it is important to highlight that quantification is not always feasible, as benefits are not always tangible and measurable in a robust and objective manner. Similarly, the monetization of benefits can be challenging, as many benefits, by nature, are not associated with a marketable value. Hence, qualitative assessments (i.e., through case studies, literature reviews, estimates' transfer from previous studies etc.) should be carried out when quantification and monetisation of benefits are not possible. To avoid underestimating the true value of the multiple benefits of energy efficiency, qualitative assessments should be incorporated into policy discussion, alongside the assessments of monetary values.

Previous studies have shown that some methods are more robust than others. The rest of this chapter provides recommendations on potential approaches to assess the co-benefits of energy efficiency. Figure 3.1 below groups the main indicators according to the feasibility of quantification and monetisation. The groupings of indicators can be defined as follow:

- *Readily quantifiable* – indicators for which there are established robust methods for quantification, and for which data is easily accessible ;
- *Challenging to quantify* – indicators that can potentially be quantified and monetized using existing approaches and models. However, the assessment of these benefits can be difficult, due to data availability or limits to the methodologies employed;

- *Not possible to quantify* – indicators for which quantification and monetization is not feasible, due to their non-marketable nature, the difficulty in obtaining usable data, and developing robust methods.

Figure 3.1 Recommendations on quantification of co-benefits



Source: Cambridge Econometrics

3.1 Industrial productivity

Although the evidence suggests a positive impact of energy efficiency on both labour productivity and industrial competitiveness, this area of research remains relatively understudied. As such, it is difficult to suggest a standardised approach to quantify and monetise the related benefits. However, the methods adopted in previous evaluation studies represent a starting point for quantification of industrial benefits.

The evaluation of labour productivity benefits, through indicators of active workdays and workforce performance is broadly straightforward but requires detailed confidential data which are not publicly available. In addition, companies can autonomously assess the wider benefits of energy efficiency, but this information is not usually shared to the public. This severely limits the availability of data and ultimately affects the quantification process. Alternatively, labour productivity losses can be estimated by multiplying the square meters of renovated commercial buildings to the annual cost savings from productivity losses per m^2. This approach fails to account for the variability of cost savings across different European countries. Therefore, this indicator is classified as *challenging to quantify* (Figure 3.1), as its measurement presents some limitations due to lack of data.

The impacts of energy efficiency on industrial competitiveness can be assessed through indicators of energy intensity, energy cost impacts and international competitiveness. This requires sectoral data on energy use, energy costs and gross value added (GVA). Existing macro-econometric models can be adopted for the quantification of these indicators for energy intensive industries in European countries. As shown in Figure 3.1, industrial competitiveness is classified as a *readily quantifiable* benefit. However, the monetisation of this benefit remains a major challenge. As a matter of fact, the indicators presented allow the evaluation of competitiveness on relevant industries but do not assign any monetary values.

3.2 Socio-economic development

The state of analysis of this macro area is well developed, as previous studies mainly focused on the impacts of energy efficiency policies on economic activity. The reason for this is two-fold. First, indicators of socio-economic development are of particular interest for policymakers and other stakeholders. Second, methodologies to quantify socio-economic development are well-known and their strengths and limitations are clear to economists and policymakers. The complexity of socio-economic impacts can be assessed through a combination of several methods and approaches.

The impact on GDP and public budgets can be robustly measured for large scale energy efficiency programmes, as this is usually quantified at the country level. Macro-econometric models can be adopted to quantify the impact of energy efficiency on economic activity, by inputting information on the investment costs required to uptake energy efficiency interventions, and impacts on energy demand. Similarly, a combination of macro-econometric models and Input-Output (I-O) analysis can be adopted to estimate employment impacts resulting from the implementation of energy efficiency measures. Robust and transparent evaluations should focus on the number of net jobs that are created or lost, directly or indirectly, through these measures. For the purpose of this project, GDP, public budget and employment are all classified as *readily quantifiable* indicators (Figure 3.1). Additional qualitative assessment may be required to complement the quantified impacts of the socio-economic indicators. This is particularly important to determine how potential spare labour capacity interacts with the skills available in the sectors affected by energy efficiency policies.

3.3 Health & well-being

The body of evidence linking energy efficiency to health outcomes has shown that quantification of impacts can be very challenging. First, the potential health and well-being benefits are numerous, hence capturing all the benefits requires extensive computations and modelling exercises. Second, the main difficulty remains the measurement of these impacts, which are usually not easily observable.

The reduction in mortality and morbidity is likely to represent the largest benefit in this area. Quantifying this benefit would require detailed information on the extent of avoided diseases and number of avoided premature deaths resulting from energy efficiency interventions. Previous analyses used data from in-depth intervention studies and cross-sectoral surveys. However, collecting these data is significantly time-consuming and beyond the scope of this project. Alternatively, this information can be retrieved from previous studies and combined with estimates of Value of Life Year and costs of treatment, to assign a monetary value on health benefits. However, care is needed when making use of values from the literature. This is because estimates from previous studies tend to use assumptions that are not usually applicable to other assessments. In addition, estimates of health benefits tend to vary across countries, therefore using a unique average value retained from the literature could result in inaccurate estimations. For these reasons, indicators of morbidity and mortality are classified as *challenging to quantify*, as their quantification is not straightforward and depends on the availability of relevant data (Figure 3.1).

Similarly, energy efficiency impacts on public health spending can potentially represent a large share of the overall benefits. As a first step, macro-econometric models can be used to derive the reduction in pollutants and emissions brought by energy efficiency interventions. The achieved reduction can then be combined with estimates of damage cost per unit of emission, to derive the savings in healthcare expenditures. Estimates of damage costs can readily be retrieved from previous studies or from official sources published by governments and international organisations. Therefore, public health spending is classified as a *readily quantifiable* indicator, as its measurement is broadly straightforward (Figure 3.1).

Finally, the quantification of benefits associated with health and well-being needs to be complemented with qualitative assessments of the social impacts of improved health. These benefits are typically assessed via qualitative surveys. These however fall beyond the scope of this project. Quantification of social impacts is also not feasible, as these are intangible benefits that are not associated with any market value. Social benefits are therefore classified as *not possible to quantify* benefits, as shown in Figure 3.1.

3.4 Environment & climate

The impact of energy efficiency measures on the environment has been investigated substantially in the literature. An important first step toward quantification of the impacts involves the measurement of the reduction in emissions brought about by energy efficiency interventions. This can be done by multiplying the average CO_2 content of electricity by the amount of saved energy. The latter is typically estimated through modelling exercises. A similar calculation can be used to estimate the reduction in air pollutants (e.g., SO_2, NO_X). Therefore, air pollution and emissions are classified as *readily quantifiable* indicators, as their estimation is broadly straightforward.

The quantification of water consumption can be carried out by multiplying the energy savings by water withdrawal coefficients. A similar estimation method can be adopted to determine the effects on land use, hence using land use coefficients. While energy savings could be estimated though modelling exercises, the land use and water withdrawal coefficients are typically retrieved from previous studies. However, it is important to highlight that the use of land and energy associated with energy generation tend to vary across countries, depending on the specific technologies adopted and resources availability. It follows that the use of average coefficients may represent a stringent assumption. Thus, the use of natural resources is classified as *challenging to quantify* indicator (Figure 3.1), as major limitations arise in the quantification process.

The impact of energy efficiency on material consumption is relatively understudied. Hence, it is difficult to identify a standard approach to quantification. Sectoral analysis and macro-econometric modelling can be used to estimate Domestic Material Consumption (DMC) for each sector in the economy. However, this would require detailed information on prices of inputs, demand of inputs and technologies adopted in each country. This information could be particularly difficult to retrieve, as usually it is not publicly available nor published by official sources. It follows, that this indicator is classified as *challenging to quantify* (Figure 3.1), as its quantification is feasible but requires data that are not easily accessible.

4 Conclusion

Energy efficiency measures are likely to bring numerous co-benefits, both direct and indirect, that could potentially affect various stakeholders. The assessment of benefits is a crucial step to guide policymakers in the design of effective energy efficiency interventions. However, the co-benefits of energy efficiency are rarely quantified and monetised in a comprehensive manner. This is mainly due to the lack of mature methodologies allowing to account for all the benefits. Moreover, quantification of benefits is not always feasible, as co-benefits are often intangible and non-marketable.

To face these challenges, an extensive literature review was carried out covering scientific articles, grey literature and former research projects sponsored by the European Union. The purpose of the review was to set up a general approach to quantification and monetisation of benefits. The literature review covered four main macro areas of co-benefits: industrial productivity, socio-economic development, health & well-being, environment and climate. Within each macro area, specific indicators were considered, and the related quantification methods reviewed. Finally, a critical approach was adopted to provide recommendations on the potential quantification methods to adopt within the REFEREE project. In particular, relevant indicators were grouped into three categories, according to the feasibility of quantification and monetisation. Co-benefits were classified as *readily quantifiable* when quantification methods are broadly straightforward, and data are easily accessible. Indicators were classified as *challenging to quantify*, when their quantification is difficult, due to data availability or lack of adequate methodologies. Finally, when quantification and monetisation are not feasible, indicators were classified as *not possible to quantify*. We therefore conclude that indicators listed as *readily quantifiable* and *challenging to quantify* should be taken forward to the quantitative assessment process. When quantification is not possible, qualitative assessment should be carried out and equally incorporated in policy decisions, alongside the estimated monetary values.

The next stage in the work is to set out precisely how these indicators will be quantified, including the specifics of the models and methods to be used (drawing upon the other half of this literature review exercise, and existing tools at the disposal of the project team). On the basis of this, we will draft a Methodology Report, which sets out the specifics of what exactly will be quantified at each stage of the modelling and analysis, and the constraints and qualifications surrounding the specific indicators ultimately produced.

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PART B EVIDENCE REVIEW OF TECHNOLOGY DIFFUSION MODELS

6 The key aspects of technology diffusion models

This chapter defines some of the key concepts which are prevalent across all modelling frameworks and define some key terminology.

6.1.1 Information & technology diffusion

Diffusion is the "process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 2003). In other words, diffusion models seek to capture the relevant interactions between individuals, drawing a picture of how innovation spreads through society. Although the spread of innovation tends to follow similar patterns to the spread of information, technology and information diffusion are not analogous (Rogers, 1962; Huang, Chen, & Anandarajah, 2017). The prior focusses on the flow of information through a social system, whereas the latter assesses how this information translate to an uptake or decay of innovations in a society.

In reference to the adoption of energy efficiency policies, an information diffusion model would be concerned with informing the population about an energy efficient technology without considering whether it would be economical to adopt. On the other hand, a technology diffusion model is primarily concerned about modelling how many individuals will adopt a new technology. It is important to note that information diffusion also plays a vital role in technology diffusion, but the reverse is not necessarily true.

6.1.2 EBMs vs. ABMs

To capture the complex nature of technology diffusion, two main modelling approaches have been used in the literature, Equation-Based Models (EBMs) and Agent-Based Models (ABMs). (Kirman, 1992) highlights that the optimal decision for a group of individuals does not lead to the same outcome as optimising the utility of the aggregate. By extension, fundamental differences can evolve from bottom-up versus top-down models2. ABMs seek to model individual behaviour by assuming that agents make choices based on a finite set of decision rules. Consequently, by correctly estimating the behaviour of the individuals, computer simulations can be used to model the impact on the whole system (Mercure J.-F. , 2018). On the other hand, EBMs tend to model diffusion through a series of differential equations (Rao & Kishore, 2010). These models assume that diffusion and the spread of innovation can mostly be

[2] A bottom-up approach starts at the micro-level and considers the macro-level to be the sum of the micro-components. Top-down models, work in reverse, considering the macro-level and disaggregating the data to the individual level (Hourcade, Jaccard, Bataille, & Ghersi, 2006).

captured by a few deterministic dynamics (Bass, 1969; Mahajan, Muller, & Bass, 1995; Rao & Kishore, 2010; Jiang & Jain, 2012). Due to the differences in approaches, ABMs are often viewed as a bottom-up approach, whereas EBMs take a top-down approach (Kiesling, Günther, Stummer, & Wakolbinger, 2012; Moglia, Cook, & McGregor, 2017).

6.1.3 Adopter groups

Irrespective of the modelling approach used, there is a consensus that network effects matter, and the uptake of new technologies is dependent on the current number of adopters. This is true for both EBMs and ABMs. According to (Rogers, 1962), adopters fall into 5 distinct categories differentiated by the speed of technology uptake (Table 1).

Table 1 - Adopter groups defined by Rogers (1962)

Adopter Group	*Share of total adopters*
Innovators	2.5%
Early Adopters	13.5%
Early Majority	34%
Late Majority	34%
Laggards	16%

The innovators are often assumed to be exogenous and independent from the other groups, as they will adopt a new technology irrespective of the current number of adopters. However, subsequent groups will depend on the number of individuals who have already adopted the innovation (Rogers, 1962; Bass, 1969). This assumption, or a variation of it, is used in almost all modelling frameworks, with the purpose of capturing information diffusion mechanisms such as word-of-mouth and bandwagon effects (Kiesling, Günther, Stummer, & Wakolbinger, 2012).

6.1.4 Path dependence

Lastly, it is important to acknowledge that the adoption of a new technology is often path dependent (Grubb, Kohler, & Anderson, 2002; Mercure J.-F. , et al., 2018). This means that the adoption of future technologies depends on which technologies have already been adopted. For example, as the adoption of electric vehicles increases, one may expect to see increased innovation into battery technologies, leading to lower costs, which encourages further uptake of electric vehicles. Furthermore, the uptake of new battery innovations is likely to be highly dependent on the uptake of electric vehicles (Sharpe & Lenton, 2021).

6.2 Structure

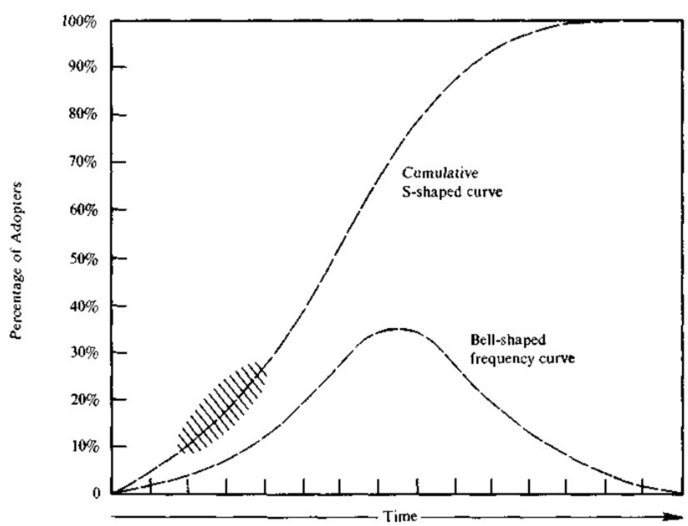
This literature review is divided into three sections. In Chapter 2, a more in-depth review is presented on the two main modelling types, EBMs and ABMs. The different modelling types are compared and evaluated based upon key considerations for using diffusion modelling for policy recommendations in Chapter 3. Finally, some concluding remarks summarise the key results of the literature review are in Chapter 4.

7 Modelling approaches

7.1 Background

The literature on technology diffusion started to get traction in the 1960s from the publication of Diffusion of Innovations (Rogers, 1962). The book highlighted five main groups of adopters to guide research: innovators, early adopters, early majority, late majority and laggards. Rogers noted that if the distribution of these five groups follows a bell-shaped frequency curve, then the rate of technology adoption can be represented with a S-shaped cumulative curve obtained by integrating over the frequency curve. This S shape reflects a slow initial uptake when a technology is in its infancy, followed by a rapid growth, and lastly, a tapering off as the technology gets more mature (Figure 2). This S-shaped pattern has been well documented from historical data and thus serves as a benchmark for all diffusion models (Mahajan, Muller, & Bass, 1995).

Figure 2 - Bell shaped frequency curve and S-shaped cumulative curve. Shaded region represents the diffusion "take off"



The next sections will highlight some of the predominant models in the literature that build on the framework laid out by (Rogers, 1962).

7.2 Equation-Based models

7.2.1 Bass model

EBMs have their foundations in the Bass model (Bass, 1969). This model considers two groups of individuals, "innovators" and "imitators". Innovators buy the product immediately and are not influenced by other adopters, whereas imitators base their decision on how many individuals have already bought the product. The relationship between innovators and imitators is represented by a non-linear differential equation which needs to be appropriately parameterised according to the available data. The key parameters are suitably named the coefficient of innovations and the coefficient of imitation. These parameters capture the initial number of innovators and the tendency for imitation, respectively. This usually results in the number of innovators being important for determining the initial rate of technological uptake but become less relevant over time.

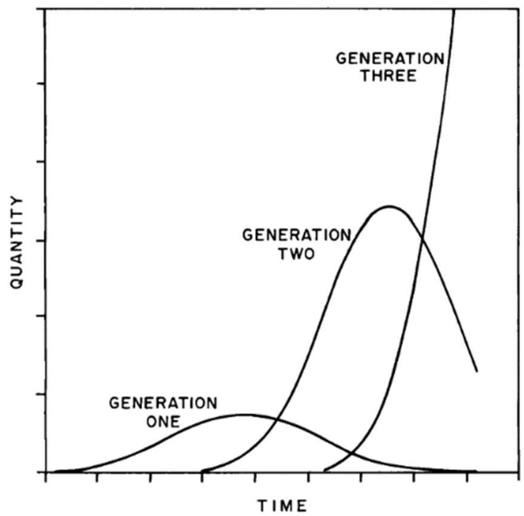
With the addition of a scalar factor to represent the total uptake, (Bass, 1969) found that the model fits remarkably well to durable goods, with an R^2 close to 0.9 for a group of 10 products. (Jeuland, 1994) extended this study by considering 35 datasets over different time periods and countries, finding that the model always provides a good fit with R^2 values greater than 0.9 (Mahajan, Muller, & Bass, 1995). Today, the Bass Model still acts as a benchmark, mostly due to its tractability and relatively good performance.

Despite its good fit, the model has been heavily criticised by economists and other social scientists due to the lack of explicit treatment of social interactions and market forces (Geroski, 2000). In addition, the model does not consider multi-generational technologies, where a new technology builds on an existing one. Consequently, technological uptake is independent of prices and the only factor which determines information diffusion is the amount of people who have already adopted a technology. Furthermore, the Bass Model considers a homogeneous group of individuals with a constant preference for imitation over time.

7.2.2 Generation Bass model

These criticisms pushed towards the extension and improvement of the Bass Model. First, the model was extended to include successive generations by allowing for both diffusion and substitution between products (Norton & Bass, 1986). Following a substitution model similar to (Peterka, 1977), the successive generations model assumes that future technologies are better versions of the current technology and that the uptake of an earlier generation depends negatively on the uptake of successive generations. This results in the peak of each diffusion curve occurring slightly after the introduction of a successive technology. The model also allows for substitution between people who have already adopted one technology to a successive generation. Figure 3provides an illustrative example of the evolution of three successive generations. When fitted against the data, on the sale of micro processing units, they found again that this adaptation to the Bass model was able to closely mimic historical data on the launch of multi-generational innovations (Norton & Bass, 1986).

Figure 3 - Example of a series of technological generations.



Source: Rogers (1962)

The second adaptation made to the Bass Model introduced prices and marketing efforts (Bass, Krishnan, & Jain, 1994). With this improvement, the model specifies a single time-varying parameter capturing pricing as well as marketing effects. Furthermore, the model also permits for time lags to capture successive generations while retaining a closed form solution. For the few cases where the Bass Model was not able to fit the data, the adaptions made to the Generalised Bass Model helped reconcile the concern in the literature and provided a better fit for some innovations. (Bass, Krishnan, & Jain, 1994) concluded by stating that the added complexity of the Generalised Bass Model only improves the fit of the model if the decision variable is time varying. In the case of a stationary decision variable or a constant time-trend there are few gains to be had by using the Generalised Bass Model. Even if the Bass model was mis-specified, but the parameters had a constant time trend or were time-invariant, it would not have a large impact on the predictive power of the original Bass model.

7.2.3 Further extensions

The Bass model and the further generalisations became the building blocks for future EBMs (Bass, 2004; Orbach, 2016). Further extensions to these models tended to result in increases in complexity without much improvement in the estimation, but a few extensions are worth mentioning.

(Fruchter & Van den Bulte, 2011) noted that the generalised Bass model implies that marketing efforts should start low and gradually ramp up. The results are in stark contrast to common marketing knowledge, where advertisement costs are front-loaded, hoping that social contagion will take over. (Jiang & Jain, 2012) suggested an extension to the multigenerational bass model which allowed for different treatment of prices and marketing efforts in the same model while retaining a closed form solution. This model, coined the Generalised Norton-Bass model, also solves for the two main forms of substitution, leapfrogging and switching. Leapfrogging is where an adopter skips an earlier generation, whereas switching is an adopter who switches from an earlier generation to a later one. The model highlights the importance of timing, as introducing a new generation too early can result in the cannibalization of older generations.

More recently, (Orbach, 2016) suggested a model which allows for spatial heterogeneity in adoption rates, even allowing the coefficients of innovation and imitation to be negative, representing barriers to diffusion. (Fan, Che, & Chen, 2017) considered a Bass model which includes sentiment analysis, where the coefficient of imitation depends on the average sentiment regarding a specific product at that time. These models started to consider heterogeneity in an EBM framework, pulling from the literature on ABMs. However, as of yet, there is little empirical evidence in support of these models.

7.3 Agent-Based models

7.3.1 Introduction to ABMs

Fundamental to the agent-based models (ABMs) is the notion of an agent. An agent can be defined as "something that acts based on observations of its environment" (Kochenderfer & Wheeler, 2022). ABMs are used to represent more than physical entities, such as individuals, animals, or vehicles, but agents can also be thought of as non-physical entities, for example nodes of a social network. Through a bottom-up approach, ABMs can capture non-linear relationships of complex systems and are apt for interdisciplinary modelling (Moglia, Cook, & McGregor, 2017). This bottom-up approach allows for the potential of more nuanced analysis of stakeholders; contrasting to the macro-level top-down approaches such as the Bass Model (Kiesling, Günther, Stummer, & Wakolbinger, 2012).

A common draw-back of ABMs is that conveying the inner workings of the model can be difficult (Grimm, et al., 2006). Although the individual decision rules are often simple, both the parameterisations and interactions between agents needs to be justified. Furthermore, until recently, ABMs have often faced challenges of reproducibility (Grimm, et al., 2006; Moglia, Cook, & McGregor,

2017) which has stifled the growth of ABMs. Due to the difficulties of succinctly describing ABMs and the vast heterogeneity of different models, this section will only focus on a few ABMs related to the technology diffusion literature. Specifically, three conventional ABMs will be considered in chronological order, and lastly the group of future technology transformation models will be discussed.

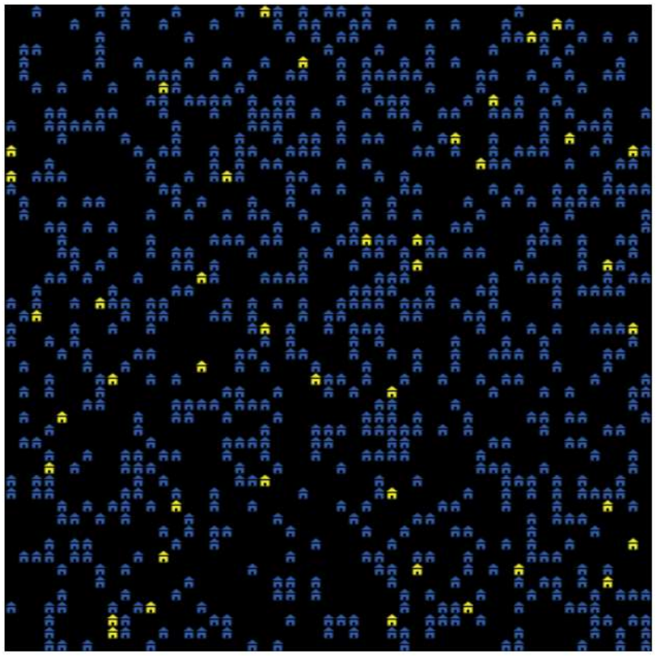
7.3.2 Agricultural innovation

The use of ABMs for diffusion modelling started to gain traction in the early 2000s, with the implementation of ABMs to model technology diffusion in the agricultural sector (Berger, 2001). The model was broken down into two sub-models: an economic sub-model and a hydrologic sub-model. The economic sub-model considers a set of simple decision rules and competition dynamics between farms. The hydrologic sub-model considers the land ownership, soil quality and other land-specific factors. Consequently, technological diffusion was determined based on the 5 adopter groups (Rogers, 1962) and the individual agent's net present value (NPV) of adopting a new technology. Only if enough people had already adopted the technology and the NPV was high enough would a farmer change to a new technology. The simulation was calibrated based upon micro-level data in Chile and tested against macro-level data, getting an R^2 value of 0.991 on the calibration data and 0.657 on the testing data. The model concluded that the uptake of new agricultural technologies was largely determined by the strength of bandwagon effects.

7.3.3 Energy innovation

(Zhang & Nuttall, 2011) used an ABM to simulate the impact of 6 suggested policies for phasing in smart meters in the UK. The authors ran a "small-world" simulation, a 250 by 250 grid of randomly assigned houses (agents) to represent the UK economy (Figure 4). Each agent has either adopted a smart grid (yellow) or uses conventional grids (blue). The interactions between agents are assumed to be a combination of 2nd order queen contiguity and a random selection of other agents. The model assumes that preferences for adopting smart meters is a function of the preferences of one's neighbours and that the market share of different suppliers determines prices. Consequently, these dynamics simulate competition between energy providers. Using this framework, they assessed the decision making of agents under different policy scenarios, where agents' traits were randomly assigned. The model predicted that the fastest way to roll-out smart meters in the UK would be through a combination of government financed-competitive roll out.

Figure 4 - "Small-World" simulation of smart meters in the UK



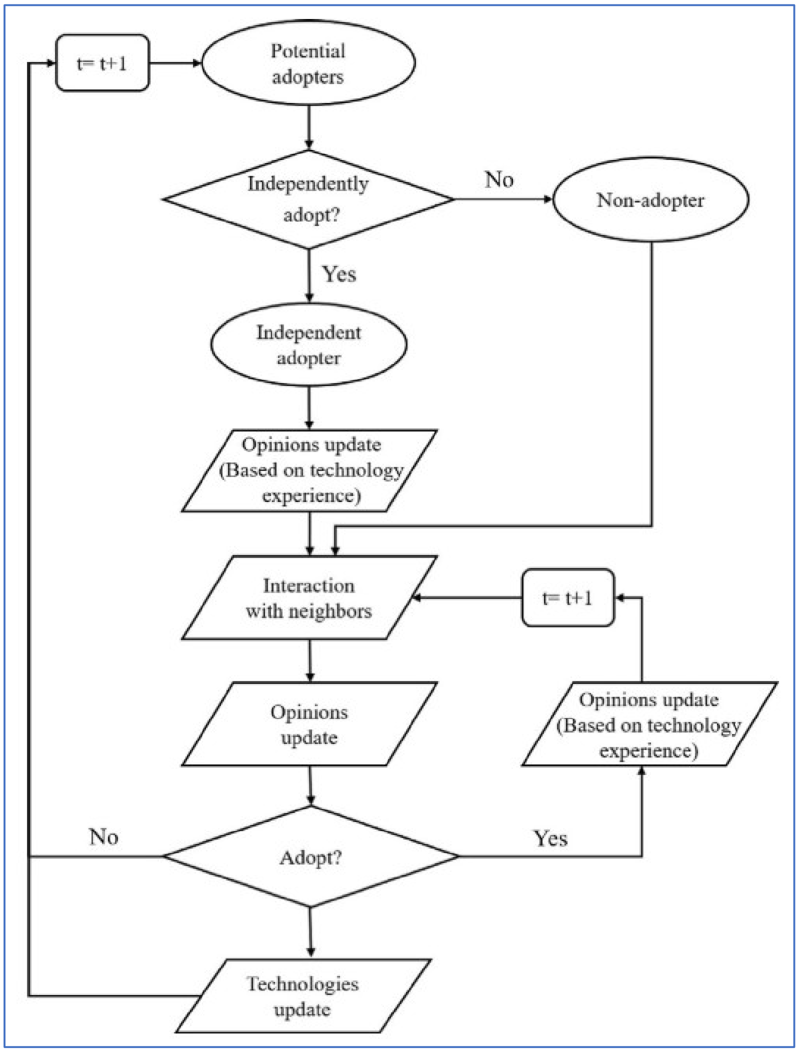
Source: Zhang and Nuttal (2011)

7.3.4 Green technology innovation

To better understand the resistance towards green technologies, (Zeng, Dong, Shi, Wang, & Li, 2020) used a relative agreement model (Deffuant, Amblard, Weisbuch, & Faure, 2002) to represent the interactions among individuals. The model assumes that agents have some initial opinion about green technology and some uncertainty surrounding whether their opinion is correct. The uncertainty parameter decreases as a technology matures, and the opinions of agents change depending on the views of neighbouring agents. Figure 5 outlines the model dynamics.

The model found similar results to the Bass model, however, with slightly faster uptake of green technologies and a slower decay. Overall, results suggested that the initial preferences of the population are more important than technological maturity. The author highlighted the importance of considering heterogeneous agents, as their initial preferences can help explain regional differences in technology uptake.

Figure 5 - Flowchart of agent-based model on green technology uptake.



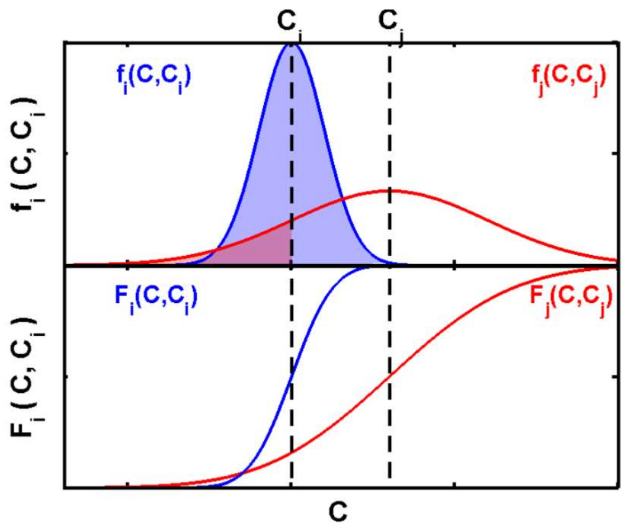
Source: Zeng et al. (2020)

7.3.5 Future Technology Transformations

Combining the literature of epidemiological models with the probabilistic properties of ABMs, Future Technology Transformations (FTT) models can be classified as discrete choice models with heterogeneous agents (Knobloch, et al., 2020). These models introduce uncertainty into the prices which agents face when deciding on new technologies; however, once an agent has observed a price, the model conducts a pairwise comparison between all potential technologies in the economy, and the one with the largest NPV is selected (Mercure J.-F. , 2012). Furthermore, the likelihood of switching to a new technology depends on the relative market shares of different technologies and follows the dynamics of the Lotka-Volterra equation (Mercure J.-F. , 2018). This captures the predator-prey dynamic of technology diffusion, where the growth of one technology results in a decrease in another. However, it also implies that all technologies need a non-zero market share to be able to take off (Mercure & Lam, 2015).

The price uncertainty in the model results in agents not always being able to correctly estimate the NPV. Consequently, this drives a switch in technologies where the "best" technologies are not always chosen (Kirman, 1992). This means that the FTT model comes closer to modelling the decisions which agents really make, instead of assuming that agents behave as if they had perfect information. Figure 6 outlines the case where agents are faced with two different overlapping cost distributions. In this case, although technology i is on average cheaper than technology j, some agents still observe a price for technology j which is lower than technology i. The resulting effect is that there will be a relatively slower uptake of technology j compared to technology i. Over time, this can result in the lock-in of certain technologies due to the growing market shares. These effects can be exacerbated when integrated with a demand-side economic model, such as E3ME, where changes in the technology composition can influence result in positive or negative feedbacks.

Figure 6 - Cost distribution of technologies (top) and cumulative probability distribution (bottom)



Source: Mercure (2012)

The inclusion of price uncertainty into the model implies that FTT takes a bottom-up approach in modelling the choices of agents, while however assuming that the uptake is also dependent on market shares. In other terms, FTT can be considered a non-spatial ABM with less parameterisation requirements than conventional ABMs. The FTT models also replicate the S-shaped adoption curves found in empirical studies.

The simplicity of the modelling framework of FTT has allowed it to tie into more complex models, serving as a technological sub-module for larger macro-economic models (Mercure J.-F. , et al., 2018). Furthermore, several adjustments have been made to FTT to calibrate it to different technologies. A FTT model of the transport sector has been combined with an Integrated Assessment Model (IAM)[3] to simulate the impact of transportation policies on emissions and the vehicle fleet composition. Additionally, it has been used to assess the impact of different climate scenarios on stranded fossil-fuel assets based on change in energy production technologies and fuel demands from transportation (Mercure J.-F. , et al., 2018). Another study, by (Knobloch, et al., 2020), also considered how changes in heating and electric vehicle uptake would impact long-term emissions, tying the FTT models in with E3ME and GENIE to model macroeconomic and environmental changes respectively. The integration of

[3] Integrated assessment models are models that try to comprehensively consider an integrated system of climate, economy, and energy use on a global level Invalid source specified..

these models allows FTT to assess the impact of complex policy scenarios on technological uptake, without directly changing the number of innovators or price. Additionally, the resulting analysis is able to give a whole systems view of the economy, considering both supply-side and demand-side impacts of technology diffusion.

8 Comparison of models

Both EBMs and ABMs have their merits as approaches to modelling technology diffusion. EBMs enable succinct and often tractable solutions, but require simplifying assumption regarding real-world interactions. ABMs, on the other hand, allow for complex simulations of individuals and provides insights into how technology diffusion may occur when faced with heterogeneous agents; however, the key drivers of these dynamic may not always be clear. The FTT class of ABMs overcomes some of these issues by adopting the tractability of EBMs while still retaining heterogeneous agents. This section will outline four of the key differences between these two modelling approaches, namely:

- Model calibration
- Treatment of path-dependence
- Modelling flexibility
- Treatment of space

By addressing how the modelling frameworks vary in terms of these key topics, this discussion aims to clarify which modelling framework is more suitable for providing policy recommendations.

8.1.1 Historical data & calibration

Both EBMs and ABMs are heavily reliant on accurate model calibration (Rahmandad & Sterman, 2008; Berger, 2001). Usually, a limited timeframe or a limited sample is used for model calibration, but most studies fail to report the sensitivity of their modelling parameters. Cross-validation techniques and other machine learning technique have been suggested to ensure the robustness of models and appropriate calibration (Moglia, Cook, & McGregor, 2017).

Although all the models discussed are prone to model misspecification, ABMs allow for the uncertainty to be embedded into the model, either through uncertainty of preferences (Zeng, Dong, Shi, Wang, & Li, 2020) or information uncertainty (Zhang & Nuttall, 2011). EBMs also face issues surrounding correct calibration, but do not allow for embedded uncertainty in the model. Although EBMs have been proven to provide good estimates ex-post, their ability to forecast future adoption remains questionable (Fagerberg & Verspagen, 2002), mostly due to the absence of sufficient information to correctly calibrate the model for new or upcoming technologies.

There is a large heterogeneity between modelling approaches within ABMs. Some studies have used survey data to calibrate the behaviour of agents (Berger, 2001; Kiesling, Günther, Stummer, & Wakolbinger, 2012; Moglia, Cook, & McGregor, 2017), whereas the FTT model relies on macro-level economic variables for the initial calibration (Mercure J.-F. , 2012). There is also a consideration to be made regarding the simulation scale. Survey based calibration may be suitable for simulating small populations with limited heterogeneity. For larger scale simulations with many heterogeneous agents, data collection from survey data can become both costly and at risk of unbalanced sampling (Moglia, Cook, & McGregor, 2017).

8.1.2 Path dependency

The notion of path-dependency and information cascades is essential for understanding the evolution of technology diffusion (Sharpe & Lenton, 2021). Although the multi-generational Bass model attempts to capture the effects of path-dependence, it typically considers successive technologies, where future technologies are purely improved version of existing technologies. In ABMs path dependence and information cascades can either be included exogenously or endogenously within the model. When FTT is combined with macroeconomic model E3ME and the climate model GENIE, it allows for technology uptake to change endogenously within the model based upon changes in the macro-economy. This results in the possibility of path dependence as certain types of technologies become increasingly locked-in (Mercure J.-F. , 2018).

8.1.3 Flexibility

The increased flexibility from using ABMs can result in the modelling outputs becoming less tractable. Although ABMs can be a very powerful tool for simulating a specific policy, the rationale or key dynamics of the model may be difficult to convey. EBMs lack the modelling flexibility of ABMs; however, for simple models such as the Bass model and several of its adaptations, it remains tractable and displays clear dynamics. The FTT models retain the tractability of simple EBMs, considering macro-level variables and predator-prey relationships between technologies, while still providing more flexibility. Primarily, the inclusion of uncertainty and a bottom-up approach allows for dynamic modelling of technology diffusion and path dependence.

8.1.4 Treatment of space

One of the main reasons for the rise in ABMs was to model the interactions between people through space, something which conventional EBMs did not address (Kiesling, Günther, Stummer, &

Wakolbinger, 2012; Noonan, Hsieh, & Matisoff, 2013; Lychagin, Pinkse, Slade, & Van Reenen, 2016; Orbach, 2016). The importance of space comes from the assumption that information travels based on geographical proximity, thus driving technology diffusion. In FTT space does not factor into the decision variables. As in EBMs, the effects of geographical proximity are assumed to be constant. This means that FTT or EBMs may not be appropriate when considering local technological diffusion, for example within cities or neighbourhoods, where social interactions are likely to play a large role in adoption.

9 Conclusions

When assessing the future uptake of energy efficiency technologies in Europe, both precision and accuracy are vital. An inaccurate model may provide large error bounds and may be over-sensitive to changes in modelling assumptions. On the other hand, an imprecise model would systematically underestimate or overestimate policy impacts, resulting in misguided policy recommendations. It is necessary therefore that a good model is both precise and accurate in its estimation for all EU Member States. If the model is biased towards certain countries, this could result in widening the gap between EU member states due to misguided policy recommendations.

As highlighted in this literature review, equation-based models have a limited ability to capture path-dependence and require a sufficiently long historical timeframe for calibration. Although agent-based models are more apt to capturing non-linear relationships and path-dependence, many agent-based models can be very sensitive to the initial calibration, and require a lot of data to accurately model heterogeneity between agents. The future technology transitions (FTT) models consolidate the heavy data requirements by assuming a distribution of aggregated variables and by allowing the model to tie into macro-economic projections. The key advantages of using high-level data are twofold: first, data with a higher level of aggregation is likely to be available more widely for all EU Member States. This means that the risk of country-level misrepresentations due to inadequate data are less likely to occur. Secondly, reducing the reliance on multiple datasets and the data intensity of the model allows for easier updating and re-calibrating of the model in the future.

With these key considerations in mind, equation-based models lack the flexibility to model behavioural changes, and many agent-based models are too sensitive to the input data. Consequently, a futures technology transition model seems to be the most appropriate modelling tool for assessing the uptake of energy efficiency technologies in Europe. With the integration of FTT with E3ME both supply-side and demand-side policies can be assessed. Furthermore, since FTT models remain tractable, while still retaining many of the nuances of ABMs, they allow for flexibility when implementing different policy scenarios. Finally, the leniency in terms of data requirements means that FTT can take advantage of the highest quality datasets, minimising the risk of inaccurate or imprecise estimates.

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