Examining the Diffusion of Insulation among Dutch Households

A Quantitative Study on Diffusion Curves, Foregone Benefits and Adoption Influences

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Abstract

Insulation is an energy-efficiency measure creating benefits for both households and society. Despite these benefits, a large proportion of Dutch dwellings is still, relatively, poorly insulated. This study therefore quantitatively examined the diffusion of insulation measures among Dutch households through three analyses, based on systematically conducted surveys on the energetic quality of the Dutch housing stock.

A diffusion curve analysis demonstrated that the average degree of insulation has generally been increasing over the years. Yet, the rate by which these measures are diffusing has been decreasing. Substantial differences in the insulation degrees of Dutch dwellings have also been found. This gap appeared between dwellings built prior to 1981 and hereafter. Similarly, apartments and social rental dwellings were found to have lower insulation degrees than other dwelling and tenure types.

A foregone benefits analysis demonstrated that additional insulation could annually have saved households 336 to 542 m^3 of natural gas on average, and 2.37 billion to 3.82 billion m^3 in total. It was found that the average and total savings were substantially lower for dwellings built after 1995 due insulation legislation and that lower insulation degrees do not necessarily translate into higher foregone benefits. Average savings were the highest for semi-detached/end-terraced and detached dwellings. The highest total savings could have been achieved by insulating all dwelling types built between 1960-1980. These findings indicate that the private benefits are not perfectly aligned with the societal benefits. Rental dwellings were found to have lower average and total savings than owner-occupied dwellings.

An adoption analysis showed that households living in dwellings built after 1995 are substantially less likely to adopt an insulation measure at all. Paradoxically, it was found that the same households living in the dwellings built after 1995 have a higher likelihood of having more different insulation measures adopted. Households living in rental housing were found considerably less likely than homeowners to adopt any insulation measure. Similarly, households part of homeowner associations were found to be less likely to adopt more insulation measures. These findings appear to indicate the presence of a principal-agent problem. Household members' income, capital, age, education level and likelihood to move did not significantly affect the adoption of insulation, suggesting that socio-demographic factors appear to play a less significant role in the uptake of insulation measures than housing factors seem to do. The findings of this study were used to formulate recommendations for research and policy.

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1. Introduction

Despite current efforts, changes in contemporary energy systems are needed to mitigate climate change. During the past decade, global energy demand and greenhouse gas (GHG) emissions rose across all major sectors and they are expected to keep rising without the strengthening of current policies, as indicated in the 2022 assessment report of the Intergovernmental Panel on Climate Change (IPCC, 2022). The building sector is one of the major sectors contributing to these trends. In 2019, buildings accounted for 21% of the global GHG emissions and of the sector's total energy demand, 70% was consumed by residential buildings (IPCC, 2022). Therefore, residential buildings and households have a significant energy-saving potential and could substantially contribute to achieving sustainable energy targets, as well as other Sustainable Development Goals, by changing the way they consume energy (IPCC, 2022).

In the Netherlands, the usage of natural gas accounted for 70% of households' energy consumption in 2021 and entailed roughly 25% of the total Dutch natural gas consumption (CBS, 2023a, 2022a). Reducing the consumption of natural gas is therefore essential for reducing the energy consumption and carbon footprint of Dutch households. Energy-efficiency (EE) measures and technologies play a key role in this, as these use less energy while performing the same function as alternatives. Insulation in particular is an EE measure that is found to significantly reduce households' gas and energy consumption, resulting in both societal and private benefits (Adan & Fuerst, 2016; Mot et al., 2023). A societal benefit, besides CO_2 reduction to mitigate climate change, is reduced gas imports which lowers societal costs and stimulates energy independence (Mot et al., 2023; Rijksoverheid, n.d.). The benefits of insulation measures and subsequent reduced gas consumption from a private, i.e. household, perspective include lower energy bills, increased financial resilience and positive health and living effects (Mot et al., 2023). A study recently concluded that for 62% of the Dutch households additional insulation measures would generate financial benefits (Mot et al., 2023).

Despite these societal and private benefits, a large proportion of Dutch dwellings is still relatively poorly insulated. In 2020, 56% of the Dutch dwellings for instance had an energy label 'C' or lower and nearly a quarter of the dwellings in the Dutch private rental sector still contained inefficient single glazed windows (Woononderzoek Nederland, 2021; Woonbond, 2022).[1] To reach the governmental goal of having zero dwellings with low energy labels by 2030, a fifth of the Dutch housing stock needs to have additional insulation measures installed during the coming years (Natuur & Milieu, 2022). A particularly interesting question, both from an academic and a policy perspective, therefore holds why households may not adopt additional insulation measures even if the return of investment seems to be positive, as economic theory would predict. Although economists have been theorising on decision-making processes and explanations for the apparent gap between predicted and observed adoption rates of EE technologies (e.g., Jaffe & Stavins, 1994a, 1994b; De Groot et al., 2004;

[1] In the Netherlands, energy labels of residential buildings are based on an 11-point scale, ranging from G to A++++ (Rijksdienst voor Ondernemend Nederland [RVO], 2023a).

Gerarden et al., 2017), there is little empirical evidence on the size of this Energy Efficiency Gap (EEG) and the effect of these explanations.[2]

The aim of this study is therefore to quantitatively examine the diffusion of insulation measures among Dutch households. This study starts with descriptively examining *how insulation measures have been diffusing among Dutch households over time*. This has currently not been thoroughly examined and such an analysis would provide more context on the diffusion of insulation measures and the decarbonisation efforts of Dutch households. Secondly, this study estimates *the foregone benefits that these households could have achieved if insulation measures had diffused to a greater extent.* While the insulation benefits for households have been priorly analysed (e.g., Menkveld et al., 2020; Faaij et al., 2022; Mol et al., 2023), these have not been aggregated or related to the diffusion process of insulation measures. Lastly, this study assesses *what household factors are affecting the adoption of additional insulation measures*. As of yet, factors influencing the observed adoption of insulation measures have solely been studied for Dutch homeowners (Ebrahimigharehbaghi et al., 2019, 2020, 2022). However, as more than a third of the contemporary Dutch housing stock consists of rental housing (CBS, 2022b), a substantial share of the Dutch households has been excluded in these studies. Besides including these households, this study is also the first to examine the adoption of insulation measures through the theoretical perspective of the EEG.

In examining the diffusion of insulation measures, this study connects and tests concepts from multiple disciplinary diffusion perspectives. The adoption of insulation, and of EE technologies in general, has insufficiently been examined from an interdisciplinary perspective. Yet by taking such an interdisciplinary perspective, it is argued that the diffusion of innovations can be better understood (Nelson et al., 2004). This study therefore integrates economic EEG concepts with adoption theories and empirical evidence from sociology and sustainability studies. Furthermore, this study takes socioeconomic gaps and the notion of energy poverty into account (Straver et al., 2020), which have received increased political attention over the past years. Characterised by high energy costs, a low income and a poorly-insulated home, research showed that of the six million Dutch households analysed, 550,000 households experienced energy poverty in 2019 (Mulder et al., 2021). Since these households are facing relatively higher fixed expenses and subsequently could be financially unable to adopt beneficial EE technologies, socioeconomic gaps might be widening. Although the widening of socioeconomic gaps is a common consequence of innovations, it is not unavoidable (Rogers, 2003). This study could thus not only assist with stimulating the decarbonisation of residential buildings, but also with ensuring an inclusive energy transition.

The structure of this study is as follows. In Section 2, disciplinary diffusion perspectives are first discussed, after which diffusion curves, the Energy Efficiency Gap (EEG), adoption influences and hypotheses are elaborated on. In Section 3, the methodologies of the three conducted analyses - on diffusion curves, foregone benefits and adoption influences - are discussed. The results of these three analyses can respectively be found in Section 4, 5 and 6, and are interpreted in Section 7. Finally, in Section 8, the findings of this study are summarised and related to several research and policy recommendations.

[2] The EEG should not be confused with the Energy Performance Gap (EPG), which entails the discrepancy between the energy consumption estimated before the construction or renovation of a building and the energy consumption observed hereafter.

2. Theory

The process of individuals adopting new technologies is commonly referred to as the diffusion of innovations (Hall, 2005).[3] Research on diffusion finds its roots in sociology (Tarde, 1903) and anthropology (Wissler, 1914, 1915), and has been taken up since by the fields of economics (e.g., Griliches, 1957; Mansfield, 1961) and marketing (e.g., Arndt, 1967; Bass, 1969). Contemporary perspectives on diffusion predominantly originate from three of these disciplines, namely economics, sociology and marketing (Hall, 2005; Tidd, 2010; Kiesling, 2012). In this section, these disciplinary diffusion perspectives are first summarised after which the need for an interdisciplinary perspective is argued for (Section 2.1). Hereafter, models concerning the diffusion over time, i.e. diffusion curves, are discussed (Section 2.2). This is followed by an elaboration on the various explanations for the Energy Efficiency Gap; reasons why EE technologies are not being adopted as expected, despite their seemingly positive net benefit (Section 2.3). Finally, these theoretical insights are related to adoption influences and empirical research, from which several hypotheses are derived (Section 2.4).

2.1 Diffusion in disciplinary research

Economics

Diffusion in economics can widely be interpreted as “the process by which the market for a new technology changes over time and from which ownership or usage patterns result.” (Stoneman & Battisti, 2010, p. 2). Economic scholars have created various econometric models on the diffusion of innovations, aiming to explain past behaviour of individuals, with a particular emphasis on firms (Tidd, 2010; Stoneman & Battisti, 2010). Underlying is the assumption that diffusion is the cumulative aggregation of rational calculations by individuals (Hall, 2005). Subsequently, in their decision-making processes individuals are assumed to assess whether the benefits of adopting outweigh the costs. This assumption and decision-making process is commonly examined through the net present value (NPV) criterion (Jaffe & Stavins, 1994a; De Groot et al., 2004). By applying the NPV it can be computed whether future, i.e. discounted, cash flows are covering for initial investment costs. Utilising the NPV approach is justified if certain conditions are fulfilled. Individual adopters should for instance make rational, profit-maximising decisions and should have complete information and sufficient financial means at their disposal (De Groot et al., 2004). However, as the adoption-decision process often occurs within an environment characterised by uncertainty and limited information (Hall, 2005), the robustness and applicability of such adoption models is often questioned.[4]

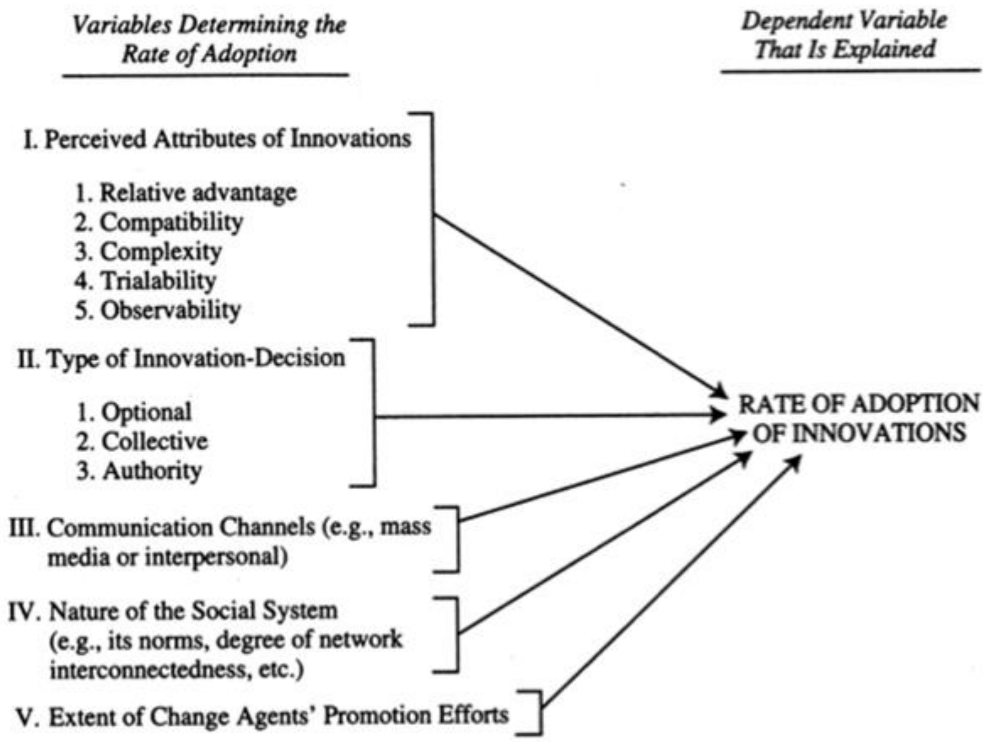
[3] ‘Individuals’ here refers to the individual decision-making units and could thus imply consumers, households, communities, businesses, organisations etc.
[4] This is further addressed in Section 2.3.

Sociology

In his seminal book, first published in 1962, Rogers outlined an influential sociological and organisational perspective on diffusion (Rogers, 2003). Here, Rogers describes diffusion as "the process in which an innovation is communicated through certain channels over time among the members of a social system." (Rogers, 2003, p. 5). Diffusion is thus essentially perceived as a type of communication that spreads novel information. The relative speed by which an innovation diffuses is referred to as the rate of adoption and is commonly measured in the number of adopters over a specific time period. Rogers (2003) elaborated that five variables determine the rate an innovation is adopted: the perceived attributes of innovations, the type of innovation-decision, the type of the communication channels, the nature of the social system and the extent of change agents' promotion efforts (Figure 1). As a particular innovation is not adopted simultaneously by all individuals, Rogers (2003) aggregated adopters based on their *innovativeness,* i.e. the relative time of their adoption. From this, five ideal types of adopters are constructed: innovators, early adopters, early majority, late majority and laggards. Based on their socioeconomic status, personality values and communication behaviour, Rogers (2003) derived several generalisations on these adopters categories. Since diffusion is regarded as a process of communication, the effects of (interpersonal) networks on diffusion have also been a key interest for sociologists.

Figure 1

Variables determining the rate of adoption



Note. Reprinted from Rogers' Diffusion of Innovations (2003, p. 222)

Marketing

In the field of marketing, diffusion research has primarily been focused on designing mathematical instruments to examine and predict buyer behaviour (Tidd, 2010). Studies for instance include how individuals react to technological innovation (e.g., Moore & Benbasat, 1991) and how their behaviour changes after adoption (e.g., Kim, 2009). User demographics and adopters' social and psychological factors have therefore gained an increasing interest in marketing studies (Tidd, 2010; MacVaugh & Schiavone, 2010). The most influential diffusion model within this field was presented by Bass (1969). This model emphasises the influence of communication on two types of adopters; innovators and imitators. Whereas innovators are solely influenced by mass-media communication (external influence), imitators are influenced word-of-mouth only (internal influence) and experience an increasing pressure if the number of previous adopters rises (Bass, 1969). The Bass model is specifically designed for one-time adoptions and has therefore been widely applied to the diffusion of consumer durables (Tidd, 2010). Limitations of the model have frequently been addressed; e.g., it does not consider the relationship with other innovations nor product and market characteristics (Mahajan et al., 1990; Kiesling, 2012). An abundance of refinements and extensions have therefore been tested, which concluded that the Bass model constitutes an empirical generalisation (Mahajan et al., 1990, 1995).

Interdisciplinary diffusion perspective

As diffusion research is vast and originates from multiple disciplines, it is not surprising that their literature and contributions can be perceived as rather fragmented. Nevertheless, differences in the disciplinary nature of diffusion studies have frequently been addressed by scholars. Whereas in economics the role of economic factors and the behavioural basis of diffusion models are emphasised, marketing literature rather focuses on forecasting performance (Zettelmeyer & Stoneman, 1993). Moreover, economic and marketing studies typically focus on the diffusion of technology, while sociologists describe diffusion as the communication of novel ideas, which can also include new practices or habits (Tidd, 2010; Rogers, 2003). As economists also tend to emphasise the decision-making of micro-economic units, they fall short in sufficiently including social factors and externalities which are favoured by sociologists (Hall, 2005; Tidd, 2010).

Despite these differences, disciplinary diffusion perspectives are often complementary to each other. The marketing model of Bass (1969) for example builds on Rogers' (2003) sociological perspective and is highly influential within the field of economics (Tidd, 2010). In other diffusion models, aspects from both marketing and economic diffusion literature have been combined (e.g., Karshenas & Stoneman, 1992). Nelson and colleagues (2004) demonstrated that "many innovations do not fit perfectly into the idealized class presumed by a particular disciplinary theory." By taking an interdisciplinary perspective and incorporating elements of multiple theories instead, the diffusion of innovations can be better understood (Nelson et al., 2004). To examine the diffusion of insulation measures, this study therefore incorporates such an interdisciplinary perspective by connecting and examining concepts from multiple diffusion perspectives.

2.2 The diffusion curve

Diffusion literature comprises various underlying research subjects and models. One particular focus area concerns the diffusion of innovations over time, also referred to as the rate of adoption. Although the rate of adoption is innovation- and context-dependent, it is considered a stylised fact that the cumulative number of adopters of any innovation follows a logistic S-shaped curve when plotted versus time (Figure 2). Or expressed differently, the number of new adopters of an innovation is argued to be normally distributed over time (Figure 3). Whereas the rate of adoption is slow at first, it will eventually accelerate and become self-sustaining, after which it slows down again as the adopter population has been saturated (Rogers, 2003; Hall, 2005; Tidd, 2010).

Two leading mechanisms could explain the empirical generalisation of the S-shaped diffusion curve; adopter heterogeneity and adopter learning (Geroski, 2000; Hall, 2005). The heterogeneity mechanism, also referred to as the probit model, assumes that adoption benefits, goals and abilities differ among individuals. Arguing that the adoption benefits are normally or uniformly distributed over these individuals and that the threshold of adopting decreases over time (e.g., due to decreasing prices), an S-shaped diffusion curve will follow (Geroski, 2000; Hall, 2005). Adopter learning, commonly known as the epidemic model, has been the more dominant mechanism portraying the diffusion of innovations. Within this model, the rate of adoption is affected by previous adopters informing potential adopters about the innovation. As information is increasingly being spread, the number of adopters will grow until no potential adopters are remaining to be informed. This epidemic mechanism results in an S-shaped diffusion curve and has served as the foundation in many diffusion perspectives (e.g., Rogers, 2003; Bass, 1969).

Although the (epidemic) S-shaped diffusion curve is widely accepted and applied within diffusion research, limitations of this diffusion model have been addressed as well. Geroski (2000) for instance claims that the S-curve paradigm is limiting and disregarding alternative diffusion models, such as information cascades and network externalities. Moreover, rather than understanding how diffusion unfolds over time, it should instead be emphasised how the process of diffusion starts (Geroski, 2000). Geroski (2000) also notes that S-curves are rarely symmetrical, arguing that the final phases of diffusion often occur more slowly than modelled in the symmetrical S-curves. Epidemic models tend to overemphasise the differences in adopter characteristics too, while understating macroeconomic and supply-side factors (Tidd, 2010). Epidemic models are therefore considered to be the most suitable for innovations of which the total potential market is known, i.e. derivatives of existing products. Contrarily, if diffusion is instead regarded as a process of persuasion rather than the spread of information, Geroski (2000) argues that decisions of individual adopters are inadequately considered within epidemic models and should in fact be emphasised more.

Additionally, it is noted that S-curves are only used to describe cases of successful innovations, i.e. innovations that have been adopted by nearly all potential adopters (Rogers, 2003). Besides the implication that S-curves are primarily suitable for ex-post analysis, it is claimed that S-curves are compromised by a sample selection bias, specifically a survivorship bias (Geroski, 2000). As most innovations are not widely adopted, Gersoki (2000) argues that any comprehensive diffusion model should take unsuccessful diffusions into account as well. Cases of non-adoption can be equally, or perhaps even more relevant to analyse, especially if the observed diffusion process deviates from predictions.

Figure 2

The cumulative number of adopters over time

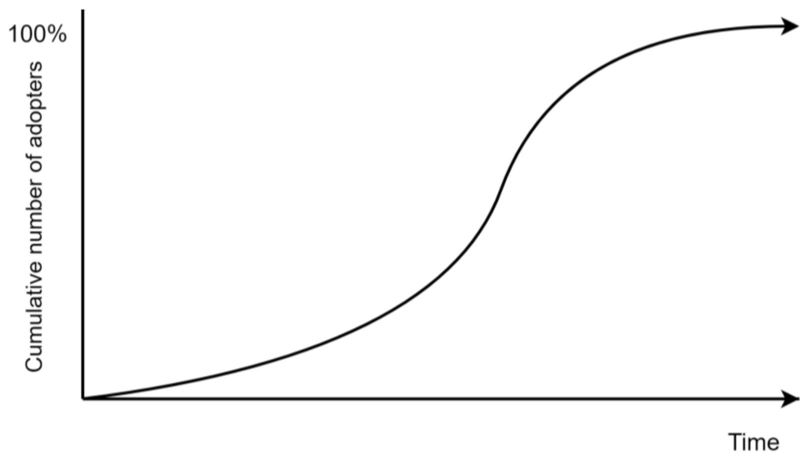


Figure 3

The distribution of the number of new adopters

Note. Reprinted from Rogers' Diffusion of Innovations (2003, p. 281).

2.3 The Energy Efficiency Gap

The individuals who need the benefits of an innovation the most, frequently turn out to be the last to actually adopt it (Rogers, 2003). For the adoption of EE technologies, this paradoxical relationship is commonly referred to as the Energy Efficiency Gap (EEG), or the energy efficiency paradox. The EEG refers to the phenomenon where EE innovations are not being adopted despite their seemingly positive net benefit - including financial gains and a reduced energy consumption - resulting in a gap between the predicted and observed adoption rates (Jaffe & Stavins, 1994b). Whereas the gap in predicted and observed adoption rates has been addressed in earlier studies (e.g., Shama, 1983), the term was first introduced by Hirst and Brown in 1990. Since, the EEG has been subject to numerous studies and various explanations for its paradoxical existence. While Hirst and Brown (1990) for instance identified structural and market barriers, Jaffe and Stavins (1994b) elaborated on market and non-market failures that cause the EEG. Based on more recent studies, factors that could explain the EEG can be categorised as *market failures, behavioural failures* and *modelling failures* (Gillingham et al., 2009; Linares & Labandeira, 2010; Gillingham & Palmer, 2014; Ramos et al., 2015; Gerarden et al., 2017; Solà et al., 2021). By combining insights from existing literature reviews on EEG explanations, these types of failures are elaborated on and summarised in Table 1. It should be noted that, while each of these failures and underlying explanations could theoretically explain the existence of the EEG, limited empirical evidence exists that substantiates the effect these potential explanations have (Gerarden et al., 2017).

Market failures

Various market failures could explain the existence of the EEG, such as for instance imperfect and asymmetric information. Whereas, imperfect information entails a lack of the information required to make an informed decision, asymmetric information refers to an information difference between economic parties. As a result, the perceived value of EE technologies could differ from the market value, making investing in these technologies more uncertain (Gillingham & Palmer, 2014; Solà et al., 2021). Similarly, additional costs might be required to engage in an economic transaction (transaction costs), which could inhibit EE adoption (Ramos et al., 2015). Principal-agent, or split incentives, problems could serve as an explanation of the EEG too. Such issues arise when the deciding party does not bear the costs or benefits of the decision. Whereas in the residential rental sector a landlord could invest in EE technologies, its tenant would be the one enjoying lower energy consumption and costs (Ramos et al., 2015). Such split incentives could subsequently inhibit adoption. Capital constraints form another market failure explanation. Potential adopters might lack financial means, which would also reduce their valuation of future benefits, resulting in them being less inclined to invest (Train, 1985). Another market failure explanation relates to energy pricing and regulations. If energy prices do not include externalities or if regulations cause energy prices to fall below marginal costs, investment incentives and profitability are low (Linares & Labandeira, 2010; Gillingham & Palmer, 2014). Learning spillovers construct the final market failure explanation being discussed. As prior adopters are experiencing the benefits of an innovation and might share this information with others, there can be an incentive to postpone adoption to learn from others and reduce uncertainty (Gerarden et al., 2017; Gillingham & Palmer, 2014).

Behavioural failures

Besides market failure explanations, behavioural failures could also contribute to understanding the EEG. In line with Ramos and colleagues (2015), this study considers the term 'behavioural failures' to reflect the situations where individual decision-makers do not correspond to the rational choice theory. Since behavioural economics has been showing that individuals are not always acting fully rational, its theories and concepts could explain the lack of adoption of EE technologies as well. The concept of bounded rationality suggests that individuals' rationality in decision-making processes is limited due to for instance cognitive or time constraints. Individuals are therefore likely to act as satisficers, choosing satisfying outcomes over optimal ones (Simon, 1955). Heuristic rules and biases present in these suboptimal decisions-making processes, e.g. placing more value on the initial investment costs of EE technologies, can then also induce inefficient adoption behaviour (Linares & Labandeira, 2010; Gillingham & Palmer, 2014; Ramos et al., 2015; Gerarden et al., 2017; Solà et al., 2021). Similarly, systematic biased beliefs could result in less than optimal adoption decisions (Gerarden et al., 2017; Stadelmann, 2017; Gillingham & Palmer, 2014). Other behavioural failures affecting such adoption decisions include inattention to energy costs and myopia (Gerarden et al., 2017; Gillingham & Palmer, 2014). Myopia, in this context, is referring to the condition of potential adopters not perceiving future savings as a benefit (Gerarden et al., 2017; Solà et al., 2021). Finally, the potential outcome of a decision made under uncertainty is usually evaluated by an individual's reference point, as depicted in the prospect theory (Kahneman & Tversky, 1979). Such reference-dependent preferences and related loss aversion, i.e. the tendency of weighing losses more heavily than equivalent gains, could too explain the existence of the EEG (Gerarden et al., 2017; Gillingham & Palmer, 2014).

Modelling failures

At last, measurement and modelling failures could serve as an 'explanation' for the EEG (Gerarden et al., 2017; Gillingham & Palmer, 2014). Incorrect assumptions underlying the modelling of the estimated state of diffusion could result in it deviating from the actual observed state. Several scholars have elaborated on this topic, arguing that the EEG is commonly overstated in size or is even non-existent (e.g., Metcalf & Hassett, 1999; Smith & Moore, 2010; Allcott & Greenstone, 2012, Stadelmann, 2017). Certain costs might for instance be present in the adoption decision-process of individuals, yet could be unobserved or understated by diffusion modellers (Gerarden et al., 2017; Gillingham & Palmer, 2014). Examples of such hidden costs include search, implementation or opportunity costs. An important opportunity cost entails the decrease in product quality (Gerarden et al., 2017; Gillingham & Palmer, 2014; Linares & Labandeira, 2010). Modellers could also insufficiently be including the heterogeneity of consumers. Benefits and costs of adoption might differ among individuals and these individuals could for instance be heterogeneous in their preferences or usage profiles. Consequently, if modellers fail to include this heterogeneity, the size of the EEG could be misstated (Gerarden et al., 2017; Gillingham & Palmer, 2014). In addition, modellers should account for the option value of waiting, i.e. the benefit of delaying adoption even if its net benefit is already positive. Due to the irreversibility of investments, flexibility in the time of adoption and uncertainty regarding energy prices and product performance, individuals might want to postpone their adoption. Similar to heterogeneity, if modellers fail to include the option value, a bias in the estimation of the EEG could occur (Gerarden et al., 2017; Gillingham & Palmer, 2014). At last, modellers could systematically overestimate energy savings or the implicit discount rates of individuals, and understate a rebound effect, resulting in upward biases in the EEG estimation (Gerarden et al., 2017; Stadelmann, 2017; Gillingham & Palmer, 2014).

Table 1

Overview of failures and factors that could explain the Energy Efficiency Gap

Type of failures	*Underlying factor*	*Literature*
Market failures	Imperfect and asymmetric information	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Transaction costs	Gillingham et al. (2009) Linares & Labandeira (2010) Ramos et al. (2015) Solà et al. (2021).
	Principal-agent problems	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Capital constraints	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Inefficient energy prices and regulation	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Learning spillovers	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014)
Behavioural failures	Bounded rationality	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Heuristics and biases	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015)

Type of failures	*Underlying factor*	*Literature*
		Gerarden et al. (2017) Solà et al. (2021)
	Systematic biased beliefs	Gillingham et al. (2009) Gillingham & Palmer (2014) Gerarden et al. (2017)
	Inattention to energy prices	Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Myopia	Gerarden et al. (2017) Solà et al. (2021)
	Reference-dependent preferences	Gillingham et al. (2009) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
Modelling failures	Hidden costs	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017) Solà et al. (2021)
	Consumer heterogeneity	Gillingham et al. (2009) Linares & Labandeira (2010) Gillingham & Palmer (2014) Ramos et al. (2015) Gerarden et al. (2017)
	Option value	Gillingham et al. (2009) Gillingham & Palmer (2014) Gerarden et al. (2017)
	Systematic overestimations	Gillingham et al. (2009) Gillingham & Palmer (2014) Gerarden et al. (2017)

2.4 Adoption influences and hypotheses

In addition to factors that explain inconsistent adoption rates, generic drivers and barriers affecting the adoption of EE technologies have received great attention from academics as well. In their literature review on the adoption of energy-efficient renovations (EER), Du and colleagues (2022) found that the lowering of energy bills and the increasing household comfort are among the most frequently mentioned drivers in academic studies. Du et al. (2022) distinguished four types of EER adoption barriers: limited financial or informational access, attitudinal and behavioural barriers, physical dwelling restrictions and institutional barriers.[5] Subsequently, Du and colleagues identified and elaborated on four related adoption influences that are present within the decision-making process of EER: socio-demographics, housing factors, social influences and environmental attitudes (Du et al., 2022). Based on the available data (see Section 3), the third analysis in this study particularly focuses on socio-demographics and housing factors in the adoption of insulation. By relating these influences to the EEG explanations and adoption concepts, hypotheses can be formulated to assess to what extent they influence the diffusion process of insulation measures.

Household income is a socio-demographic factor often included in quantitative adoption studies. For EE measures, several studies showed that households with a higher income are more likely to invest in such measures (e.g., Dolšak et al., 2020; Barbose et al., 2020; Schleich, 2019; Trotta, 2018; Vasseur & Kemp, 2015; Achtnicht & Madlener, 2014; Nair et al., 2010). However, there are also studies that did not find this significant relationship between household income and EE adoption (e.g., Pettifor et al., 2015; Pelenur and Cruickshank, 2014, 2012). Interestingly, Gamtessa (2013) and Hamilton et al. (2016) found that high-income households were in fact less likely to adopt EE measures. Due to these contradictory results and theories on the EEG and diffusion barriers suggesting financial constraints to inhibit adoption, it is deemed relevant to analyse the effect of income on insulation adoption. Moreover, while Rogers (2003) did not formulate an income-based generalisation specifically, he argued that a higher socioeconomic status is a key characteristic of earlier adopters. These insights lead to the first two hypotheses, which could relate to the capital constraints explanation of the EEG:

Hypothesis 1: The higher the household income, the more likely a household adopts insulation measures.

Hypothesis 2: The higher the household capital, the more likely a household adopts insulation measures.

[5] Note the similarities of these barriers and the market and behavioural EEG explanations discussed in Section 2.3.

In addition to socioeconomic status, Rogers (2003) did explicitly argue that earlier adopters generally enjoy more years of formal *education* than later adopters. Applied to EE measures, studies have both supported (Ebrahimigharehbaghi et al., 2020) and rejected (Pettifor et al., 2015; Pelenur & Cruickshank, 2014) this relationship between education and adoption. From the perspective of the EEG explanations, it can be argued that higher educated households deal with less imperfect information, experience less bounded rationality and act economically more rational than lower educated households. This study will therefore test:

Hypothesis 3: The higher the household education, the more likely a household adopts insulation measures.

Age is another socio-demographic factor frequently analysed in adoption studies. Rogers (2003) argued that there is generally no age difference between earlier and later adopters, which was supported by some studies on EE technologies as well (e.g, Pelenur & Cruickshank, 2014; Pettifor et al., 2015). Yet several studies found a significant positive relationship of age on adoption; older households were more likely to adopt EE measures (e.g., Ebrahimigharehbaghi et al., 2019; Schleich 2019; Trotta, 2018). However, it has also been found that there is a negative relation between age and adoption; older households could be less aware of EE technologies and might be facing more uncertainty (imperfect information) on the profitability of long-term EE investments (Schleich, 2019; Carlsson-Kanyama et al., 2005). Based on these contractionary insights, it can be argued that the relation between age and EE adoption is non-linear. Therefore the following hypotheses are therefore derived:

Hypothesis 4a: Household members younger than 45 are more likely to adopt insulation measures than household members aged between 45-54.[6]

Hypothesis 4b: Household members older than 54 are less likely to adopt insulation measures than household members aged between 45-54.

Home-ownership, or owner-occupancy, is another relevant socio-demographic to consider in the analysis. As discussed in EEG literature, landlord-tenant problems are a typical example of the principal-agent problem and could inhibit the adoption of EE technologies (Ramos et al., 2015). Similarly, Rogers (2003) indicates that the type of innovation-decision affects the rate of adoption. Adoption can for instance be prohibited by a higher authority (the landlord), despite it being desired by the associated user (the tenant). It can be argued that households living in dwellings they mortgage or own themselves, compared to those renting such properties, are not restrained by a landlord-tenant problem and are thus more likely to adopt EE measures. Several studies have indicated that such innovations are indeed less likely adopted in rental properties (e.g., Schleich et al., 2019; Trotta, 2018; Hamilton et al., 2016). Therefore, the next hypothesis is formulated as follows:

Hypothesis 5: Insulation measures are more likely to get adopted in owner-occupied housing than in rental properties.

[6] Household members with an age between 45-54 have been selected as the reference group, as this group belongs to the middle age category included in the secondary datasets (Section 3.2).

Related to the prior hypothesis and elaboration are *homeowner associations* (HOAs). These are private associations that govern the interest of homeowners who are often living in buildings with multiple owner-occupancies. Due to the buildings being shared, EE renovations have to be initiated and approved by the homeowner association. Whereas typical homeowners and tenants are respectively facing an optional and authority innovation decision, HOAs have to make a collective innovation decision (Rogers, 2003). Similar to the landlord-tenant problem where costs and benefits are unevenly split among the parties, homeowners part of a HOA might benefit unevenly from EE renovations as well. The combination of such a collective adoption decision with potential split incentives can result in adoption being delayed or rejected (Rogers, 2003). While Tiellemans and colleagues (2021) showed that Dutch HOA members are generally willing to make concessions regarding sustainable energy measures, they also found that their willingness decreases when opinions on important outcomes vary substantially. Research conducted by the Dutch advocate for homeowners and HOAs has found that such collective decision-making processes strand the adoption of EE measures for about a third of the studied HOAs (Vereniging Eigen Huis, 2022). Based on these insights and a lack of further research on EE adoption among HOAs, the following hypothesis is derived:

Hypothesis 6: Households part of a homeowner association are less likely to adopt insulation measures.

At last, two adoption influences will be included as control variables in the third analysis. Studies have shown that the age of the building is significantly related to EE adoption; households living in older buildings are more likely to adopt than households living in newer ones (Dolšak et al., 2020; Ebrahimigharehbaghi et al., 2019; Schleich, 2019; Hamilton et al., 2016; Pettifor et al., 2015). This study will therefore include the *construction year* of dwellings as a control variable.[7] Similarly, households that are more *likely to move* are found to be less likely to adopt and invest in long-term EE measures, making it a control variable relevant to include as well (Ebrahimigharehbaghi et al., 2020; Schleich et al., 2019).

[7] Initially, dwelling type was also included as control variable, as households living in flats or terraced houses were found to be less likely to adopt energy-efficient measures compared to (semi-)detached houses (Trotta, 2018; Gamtessa, 2013; Schleich, 2019; Ebrahimigharehbaghi et al., 2020). This control variable has however been excluded due to a high correlation with the homeowner association variable.

3. Methodology

3.1 Data collection

To examine the diffusion of insulation, a quantitative research design is applied and elaborated on in this section. There has been made use of secondary data from two nation-wide surveys: the Qualitative Housing Registration (KWR) and the Netherlands' Housing Survey (WoON). Commissioned by the former Dutch Ministry of Housing, Spatial Planning and the Environment (VROM), KWR was conducted four times between 1983 and 2001 with the aim to provide insights into the quality of the Dutch housing stock (DISCO, n.d.). The KWR surveys consisted of a representative sample of at least 15,000 households. Since 2006, KWR has been succeeded by WoON; the present day nation-wide survey on the housing and living situations of Dutch households. WoON is conducted every three years by Statistics Netherlands (CBS) and the Dutch Ministry of the Interior and Kingdom Relations (BZK) (CBS, n.d.-a). Every six years, an extensive energy module is included in WoON, providing insights in the energetic quality of Dutch dwellings and the energy consumption and behaviour of households. The WoON energy modules are based on a representative sample consisting of approximately 4500 households. Authorised access to these survey data has been granted through the Netherlands Organisation for Applied Scientific Research (TNO). The KWR or WoON data served as input for three related analyses (see Appendix A), which are elaborated on in the next subsection.

3.2 Data analysis

Analysis 1 - Deriving diffusion curves

The first type of analysis was descriptive in nature. Insulation diffusion curves have been derived and examined, to provide more context on the diffusion of insulation measures over time and the decarbonisation efforts of households in the Netherlands. Per survey year and building component - roof, floor, windows and facade - the average degree of insulation has been computed (Equation 1), indicating the extent insulation has diffused among the Dutch households and dwellings. As the KWR and WoON surveys assigned weighting factors to the participating respondents, indicating the number of similar households/dwellings present in the Netherlands, the computed average insulation degree is generalisable for the Dutch housing stock. Additionally, the average insulation degree over the years has been subdivided into construction year classes, dwelling types and tenure types.

$$\underline{x} = \frac{\sum_{i=1}^{n} x_i \cdot w_i}{\sum_{i=1}^{n} w_i} \qquad (1)$$

where

$\underline{x}$ = $average\ insulation\ degree$

n = $number\ of\ households/dwellings$

x = $insulation\ degree\ of\ building\ component$

w = $weighting\ factor\ household/dwelling$

To compute the average insulation degrees, data from the KWR and WoON surveys (see Appendix A) have been merged into a single dataset using SPSS and Excel. Variables representing the insulation degrees, dwelling types and tenure types have been re-operationalised as the operationalisation of these variables differed between and within the KWR and WoON surveys (see Appendix B for a detailed overview of the operationalisation applied in Analysis 1). Most notable changes were made to the insulation degrees of households. In the surveys from 1995 and onwards, the insulation degree of building surfaces have been expressed on a scale from 0 to 100%, i.e. representing the percentage of the respective building component that has been insulated. In KWR 1989, however, the insulation degree was measured on an ordinal level (not insulated; less than half insulated; more than half insulated; fully insulated) for roofs, floors and facades, while the insulation degree for windows was not captured within a single variable. For the roof, floor and facade of each household a numerical insulation degree has therefore been derived based on several sensitivity analyses (see Appendix C). This allowed for the KWR 1989 survey to still be partially included in this analysis.[8]

Moving on, it should be noted that a substantial share of households within the surveys did not have an insulation degree assigned. As it was unclear whether this data was simply missing or whether assigning an insulation degree was not possible (e.g., for apartments which have no roof or floor to be insulated), these households were assigned a calculated insulation degree. While this has been calculated using several methods (see Appendix C), it is decided to substitute the missing insulation degrees values within each survey with the weighted average insulation degrees calculated for the other dwellings of the same construction year class.

Analysis 2 - Estimating foregone benefits

To provide further context on the diffusion of insulation measures, the second analysis entailed an estimation of foregone benefits; natural gas (cost) savings that could have been achieved if additional insulation measures were adopted. This analysis built on a preceding study conducted by TNO, in which costs and benefits of insulation measures were estimated for various dwelling categories using the data from the WoON 2018 energy module (Menkveld et al., 2020). Supplementing Menkveld and colleagues (2020), Analysis 2 explicitly focused on the annual natural gas (cost) savings and also subdivided these into the construction year classes, dwelling types and tenure types used in Analysis 1.

The described foregone benefits have been estimated as follows. Menkveld et al. (2020) distinguished between three insulation levels and corresponding insulation measures: level 2, 3 and 4.[9] Insulation levels 2 and 3 reflect the lower and upper limit of supplementary conventional insulation measures, which can respectively be implemented by households themselves and professionals (Menkveld et al., 2020; Cornelisse et al., 2021).[10] Level 4 entails extensive insulation measures, which are assumed to be sufficient for future low-carbon

[8] This study also used a corrected version of the WoON 2012 dataset, in which the former Energy Research Centre of the Netherlands (ECN), now part of TNO, re-estimated the insulation degrees.

[9] Level 0 and 1 respectively describe the insulation level at the time of construction and at the present situation (Cornelisse et al., 2021).

[10] For more detailed renovation measures and corresponding Rc-values, refer to Cornellise et al. (2021).

standards (Cornelisse et al., 2021). For the households and dwellings of the WoON 2018 energy module, Menkveld et al. (2020) and engineering firm DGMR computed the potential energy savings, in m^3 natural gas, if these insulation levels were to be achieved.[11] In the present analysis, these individual foregone benefits have been aggregated and also subdivided into construction year classes, dwelling types and tenure types, similar to Analysis 1. Here, only the natural gas savings associated with insulation levels 2 and 3 have been considered, as the level 4 insulation measures are deemed as rather extensive for reaching the contemporary minimum insulation standard (Menkveld et al., 2020; RVO, 2023b).[12] The costs that households would subsequently save due to a lower energy consumption have been derived based on the average natural gas price in 2018, i.e. €0.682 per m^3 natural gas (CBS, 2023b).

Analysis 3 - Testing adoption influences

In the final analysis, the hypotheses derived in Section 2.4 were tested by determining the effect of household factors on the adoption of insulation. Analysing such adoption influences contributes to interpreting the development of the insulation diffusion curves (Analysis 1) and to understanding why benefits of insulation adoption (Analysis 2) have not been realised. Adoption influences were tested based on the WoON 2012 and WoON 2018 surveys. Including two surveys conducted in different years increases the reliability of the results. This analyse made use of WoON 2012 and WoON 2018 specifically, as it has only been tested whether households have adopted insulation measures in the past since the WoON 2012 survey.

The effect of household factors have been investigated in RStudio using count regressions. Count regressions are used to estimate the number of times a particular event is expected to occur; the dependent variable consists of non-negative integer numbers. In this study, the adoption of a distinct insulation measure is considered as the occurred event. Whereas the WoON surveys distinguished between the adoption of roof, floor, window and facade insulation, this study conceptualises the adoption of these insulation measures with a single count variable. The four insulation measures and their adoption are thus assumed to be homogenous to one another. For the independent variables, this study occasionally used an altered operationalisation, as variables have been measured differently in the WoON 2012 and WoON 2018 surveys (see Appendix B).

Regarding the type of count regression, this study used zero-inflated negative binomial (ZINB) models. In the context of this study, ZINB models are argued to be more suitable than the standard count (Poisson) regressions for two reasons. First, a negative binomial (negbin) model is able to account for overdispersion, i.e. a substantial difference between the mean and variance of the dependent variable. Since overdispersion was observed in the data, using

[11] The change in natural gas consumption is based on households' actual natural gas consumption in 2017 (Menkveld et al., 2020; Janssen-Jansen, 2019). Only the dwellings heated with natural gas have thus been included; dwellings heated by district heating or an all-electric heat pump were excluded (Menkveld et al., 2020).

[12] Each insulation level is associated with a default set of insulation measures. As the energetic baseline of dwellings differs, these default sets of insulation measures and subsequent energy savings might not be the most efficient for achieving the overarching minimum insulation standard (Menkveld et al., 2020; Cornelisse et al., 2019).

a negbin model was deemed more appropriate. Second, the frequency of the insulation measures adopted appeared to be inflated with zeroes, while it should be normally distributed for standard count models. Zero-inflated models can be used to account for an excess amount of zeros, as they distinguish between 'structural' zeros and 'random' zeros and assume that these zeros are generated by distinct processes (Blasco-Moreno et al., 2019). It is likely that the datasets used in this study also contained these two types of zeros. Naturally, some households already live in a sufficiently insulated dwelling and therefore do not adopt further insulation measures. For these households, the number of insulation measures recently adopted will structurally be zero. For households living in insufficiently insulated dwellings, the number of adopted insulation measures can be zero or higher. While the WoON data does not allow distinguishing between these types of households (a limitation which is discussed in Section 3.3), this distinction is still partially considered when using a zero-inflated model. Using ZINB models, this study has thus analysed the effect of household factors on the probability of households adopting an insulation measure at all (logistic model), as well as on the number of insulation measures adopted (negbin model).

To examine the effect of household factors on insulation adoption, three ZINB models have been estimated; a 2012 household model, a 2012 homeowner model and a 2018 homeowner model. Since the WoON 2018 survey examined insulation adoption solely among owner-occupied households, the tenure type hypothesis could not be tested using this survey. To still compare the results of WoON 2018 with WoON 2012, while additionally also examining the effect of tenure type on adoption, a regression with the tenure type variable (household model) and a regression without the tenure type variable (homeowner model) has been run for the WoON 2012 dataset. The operationalisation of the variables and the descriptive statistics of these three models are summarised in Table 2 and 3.

Table 2

Operationalisation and descriptive statistics of the continuous variables

Model	Continuous variables	Mean	SD	Min.	Q1	Med.	Q3	Max.
2012 household model	Income (1,000 euros)	37.16	21.28	-94.00	22.75	33.23	47,54	289.24
	Capital (10,000 euros)	13.87	24.11	-104.66	0.24	4.60	20.36	315.06
2012 homeowner model	Income (1,000 euros)	45.41	21.97	-94.00	31.48	41.80	54.85	289.24
	Capital (10,000 euros)	21.43	28.17	-104.66	4.26	15.81	29.24	315.06
2018 homeowner model	Income (1,000 euros)	52.56	34.08	-4.14	35.89	47.42	62.67	1,274.5
	Capital (10,000 euros)	27.55	41.44	-86.51	6.17	18.11	35.19	565.40

Table 3

Operationalisaiton and the descriptive statistics of the categorical variables

		Model		
Categorical variables	Categories	2012 household frequency (%)	2012 homeowner frequency (%)	2018 homeowner frequency (%)
Number of insulation measures adopted	0	3,793 (79.9)	1,973 (70.7)	1,911 (67.3)
	1	589 (12.4)	498 (17.8)	546 (19.2)
	2	233 (4.9)	205 (7.4)	212 (7.5)
	3	96 (2.0)	85 (3.1)	114 (4.0)
	4	38 (0.8)	30 (1.1)	58 (2.0)
Education	Lower	1,535 (32.3)	601 (21.5)	528 (18.6)
	Intermediate	1,524 (32.1)	928 (33.3)	778(27.4)
	Higher	1,690 (35.6)	1,262 (45.2)	1,535 (54.0)
Age	17-24	105 (2.2)	27 (1.0)	18 (0.6)
	25-34	511 (10.8)	318 (11.4)	259 (9.1)
	35-44	792 (16.7)	549 (19.7)	361 (12.7)
	45-54	899 (18.9)	580 (20.8)	480 (16.9)
	55-64	1,151 (24.2)	703 (25.2)	730 (25.7)
	65-74	810 (17.1)	432 (15.5)	756 (26.6)
	≥75	481 (10.1)	182 (6.5)	237 (8.3)
Tenure type	Owner-occupied	2,791 (58.8)	n/a	n/a
	Private rental	363 (7.6)	n/a	n/a
	Social housing	1,595 (33.6)	n/a	n/a

Homeowner association	Yes	438 (9.2)	433 (15.5)	454 (16.0)
	No	4,311 (90.8)	2,358 (84.5)	2,387 (84.0)
Construction year	≤1930	667 (14.0)	426 (15.3)	399 (14.0)
	1931-1959	803 (16.9)	472 (16.9)	379 (13.3)
	1960-1980	1,430 (30.1)	710 (25.4)	850 (29.9)
	1981-1995	1,120 (23.6)	660 (23.7)	631 (22.2)
	>1995	729 (15.4)	523 (18.7)	582 (20.5)
Likely to move	Yes	1,119 (23.6)	557 (20.0)	820 (28.9)
	No	3,630 (76.4)	2,234 (80.0)	2,021 (71.1)
Number of observations		4,749	2,791	2,841

3.3 Strengths and limitations

At last, the strengths and limitations of this study and their implications in terms of its reliability and validity are discussed. This study is made possible due to the availability of secondary data commissioned and collected by Dutch governmental institutions, which is considered to be of high quality. The surveys consisted of rigorous sampling procedures and weighting factors and as a result, this allows for robust and highly generalisable analyses (CBS, n.d.-a; Bryman, 2016). As the surveys are still based on sampling, their data should however be regarded as estimations.[13] Nevertheless, by incorporating data that has been collected over multiple years, i.e. data triangulation, these results can be compared and are considered of having a higher generalisability too. The validity of this research is furthermore stimulated by theory triangulation, as insights of multiple theoretical perspectives and empirical studies have been integrated.

Simultaneously, the usage of secondary data also comprises several limitations of this study. The hypotheses that can be tested in this study are dependent on the availability and operationalisation of pre-existing data. Consequently, the variables that have been tested were not designed for this study specifically, which might affect the validity of its findings. An implication for the diffusion curve analysis is that the degree of insulation only refers to the surface quantity of insulation, while it does not reflect the thickness of the insulation nor its material type, both determining the insulation quality. Including these insights could have facilitated a more thorough examination of the diffusion of insulation. However, in the absence

[13] CBS applied a confidence interval of 95% (CBS, n.d.-a).

of this information, it is argued that the present insulation degree is still a suitable indicator. Additionally, there are also some measurement inconsistencies and unclarities present in the initial computation of dwellings' insulation degrees, as discussed in Section 3.2.

Another consequence for the analysis on adoption influences is that behavioural and social factors and EEG explanations could not (directly) be tested in this study.[14] Similarly, the variable 'tenure type' could only be included in a WoON 2012 model, since insulation adoption was only measured among homeowners in WoON 2018. Furthermore, data prior to the time of insulation adoption has not been collected and was thus not available. It should therefore be noted that values of some independent variables (e.g., income or age) might have changed between the time of adoption and the time the WoON surveys collected the data. This general issue also concerns the dependent variable; there is no information on the insulation degree of dwellings prior to adoption. As a result, households that could not adopt additional insulation, since they are already living in fully insulated dwellings, are also included in the analysis on adoption influences. Ideally, the analysis should exclude this cohort and focus only on households with lower insulation degrees. To still consider this distinction, ZINB regressions are argued to act as an suitable alternative and have therefore been applied instead. The final drawback of the absence of longitudinal data is that it refrained this study from conducting longitudinal analyses and drawing causal conclusions on the effect of household factors on insulation adoption. Instead, this study provides insights on the correlation effect and likelihood of household factors on insulation adoption.

Finally, the estimation of the annual foregone benefits has been based on the energy consumption and energetic quality of representative dwellings included in WoON 2018 and on the average natural gas price of 2018. Since these values (might) have changed since, the computed annual foregone benefits can be less generalisable for future years and should be regarded as an estimation. To still stimulate the robustness of these findings, they have been evaluated with alternative estimations (see Section 7). It should also be acknowledged that only the natural gas (cost) savings of households are considered as foregone benefits in this analysis. While in practice other private and societal benefits would result from insulation adoption, these have not been included. Similarly, foregone benefits should be regarded as 'gross' foregone benefits, as the additional costs resulting from insulation adoption have not been taken into account either. While considering these costs and benefits is essential for a thorough (economic) examination of households decision-making processes, for instance through the NPV criterion, this was beyond the scope of this study.

[14] This is further addressed in Section 7.

4. Insulation diffusion curves

Table 4 and Figure 4 show the diffusion of the four insulation measures among Dutch households over the years. This diffusion analysis demonstrates that the average degree of insulation has been increasing for all four insulation measures. Between 1989 and 1995, a decrease in the insulation degree of roofs and facades is however visible. This seems inconsistent in contrast to the general trend and can potentially be the result of the measurement inconsistency described in Section 3.2. Despite this inconsistency the developments in the degree of insulations are still described from the period between 1989 and 2018.

Households' windows and roofs have been enjoying the highest average degree of insulation. The average insulation degree of roofs has been increasing from 49.1% in 1989 to 82.0% in 2018. While the average insulation degree of windows could not be estimated for 1989, its insulation degree rose from 56.2% in 1995 to 85.3% in 2018. This results in windows having the highest average insulation degree in 2018, as well as in all prior years. The average insulation degree of windows shows to have decreased by 0.4 percentage point in the period between 2012 and 2018, which could be the result of inconsistencies within the data or definition that has been applied for the insulation degree. The average degree of facade insulation has been rising from 43.6% to 72.9% and is characterised by the steepest increase in insulation degree of all insulation measures (15.2 percentage point between 2006-2012). Whereas the average insulation degree of floors has been the lowest of all insulation measures, it has experienced the largest total increase (39 percentage points) from 21.2% towards 60.2% between 1989 and 2018.

While the average insulation degree has been increasing for all four measures, it is noticed that the rate by which these measures are diffusing has been decreasing. The diffusion curves of floor, window and facade insulation have developed less steeply since 2012 and for roof insulation since 2006. To examine the diffusion of insulation more thoroughly, the average insulation degrees have been examined per construction year class, dwelling type and tenure type. The results of these analyses are elaborated on in the next subsections.

Figure 4

Average insulation degree per insulation measure over time

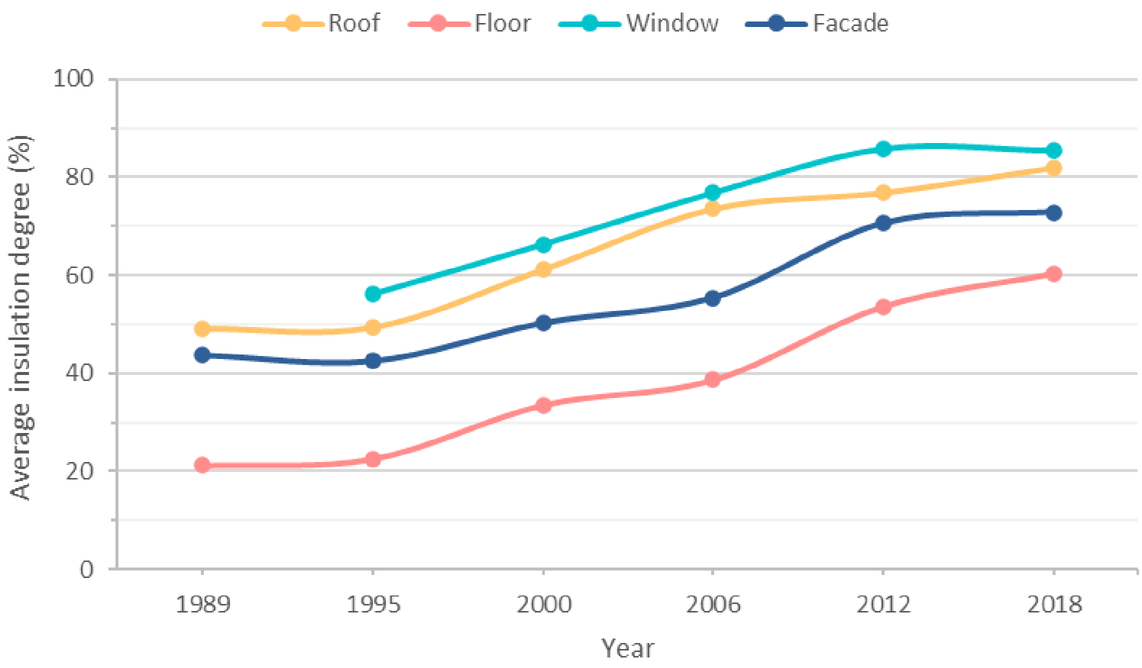


Table 4

Average insulation degree per insulation measure over time

Average insulation degree	Roof	Floor	Window	Facade
1989	49.1%	21.2%	n/a	43.6%
1995	49.3%	22.6%	56.2%	42.4%
2000	61.1%	33.5%	66.3%	50.2%
2006	73.6%	38.6%	76.7%	55.4%
2012	76.9%	53.6%	85.7%	70.6%
2018	82.0%	60.2%	85.3%	72.9%

4.1 Diffusion per construction year class

Expressing the insulation degree in construction year classes shows that dwellings built after 1980 have had the highest average insulation degree for all insulation measures (see Tables and Figures 5 to 8). Especially for the roof, floor and facade insulation degree, there appears to be a substantial gap between dwellings built prior to 1981 and dwellings built after. For the dwellings built after, differences are negligible in the average insulation degree of their roofs and facades. The average facade insulation degree of these two dwellings classes (built between 1981-1995 and after 1995) has been approximately 100%. Their average roof insulation degree has been varying between ±93% and ±97%, with a minor yet noticeable decrease in the period between 2006-2012. While dwellings built between 1981-1995 saw their average floor insulation degree increase from 73.5% to 93.0%, dwellings built after 1995 experienced a decrease of ± six percentage points. Similarly, the average insulation degree of windows increased for the former class (80.5% to 90.2%) and decreased for the latter (±99% to 90.5%).

For the three classes of dwellings built before 1981, average insulation degrees have generally been increasing over the years, with an apparent exemption between 1989-1995 for dwellings constructed between 1960-1980. Still, these dwellings have a higher average insulation degree for all insulation measures compared to dwellings built before 1960. Here, insulation degrees particularly differ for roof and facade insulation. For roof insulation, the average insulation degree of dwellings constructed between 1960-1980 increased from 51.9% in 1989 to 79.6% in 2018. The two classes of dwellings built before 1960 saw an increase from ±26% to ±66%. The facade insulation degree of these two dwelling classes increased from ±17% to ±40%, compared to an increase from 46.9% to 67.2% for dwellings built between 1960-1980. Up until 2006, the average floor insulation degree differed not substantially between the dwellings built before 1981. After 2006, this insulation degree increased especially for the 1960-1980 dwellings. For windows insulation, the three building classes increased with a similar trend.

Figure 5

Average roof insulation degree per construction year class over time

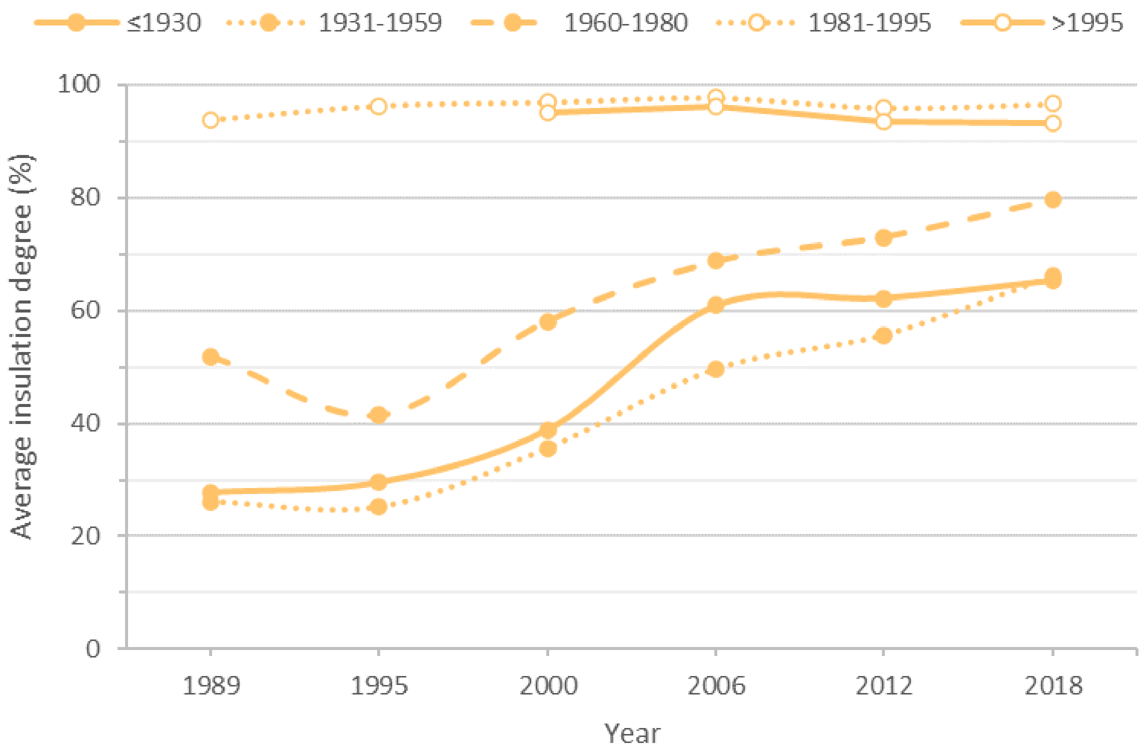


Table 5

Average roof insulation degree per construction year class over time

Roof insulation	≤1930	1931-1959	1960-1980	1981-1995	>1995
1989	27.7%	26.1%	51.9%	93.7%	n/a
1995	29.5%	25.2%	41.4%	96.2%	n/a
2000	38.9%	35.6%	58.1%	96.9%	95.1%
2006	60.8%	49.6%	68.7%	97.7%	96.1%
2012	62.2%	55.7%	73.0%	95.9%	93.3%
2018	65.3%	66.1%	79.6%	96.6%	93.2%

Figure 6

Average floor insulation degree per construction year class over time

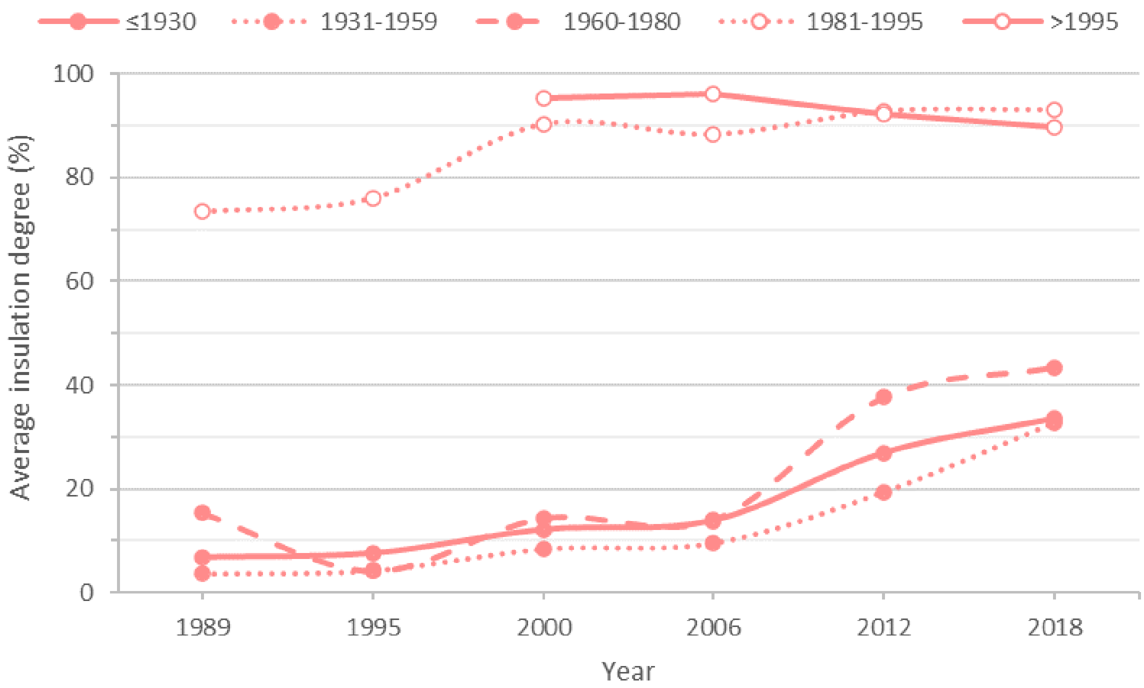


Table 6

Average floor insulation degree per construction year class over time

Floor insulation	≤1930	1931-1959	1960-1980	1981-1995	>1995
1989	6.8%	3.7%	15.4%	73.5%	n/a
1995	7.5%	4.3%	4.2%	76.1%	n/a
2000	12.1%	8.4%	14.4%	90.3%	95.4%
2006	13.9%	9.6%	14.1%	88.3%	96.1%
2012	27.0%	19.4%	37.7%	92.8%	92.3%
2018	33.5%	32.7%	43.5%	93.0%	89.6%

Figure 7

Average window insulation degree per construction year class over time

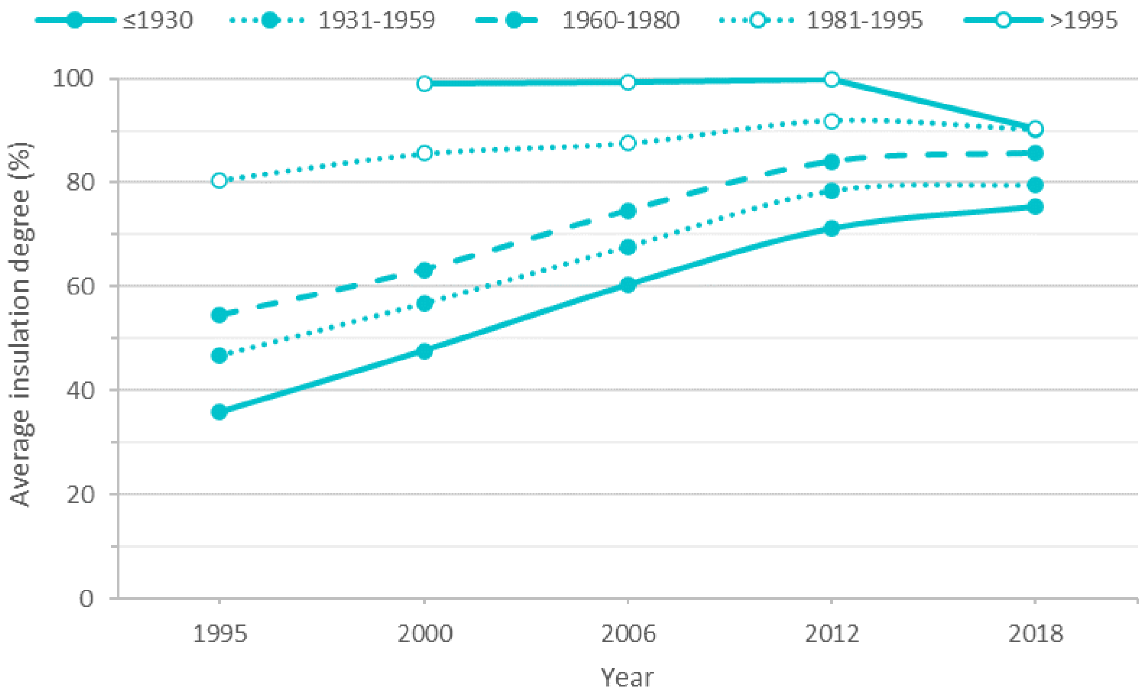


Table 7

Average window insulation degree per construction year class over time

Window insulation	≤1930	1931-1959	1960-1980	1981-1995	>1995
1989	n/a	n/a	n/a	n/a	n/a
1995	35.8%	46.7%	54.5%	80.5%	n/a
2000	47.6%	56.7%	63.3%	85.6%	98.9%
2006	60.3%	67.7%	74.6%	87.6%	99.3%
2012	71.1%	78.4%	84.0%	91.9%	99.8%
2018	75.3%	79.6%	85.7%	90.2%	90.5%

Figure 8

Average facade insulation degree per construction year class over time

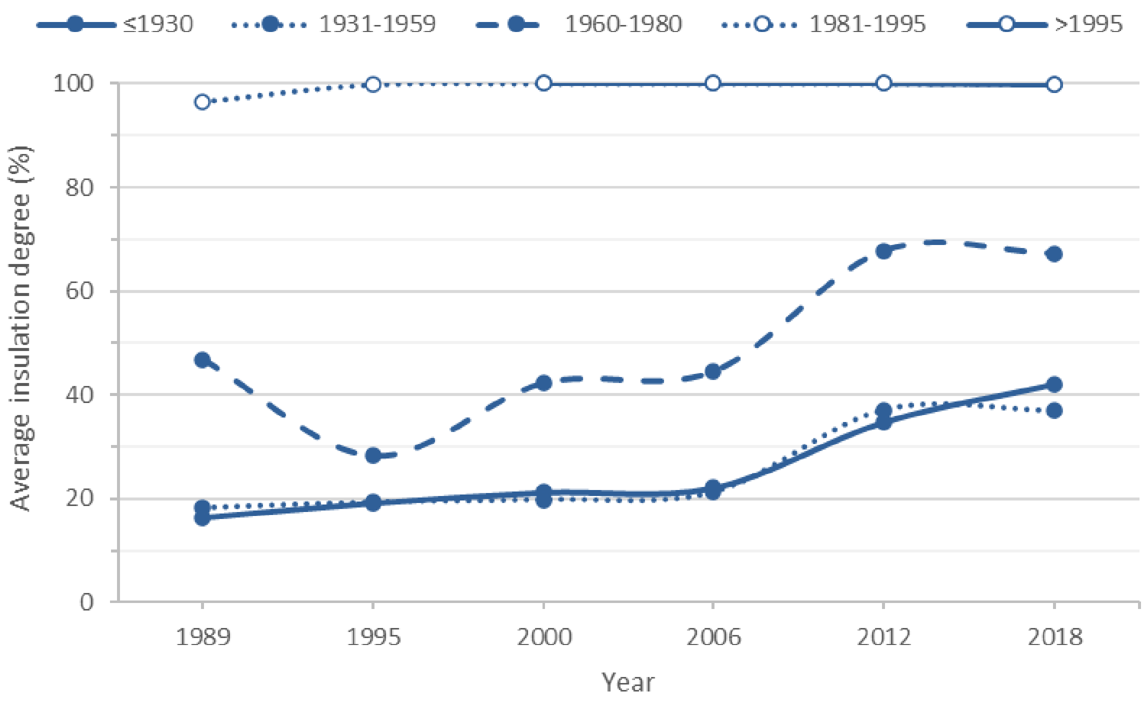


Table 8

Average facade insulation degree per construction year class over time

Facade insulation	≤1930	1931-1959	1960-1980	1981-1995	>1995
1989	16.4%	18.2%	46.9%	96.6%	n/a
1995	19.2%	19.3%	28.2%	99.8%	n/a
2000	21.2%	19.8%	42.2%	100%	100%
2006	22.1%	21.2%	44.5%	100%	100%
2012	34.7%	37.1%	67.8%	100%	100%
2018	420.%	36.9%	67.2%	99.9%	99.9%

4.2 Diffusion per dwelling type

As illustrated in Tables and Figures 9 to 12, insulation measures have been diffusing rather comparably among the first three types of dwellings: detached, semi-detached/end-terraced and mid-terraced dwellings. In contrast, the average insulation degrees of the fourth dwelling type, apartments, have been lower than the other dwelling types. For roof insulation, the insulation degree of apartments for instance increased from 41.8% to 71.8% between 1989-2018, compared to an increase from ±52% to ±87% for the other dwelling types.

Similarly, the average floor and facade insulation degrees have generally been lower for apartments. Apartments' average floor and facade insulation degree respectively increased from 17.1% to 51.7% and 36.1% to 63.2%, both with a steep increase between 2006-2012. Detached dwellings, in contrast, have been enjoying the highest average floor insulation degree, which increased from 24.2% to 68.6%. Interestingly, the average floor insulation degree of apartments was similar to those of semi-detached/end-terraced and mid-terraced dwellings in 1995, while the average degree of facade insulation of apartments (40.0%) was even higher than that of detached dwellings (38.9%). In the years after, however, these insulation degrees increased less rapidly for apartments than for the dwelling types they equalled in 1995.

At last, the window insulation degree of apartments has been the most similar to the other dwelling types. In 1995 and 2000, apartments, semi-detached/end-terraced and mid-terraced dwellings had average window insulation degrees of ±55% and ±65.5%. From 2006, the average window insulation degree of the latter two dwelling types developed more towards that of detached dwellings, which started at 61.7% in 1995 and increased to 85.5% in 2018. Apartments' had a slightly lower, yet still resembling average insulation degree of 83.4%. Compared to the other insulation measures, apartments have had the highest average insulation degree for windows.

Figure 9

Average roof insulation degree per dwelling type over time

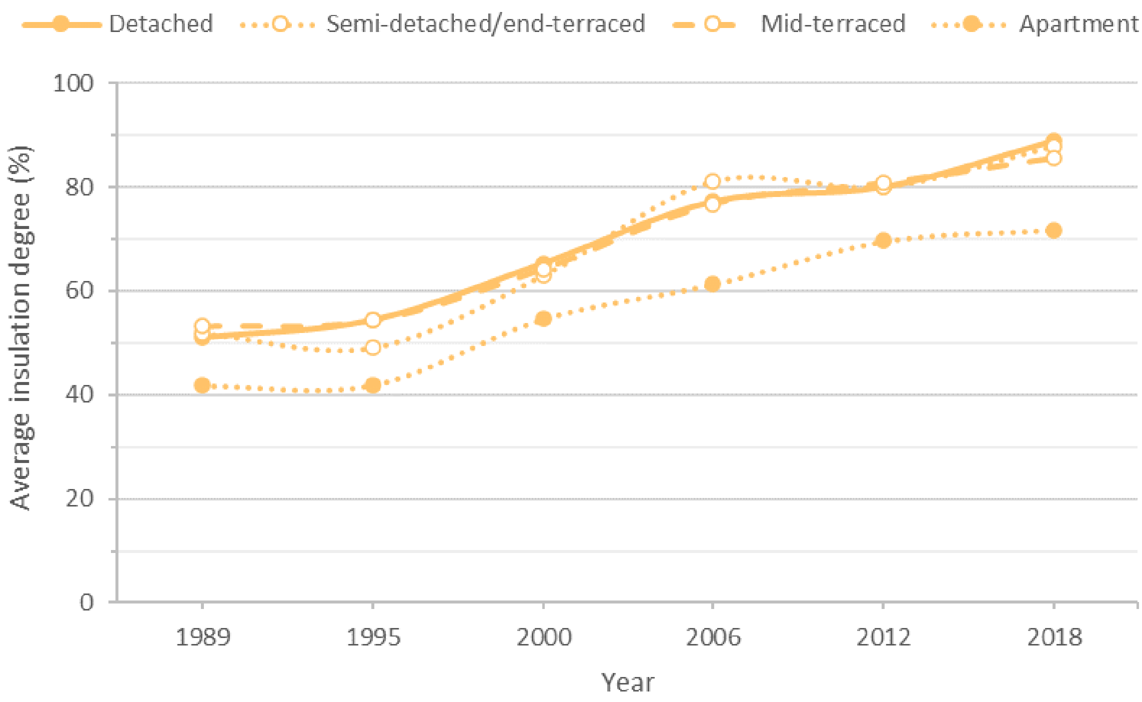


Table 9

Average roof insulation degree per dwelling type over time

Roof insulation	Detached	Semi-detached / end-terraced	Mid-terraced	Apartment
1989	51.0%	51.8%	53.2%	41.8%
1995	54.4%	49.0%	54.3%	41.9%
2000	65.3%	62.9%	64.3%	54.6%
2006	77.3%	81.1%	76.7%	61.3%
2012	80.0%	80.0%	80.8%	69.6%
2018	89.0%	87.8%	85.5%	71.8%

Figure 10
Average floor insulation degree per dwelling type over time

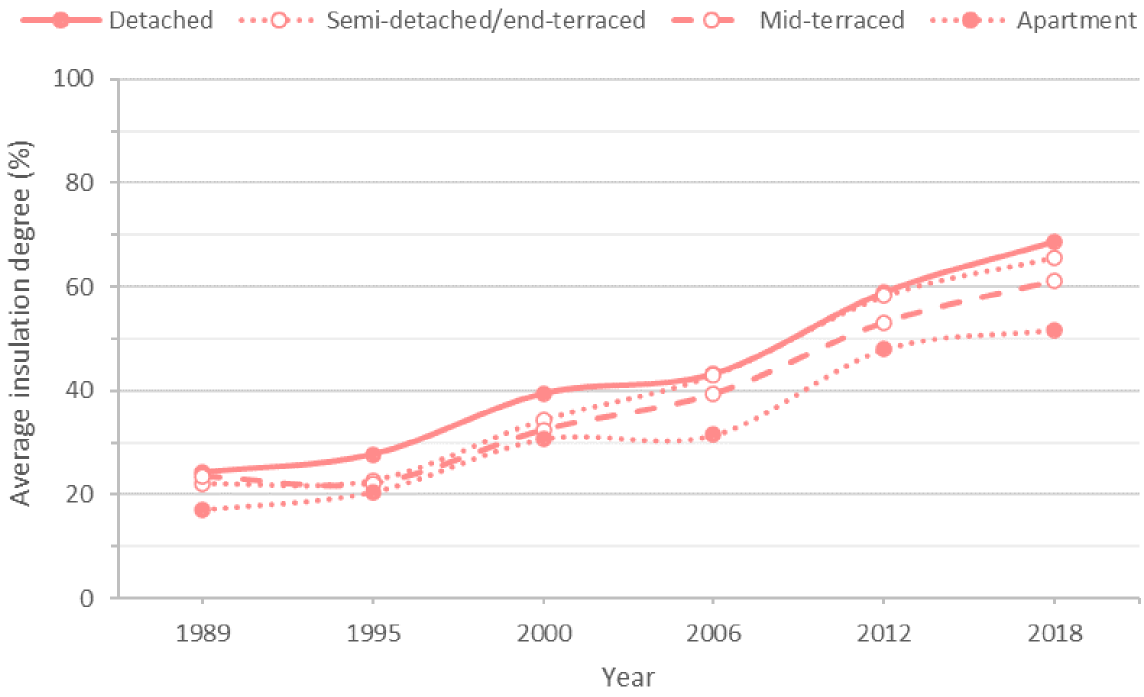


Table 10
Average floor insulation degree per dwelling type over time

Floor insulation	Detached	Semi-detached / end-terraced	Mid-terraced	Apartment
1989	24.2%	22.0%	23.5%	17.1%
1995	27.7%	22.6%	22.1%	20.5%
2000	39.4%	34.3%	32.4%	30.7%
2006	43.2%	42.9%	39.3%	31.4%
2012	58.9%	58.2%	53.1%	47.9%
2018	68.6%	65.7%	61.2%	51.7%

Figure 11

Average window insulation degree per dwelling type over time

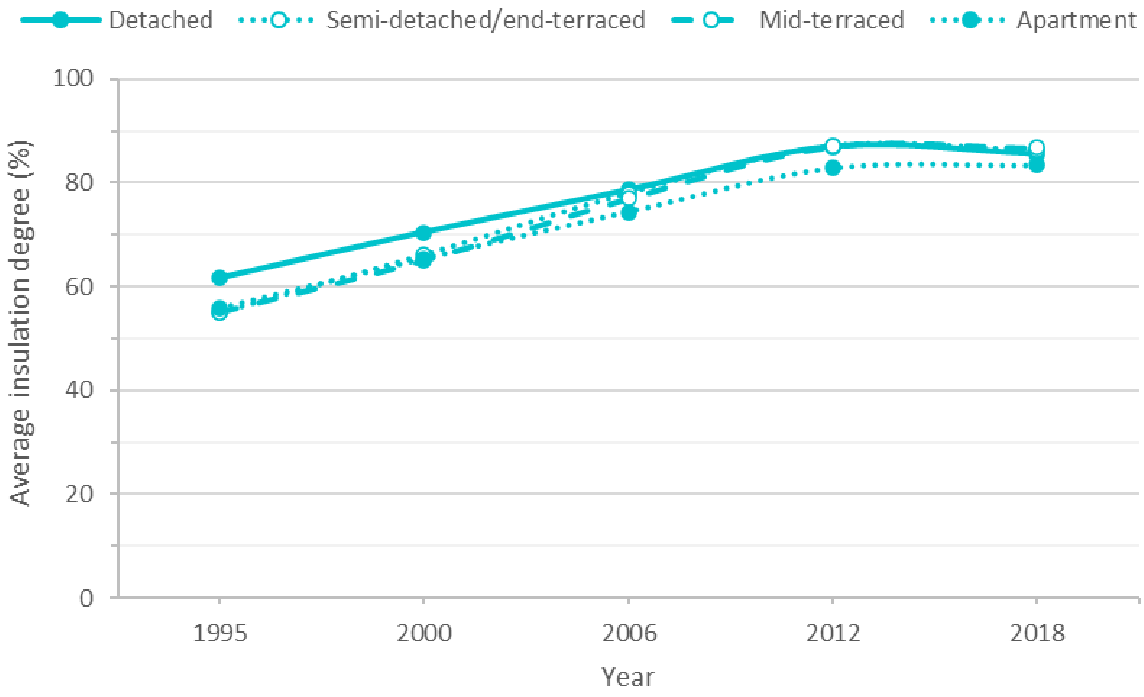


Table 11

Average window insulation degree per dwelling type over time

Window insulation	Detached	Semi-detached / end-terraced	Mid-terraced	Apartment
1989	n/a	n/a	n/a	n/a
1995	61.7%	54.9%	55.0%	55.8%
2000	70.5%	66.1%	65.0%	65.4%
2006	78.6%	78.0%	76.9%	74.4%
2012	87.0%	87.1%	87.0%	82.8%
2018	85.5%	86.3%	86.7%	83.4%

Figure 12

Average facade insulation degree per dwelling type over time

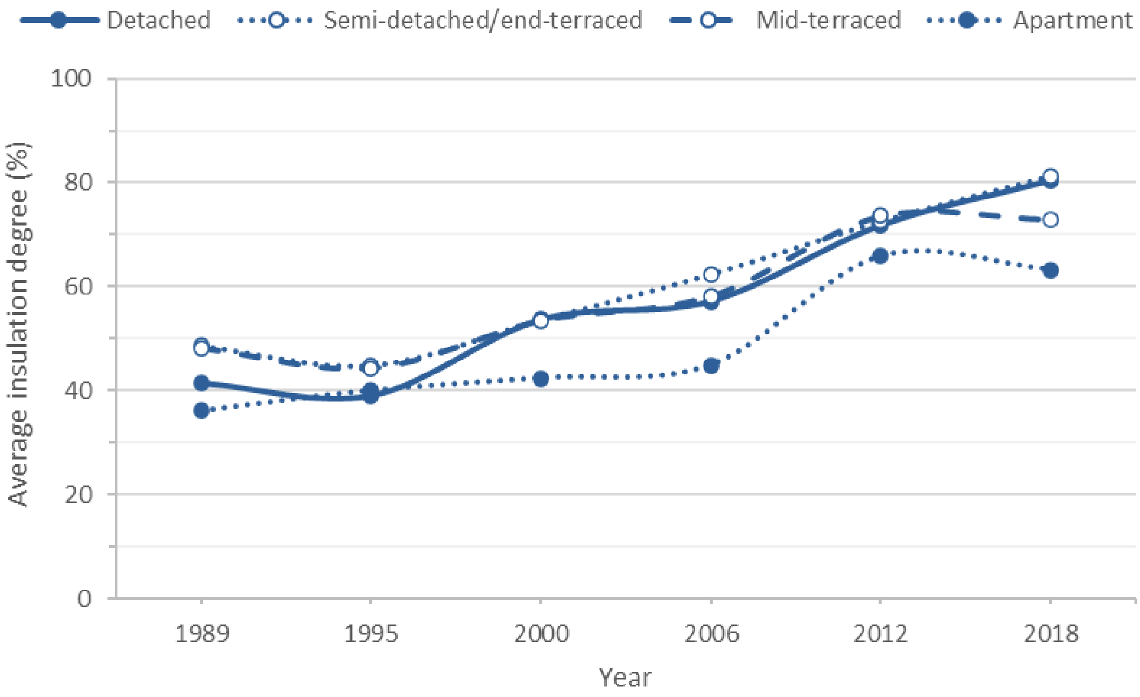


Table 12

Average facade insulation degree per dwelling type over time

Facade insulation	Detached	Semi-detached / end-terraced	Mid-terraced	Apartment
1989	41.3%	48.6%	48.1%	36.1%
1995	38.9%	44.9%	44.2%	40.0%
2000	53.6%	53.6%	53.4%	42.4%
2006	57.1%	62.4%	58.2%	44.9%
2012	71.7%	72.5%	73.6%	65.8%
2018	80.3%	81.2%	73.0%	63.2%

4.3 Diffusion per tenure type

At last, the diffusion of insulation has been expressed among the different types of housing tenure (see Tables and Figures 13 to 16). The average insulation degree for all four insulation measures over time has been the lowest for households living in social housing. For roof and floor insulation, owner-occupied households have been enjoying the highest average degree of insulation. Between 1989-2018, their roof insulation increased from 54.9% to 87.4%, while floor insulation saw an even larger increase from 24.2% to 65.4%. The average insulation degrees for roofs and floors of private rental housing have been remaining in between those of owner-occupied and social housing. For window insulation the average insulation degree of private rental housing has however been similar to that of owner-occupied housing. Between 1995-2018, these followed a similar trend, increasing from ±59% to ±87%. Interestingly, facade insulation of private rental housing has been rather constant between 1989-2006 (±53%), and higher than that of owner-occupied households between 1989-2000.

Figure 13
Average roof insulation degree per tenure type over time

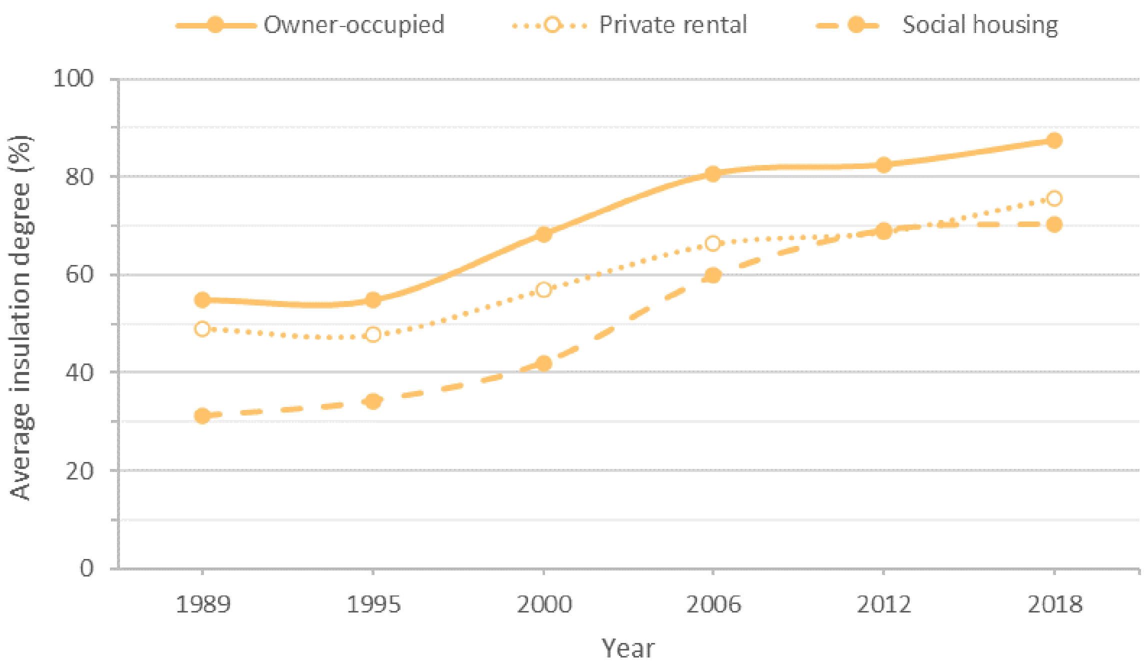


Table 13
Average roof insulation degree per tenure type over time

Roof insulation	Owner-occupied	Private rental	Social housing
1989	54.9%	49.1%	31.1%
1995	54.8%	47.8%	34.2%
2000	68.3%	57.0%	42.0%
2006	80.6%	66.3%	59.8%
2012	82.4%	68.8%	69.1%
2018	87.4%	75.7%	70.4%

Figure 14
Average floor insulation degree per tenure type over time

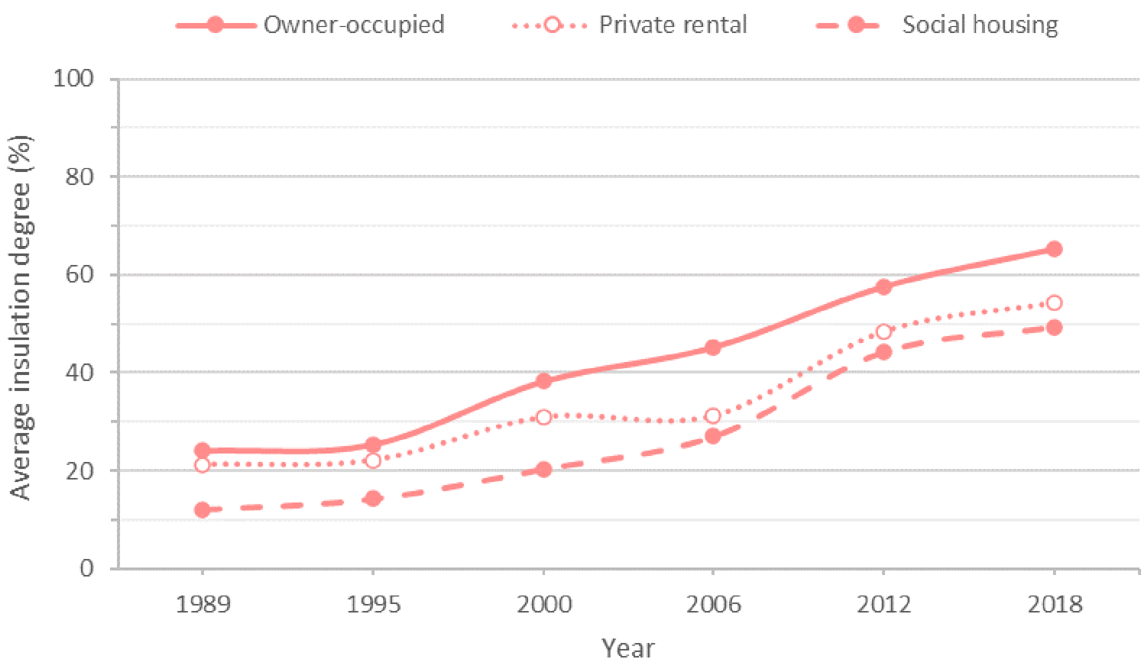


Table 14
Average floor insulation degree per tenure type over time

Floor insulation	Owner-occupied	Private rental	Social housing
1989	24.2%	21.3%	12.1%
1995	25.4%	22.1%	14.3%
2000	38.3%	30.9%	20.3%
2006	45.3%	31.2%	27.0%
2012	57.7%	48.4%	44.3%
2018	65.4%	54.3%	49.3%

Figure 15

Average window insulation degree per tenure type over time

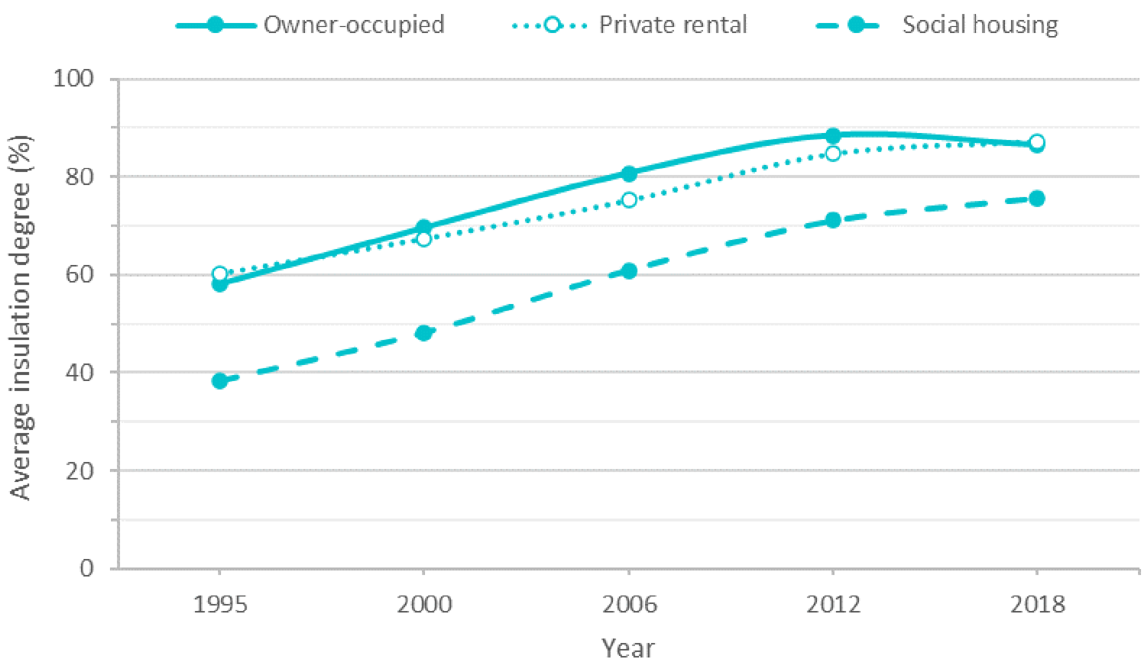


Table 15

Average window insulation degree per tenure type over time

Window insulation	Owner-occupied	Private rental	Social housing
1989	n/a	n/a	n/a
1995	58.2%	60.2%	38.4%
2000	69.6%	67.3%	48.2%
2006	80.8%	75.2%	61.0%
2012	88.5%	84.8%	71.1%
2018	86.5%	87.3%	75.7%

Figure 16

Average facade insulation degree per tenure type over time

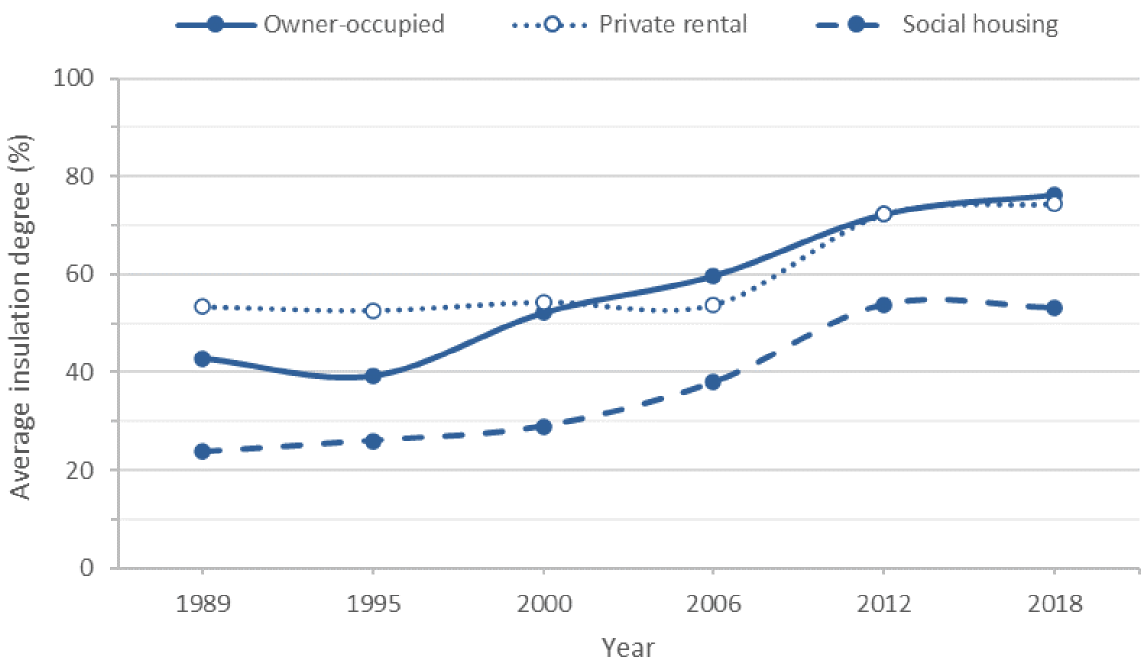


Table 16

Average facade insulation degree per tenure type over time

Facade insulation	Owner-occupied	Private rental	Social housing
1989	42.9%	53.4%	23.8%
1995	39.3%	52.6%	26.1%
2000	52.2%	54.3%	29.0%
2006	59.7%	53.7%	38.0%
2012	72.3%	72.3%	53.8%
2018	76.3%	74.5%	53.1%

5. Foregone insulation benefits

In the foregone benefits analysis, the annual natural gas (cost) savings that Dutch households could have achieved, if additional and conventional insulation measures were adopted, have been examined. The estimated average savings are shown in Table 17 and Table 18, whereas an overview of total savings and the energy costs savings can be found in Appendix D. This analysis found that the average household could have saved 336 to 542 m^3 natural gas if the additional insulation measures were implemented. With the annual average natural gas price of €0.68 euros/m^3, the average household would have saved €229 to €337 on energy costs. Considering the entire Dutch housing stock, households could have saved 2.37 billion to 3.82 billion m^3 of natural gas in total. In energy costs, households' total savings would then have been between €1.61 billion and €2.62 billion euros.

Expressed in construction year classes (Table 17 and Table 18), dwellings built between 1960-1980 showed to have the highest energy saving potential. The average dwelling built within this period could have saved 466-766 m^3 natural gas. In sum, the potential savings of these dwellings would account for ±45% of the total potential savings, i.e. 1.06 billion to 1.74 billion m^3 of natural gas. Natural gas savings of dwellings constructed between 1931-1959 and 1980-1995 would each account for 17-20% of the total potential savings, with average household savings respectively ranging from 421-625 and 285-522 m^3 of natural gas. Estimated savings for dwellings built before 1930 account for ±13% of the total potential savings, with average household savings between 318-484 m^3 natural gas. Dwellings built after 1995 have the lowest potential natural gas savings, 104-137 m^3 on average, which accounts for just ±5% of the total potential energy savings.

When examining the natural gas savings per dwelling type (Table 19), detached dwellings are found to have the highest average saving potential, ranging from 501-854 m^3 of natural gas. Estimated natural gas savings were 399-656 m^3 on average for semi-detached/end-terraced dwellings and 325-536 m^3 for mid-terraced dwellings. Apartments had the lowest saving potential on average, with 222-317 m^3 of natural gas savings. Similarly, the total estimated natural gas savings of apartments are found to be the lowest of all dwelling types, which would have been ±20% of the total potential savings. While detached dwellings were found to have the highest average savings, in sum they account for ±22% of the total potential natural gas savings. Instead, mid-terraced and semi-detached/end-terraced dwellings would have enjoyed the largest total savings, respectively accounting for ±27% and ±30% of the total potential natural gas savings.

In Figure 17 and Figure 18, the average and total natural gas savings have respectively been ranked for each combination of construction year class and dwelling type, based on the savings associated with level 3 insulation measures. These figures show that all dwelling types built after 1995 have both the lowest average and lowest total natural gas saving potential compared to other dwelling categories. While the average natural gas savings of priorly built apartments are also found to be lower than the average savings of other dwellings, in total these apartments do not necessarily have lower natural gas savings. Similarly, whereas detached dwellings built in or before 1995 were found to have the highest average savings, in total the highest natural gas savings could have been achieved by insulating dwelling types constructed between 1960-1980 instead.

Lastly, regarding tenure type (Table 17 and Table 18), owner-occupied dwellings were found to have the highest natural gas saving potential. On average, natural gas savings for homeowners were estimated at 373-616 m^3. The natural gas savings of all owner-occupied dwellings would account for ±67% of the total potential energy savings. Estimated savings for private rental dwellings accounted for ±12% of the total potential savings, with average natural gas savings ranging between 305-450 m^3. The natural gas savings of social rental dwellings, 269-424 m^3 on average, accounted for ±11% of the total potential savings.

Table 17

Heat map of average foregone natural gas savings - level 2 insulation

Average natural gas savings (m^3)	Owner-occupied	Private rental	Social housing	Total average
≤1930	**355**	**294**	**203**	**318**
Detached	485	451	134	479
Semi-detached/end-terraced	340	562	483	363
Mid-terraced	305	377	194	297
Apartment	255	233	153	221
1931-1959	**448**	**393**	**381**	**421**
Detached	591	267	n/a	545
Semi-detached/end-terraced	516	571	515	517
Mid-terraced	362	454	355	364
Apartment	278	398	334	336
1960-1980	**534**	**437**	**356**	**466**
Detached	787	575	435	771
Semi-detached/end-terraced	546	677	427	519
Mid-terraced	442	489	421	439
Apartment	339	348	278	308
1981-1995	**341**	**298**	**172**	**285**
Detached	466	625	n/a	468
Semi-detached/end-terraced	369	262	240	345
Mid-terraced	278	324	220	271
Apartment	197	280	143	178
>1995	**121**	**64**	**70**	**104**
Detached	162	0	n/a	161
Semi-detached/end-terraced	119	141	141	122
Mid-terraced	102	75	75	96
Apartment	101	57	56	73
Total average	**373**	**305**	**269**	**336**

Table 18
Heat map of average foregone natural gas savings - level 3 insulation

Average natural gas savings (m³)	Owner-occupied	Private rental	Social housing	Total average
≤1930	**562**	**404**	**287**	**484**
Detached	815	657	305	790
Semi-detached/end-terraced	536	703	625	552
Mid-terraced	470	568	292	455
Apartment	356	307	218	301
1931-1959	**689**	**551**	**534**	**625**
Detached	972	497	n/a	904
Semi-detached/end-terraced	778	943	742	774
Mid-terraced	563	631	517	549
Apartment	361	519	444	442
1960-1980	**893**	**670**	**574**	**766**
Detached	1341	1148	845	1327
Semi-detached/end-terraced	912	1047	720	866
Mid-terraced	739	755	719	734
Apartment	526	492	407	453
1981-1995	**630**	**501**	**323**	**522**
Detached	856	982	n/a	858
Semi-detached/end-terraced	679	499	458	637
Mid-terraced	529	617	414	515
Apartment	340	413	266	307
>1995	**166**	**72**	**80**	**137**
Detached	255	86	n/a	254
Semi-detached/end-terraced	170	175	190	172
Mid-terraced	132	108	99	125
Apartment	100	57	56	73
Total average	**616**	**450**	**424**	**542**

Table 19
Average foregone natural gas savings per dwelling type

Average natural gas savings (m^3)	Insulation level 2	Insulation level 3
Detached	501	854
Semi-detached/end-terraced	399	656
Mid-terraced	325	536
Apartment	222	317
Total average	**336**	**542**

Figure 17

Average foregone natural gas savings per construction year class and dwelling type

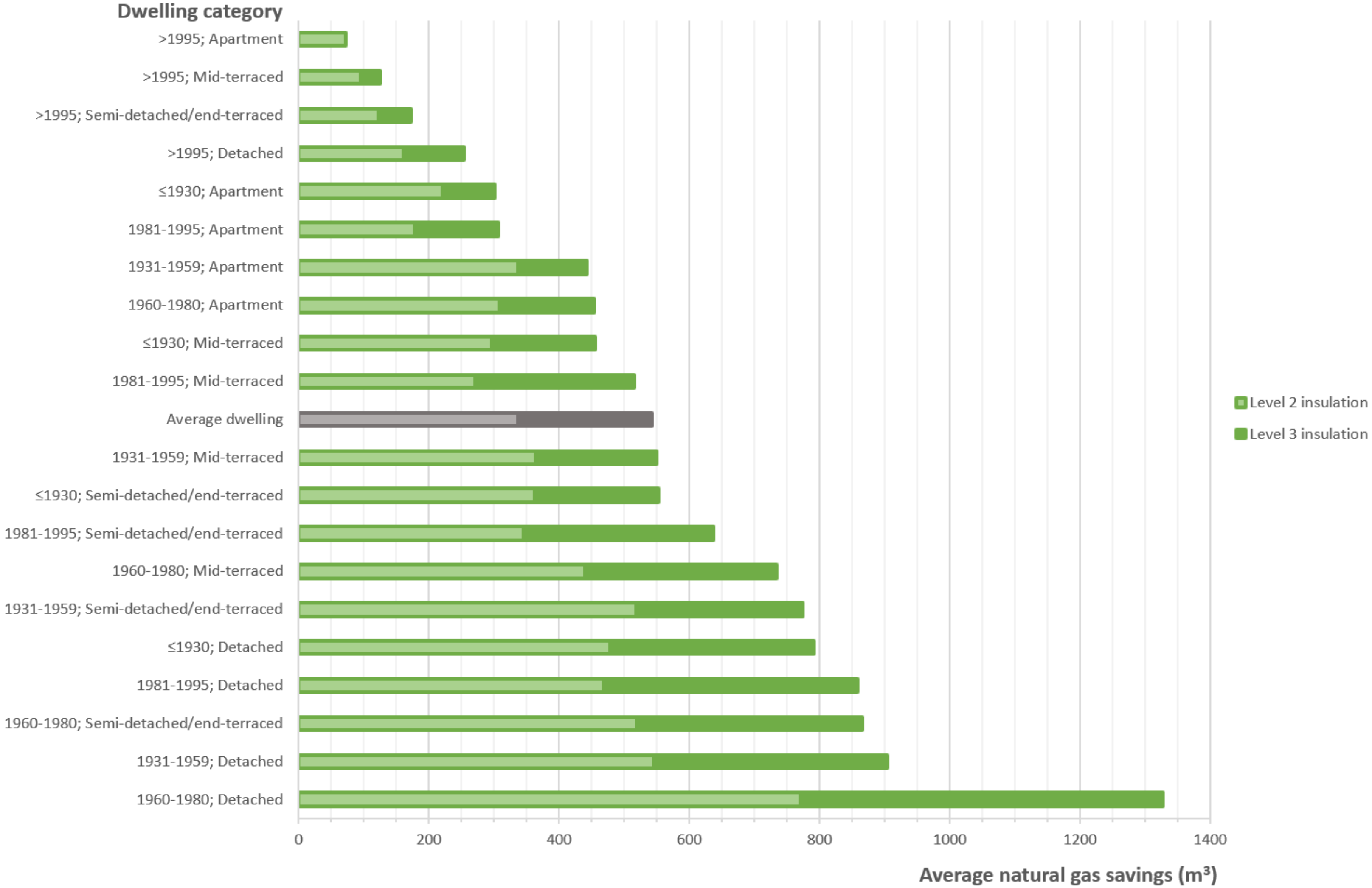
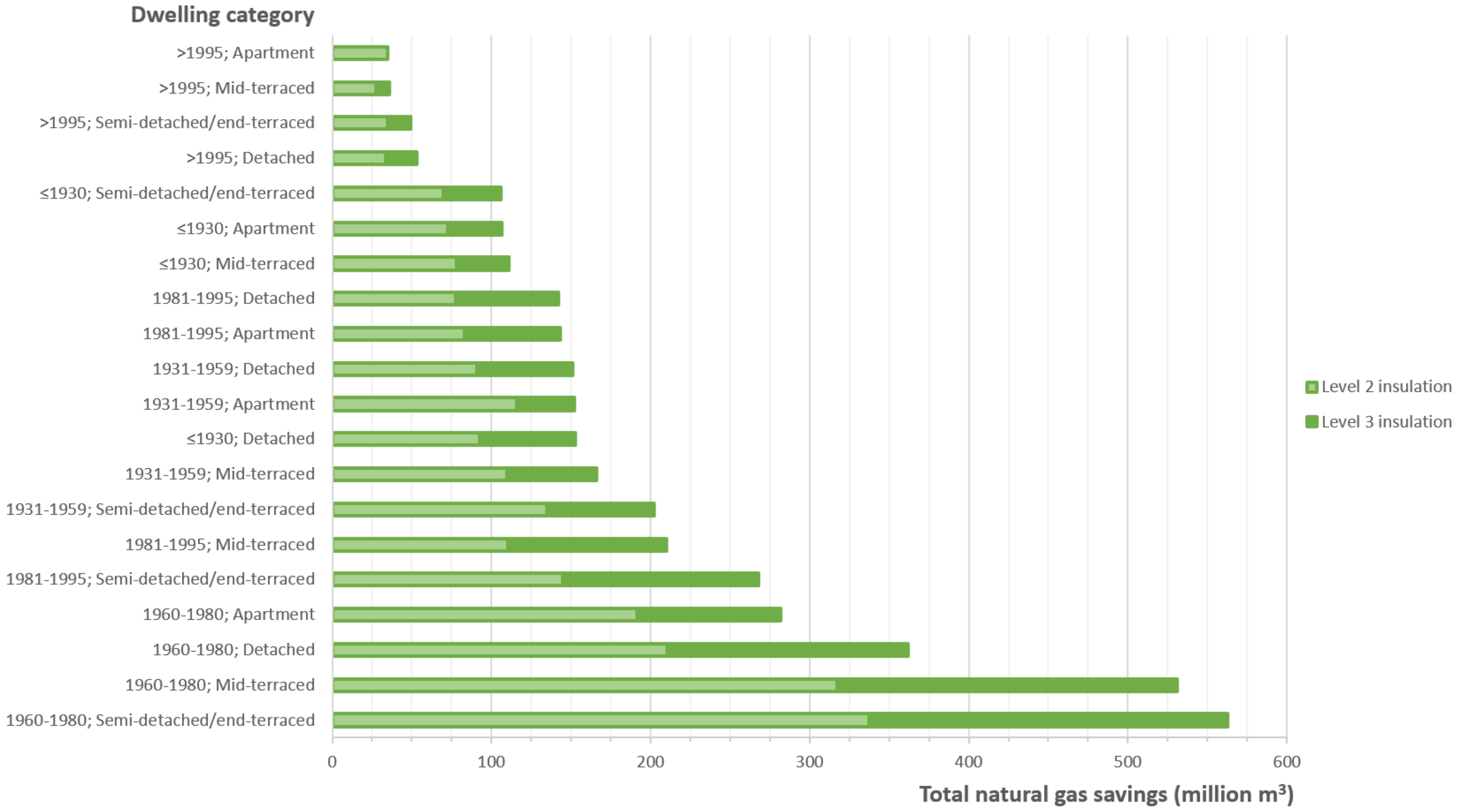


Figure 18

Total foregone natural gas savings per construction year class and dwelling type



6. Influences on insulation adoption

In the third analysis, insulation adoption influences and hypotheses have been tested using three ZINB regressions. These three models are discussed in Sections 6.1 to 6.3, after which they are compared and linked to the adoption hypotheses in Section 6.4.

6.1 Adoption influences among Dutch households in 2012

Starting with the logistic part of the 2012 household model (Table 20), the analysis shows that tenure type and construction year significantly affect the odds of Dutch households not adopting any insulation measures. Households living in owner-occupied dwellings, i.e. homeowners, are found to have significantly lower odds of having zero insulation measures adopted in their dwelling than households living in social housing ($p \ll 0.001$). Similarly, households living in dwellings built in or before 1995 have significantly lower odds of adopting zero insulation measures than the households living in the dwellings built hereafter ($p \ll 0.001$).

Moving on to the negbin part of the model (Table 20), three variables demonstrate significant effects on the number of insulation measures adopted: age, homeowner association and construction year. Household members aged between 25-44 have significantly higher odds of adopting more insulation measures than those aged between 45-54 ($p<0.05$). No significant effects are found for the other age groups. HOAs are found to have a significantly negative effect on the number of insulation measures adopted as well. Households part of HOAs have significantly lower odds of adopting a larger number of insulation measures than households not part of such associations ($p \ll 0.001$). Additionally, households living in dwellings built before 1931, between 1931-1959 and between 1960-1995 show to have significantly lower odds of having a greater number of insulation measures adopted than households living in younger dwellings ($p<0.05$, $p<0.01$ and $p \ll 0.001$, respectively).

Table 20

Zero-inflated negative binomial model on insulation adoption among households (2012)

Logistic part of the model

Variables	Est.	S.E.	Sig.	Odds ratio
Income (1,000 euros)	-0.004	0.008	0.611	0.996
Capital (10,000 euros)	0.003	0.005	0.516	1.003
Education (ref = Lower)				
Intermediate	-0.063	0.230	0.786	0.939
Higher	-0.214	0.231	0.354	0.807
Age (ref = 45-54)				
17-24	-0.639	0.499	0.201	0.528
25-34	-0.015	0.295	0.960	0.985
35-44	-0.121	0.258	0.639	0.886
55-64	-0.164	0.271	0.546	0.849
65-74	-0.259	0.302	0.390	0.772
≥75	0.312	0.428	0.466	1.367
Tenure type (ref = social housing)				
Owner-occupied	-2.537	0.261	<< 0.001***	0.079
Private rental	-0.020	0.328	0.952	0.980
Homeowner association (ref = no)	0.534	0.392	0.173	1.707
Construction year (ref = >1995)				
≤ 1930	-3.279	0.272	<< 0.001***	0.038
1931-1959	-3.614	0.321	<< 0.001***	0.027
1960-1980	-3.598	0.275	<< 0.001***	0.027
1981-1995	-2.738	0.454	<< 0.001***	0.065
Likely to move (ref = no)	0.072	0.195	0.710	1.075

Negative binomial part of the model

Variables	Est.	S.E.	Sig.	Odds ratio
Income (1,000 euros)	0.003	0.003	0.314	1.003
Capital (10,000 euros)	-0.002	0.002	0.447	0.998
Education (ref = Lower)				
Intermediate	-0.008	0.117	0.949	0.993
Higher	0.005	0.114	0.967	1.005
Age (ref = 45-54)				
17-24	0.246	0.289	0.395	1.279
25-34	0.357	0.146	0.014*	1.429
35-44	0.250	0.122	0.041*	1.284
55-64	-0.027	0.129	0.831	0.973
65-74	0.004	0.143	0.977	1.004
≥75	-0.403	0.252	0.111	0.912
Tenure type (ref = social housing)				
Owner-occupied	-0.034	0.148	0.819	0.967
Private rental	-0.056	0.284	0.845	0.946

Homeowner association (ref = no)	-0.676	0.200	<< 0.001***	0.509
Construction year (ref = >1995)				
≤ 1930	-0.445	0.176	0.011*	0.641
1931-1959	-0.534	0.186	0.004**	0.586
1960-1980	-0.673	0.172	<< 0.001***	0.510
1981-1995	-1.307	0.268	<< 0.001***	0.271
Likely to move (ref = no)	-0.092	0.098	0.350	0.912
Number of observations	4,749			
Degrees of freedom	39			
Log likelihood	-2870.6			
AIC	5819.2			

Note. *** p<0.001, ** p<0.01, * p<0.05.

6.2 Adoption influences among Dutch homeowners in 2012

In the logistic part of the 2012 homeowners model (Table 21) it appears that the construction year of a dwelling is the only variable that significantly affects the odds of homeowners not adopting any insulation measure. Compared to homeowners living in dwellings built after 1995, homeowners living in priorly built dwellings have significantly lower odds of adopting zero insulation measures (p<<0.001).

Regarding the negbin part of the model (Table 21), several variables are found to significantly affect the number of insulation measures that homeowners adopt: age, homeowner association and construction year. Homeowners aged between 25-34 and 35-44 turn out to have significantly higher odds of adopting a larger number of insulation measures than homeowners 45-54 years old (p<0.05). Homeowners being 75 or older are found to have significantly lower odds to adopt a higher number of insulation measures (p<0.05). No significant effect was found for the age groups 17-24, 55-64 and 64-74. Secondly, when homeowners are part of HOAs, they appear to have significantly lower odds of adopting more insulation measures (p<<0.001). Lastly, homeowners living in dwellings built prior to 1960 and between 1960-1995 are demonstrated to have significantly lower odds of adopting a higher number of insulation measures than the homeowners living in dwellings built hereafter (p<0.05 and p<<0.001, respectively).

Table 21
Zero-inflated negative binomial model on insulation adoption among homeowners (2012)

Logistic part of the model

Variables	Est.	S.E.	Sig.	Odds ratio
Income (1,000 euros)	$3.7*10^{-4}$	0.005	0.941	1.000
Capital (10,000 euros)	0.004	0.004	0.344	1.004
Education (ref = Lower)				
Intermediate	0.209	0.394	0.595	1.233
Higher	-0.067	0.376	0.858	0.935
Age (ref = 45-54)				
17-24	-0.979	1.161	0.399	0.376
25-34	-0.159	0.372	0.668	0.853
35-44	0.058	0.309	0.852	1.060
55-64	-0.130	0.356	0.716	0.879
65-74	-0.077	0.412	0.852	0.926
≥75	0.082	0.707	0.908	1.085
Homeowner association (ref = no)	0.513	0.458	0.263	1.670
Construction year (ref = >1995)				
≤ 1930	-3.526	0.358	<< 0.001***	0.029
1931-1959	-3.616	0.381	<< 0.001***	0.027
1960-1980	-3.782	0.365	<< 0.001***	0.023
1981-1995	-2.218	0.328	<< 0.001***	0.109
Likely to move (ref = no)	-0.184	0.306	0.547	0.832

Negative binomial part of the model

Variables	Est.	S.E.	Sig.	Odds ratio
Income (1,000 euros)	0.003	0.002	0.095	1.003
Capital (10,000 euros)	-0.001	0.002	0.646	0.999
Education (ref = Lower)				
Intermediate	0.089	0.149	0.550	1.093
Higher	0.078	0.140	0.580	1.081
Age (ref = 45-54)				
17-24	0.429	0.315	0.173	1.536
25-34	0.321	0.148	0.030*	1.378
35-44	0.282	0.128	0.028*	1.326
55-64	-0.080	0.141	0.572	0.923
65-74	0.018	0.160	0.910	1.018
≥75	-0.666	0.290	0.022*	0.514
Homeowner association (ref = no)	-0.728	0.206	<< 0.001***	0.482
Construction year (ref = >1995)				
≤ 1930	-0.456	0.192	0.018*	0.634
1931-1959	-0.463	0.198	0.020*	0.630
1960-1980	-0.662	0.185	<< 0.001***	0.516
1981-1995	-1.022	0.1232	<< 0.001***	0.360

Likely to move (ref = no)	-0.132	0.112	0.239	0.876
Number of observations		2,791		
Degrees of freedom		35		
Log likelihood		-2250.0		
AIC		4569.9		

Note. *** p<0.001, ** p<0.01, * p<0.05.

6.3 Adoption influences among Dutch homeowners in 2018

From the logistic part of the model 2018 homeowners model (Table 22), two variables are found to significantly affect the odds of homeowners not adopting any insulation measures: age and construction year. Compared to household members aged between 45-54, the model demonstrates that household members between 25-34, 35-44 and 55-64 years old have significantly lower odds of adopting zero insulation measures (p<0.01, p<0.05 and p<0.05, respectively). No significant effect is found for household members younger than 25 or older than 64. Regarding dwellings' construction year, the model shows that households living in all classes of dwellings constructed before 1996 have lower odds of adopting zero insulation measures than households living in younger dwellings (p<<0.001).

For the model's negbin part, numerous variables indicate a significant effect on the number of insulation measures adopted: income, education, age, homeowner association and construction year. While the effect of income on the number of insulation measures adopted appears to be significant (p<0.05), it comes with a marginally small effect size, i.e. the odds ratio approximates 1. Regarding education, the model demonstrates that households with intermediate education have significantly higher odds of adopting a greater number of insulation measures than lower educated households (p<0.05). For higher educated households, no significant effect is found. Compared to household members aged between 45-55, household members between 55-64 and 75 or older turn out to have significantly lower odds of adopting more insulation measures (p<0.05 and p<0.01, respectively). No significant effect is found for the other age groups. Additionally, households part of a HOA have significantly lower odds of adopting a greater number of insulation measures (p<<0.001). Lastly, households living in dwellings built between 1960-1980 and 1981-1995 have significantly lower odds of adopting more insulation measures than households living in the younger dwellings (p<0.05 and p<<0.001, respectively).

Table 22

Zero-inflated negative binomial model on insulation adoption among homeowners (2018)

Logistic part of the model

Variables	Est.	S.E.	Sig.	Odds ratio
Income (1,000 euros)	-0.001	0.002	0.676	0.999
Capital (10,000 euros)	0.002	0.002	0.243	1.002
Education (ref = Lower)				
Intermediate	0.507	0.362	0.161	1.661
Higher	0.574	0.349	0.010	1.776
Age (ref = 45-54)				
17-24	-1.061	0.982	0.280	0.346
25-34	-1.065	0.385	0.006**	0.345
35-44	-0.775	0.340	0.023*	0.460
55-64	-0.659	0.331	0.047*	0.518
65-74	-0.259	0.312	0.407	0.772
≥75	-0.654	0.774	0.398	0.520
Homeowner association (ref = no)	0.231	0.361	0.523	1.259
Construction year (ref = >1995)				
≤ 1930	-2.690	0.289	<< 0.001***	0.068
1931-1959	-4.117	0.672	<< 0.001***	0.016
1960-1980	-3.886	0.469	<< 0.001***	0.021
1981-1995	-2.311	0.357	<< 0.001***	0.099
Likely to move (ref = no)	0.165	0.233	0.480	1.179

Negative binomial part of the model

Variables	Est.	S.E.	Sig.	Odds ratio
Income (1,000 euros)	0.003	0.001	0.029*	1.003
Capital (10,000 euros)	0.001	0.001	0.395	1.001
Education (ref = Lower)				
Intermediate	0.240	0.115	0.037*	1.271
Higher	0.173	0.108	0.108	1.189
Age (ref = 45-54)				
17-24	0.288	0.383	0.452	1.334
25-34	0.142	0.135	0.293	1.152
35-44	0.081	0.122	0.511	1.084
55-64	-0.244	0.123	0.048*	0.784
65-74	-0.059	0.125	0.641	0.943
≥75	-0.557	0.211	0.008**	0.573
Homeowner association (ref = no)	-0.599	0.147	<< 0.001***	0.549
Construction year (ref = >1995)				
≤ 1930	-0.137	0.182	0.451	0.872
1931-1959	-0.275	0.182	0.130	0.759
1960-1980	-0.387	0.175	0.027*	0.679
1981-1995	-0.907	0.223	<< 0.001***	0.404

Likely to move (ref = no)	-0.087	0.082	0.288	0.916
Number of observations	2,841			
Degrees of freedom	35			
Log likelihood	-2540.8			
AIC	5151.7			

Note. *** p<0.001, ** p<0.01, * p<0.05.

6.4 Hypotheses

To compare the results of the three ZINB models and link these to the adoption hypotheses, the odds ratios and significance of their variables are summarised in Table 23 and elaborated on below.

Starting with the control variables, the three models show that construction year is a significant variable in both the logistic and negbin parts of the models. In the three logistic parts, all construction year classes significantly affect the odds of Dutch households not adopting any insulation measures. Households living in dwellings built in or before 1995 have significantly lower odds of adopting zero insulation measures, which would imply that they have higher odds of adoption. Interestingly, when looking at the negbin parts of the models, these households simultaneously have significantly lower odds of adopting a larger number of insulation measures than households living in dwellings built after 1995. This applies to dwellings from all construction year classes in the two 2012 models and to the dwellings built between 1960-1995 for the 2018 model. Moving on the second control variable, 'likely to move' does not appear to significantly affect the adoption of insulation in any computed model.

To test the first two hypotheses, stating *'the higher the household income, the more likely a household adopts insulation measures (H1)'* and '*the higher the household capital, the more likely a household adopts insulation measures (H2)'*, households' disposable income and financial capital have been included in the models. Except for the 2018 negbin part, household income does not appear to have a significant effect on the adoption of insulation measures. While the effect of income is significant in the 2018 model, its effect size is marginal (odds ratio ≈ 1). Based on these largely insignificant results, the first hypothesis can thus be rejected. Similarly, the three models indicate that household capital does not significantly affect the adoption of insulation either. The second hypothesis is therefore also rejected.

The third hypothesis related to household education, stating that *'the higher the household education, the more likely a household adopts insulation measures (H3)'*. In neither of the logistic parts of the model do intermediate and higher education levels appear to significantly affect insulation adoption, compared to that of lower educated households. The same generally applies to the models' negbin parts . Here, a significant effect is only found for the intermediate education level in the 2018 homeowner model. However, since the effect of higher educated homeowners is not significant (nor larger) in the 2018 negbin part and education level is not found to be significant in any other part or model, the third hypothesis is rejected.

The fourth hypothesis has been divided into two sub-hypotheses: *'household members younger than 45 are more likely to adopt insulation measures than household members aged between 45-54 (H4a)'* and *'household members older than 54 are less likely to adopt insulation measures than household members aged between 45-54 (H4b)'*. The three computed models show mixed results when estimating the effect of age on insulation adoption. In the logistic parts of the two 2012 models, age does not demonstrate significant effects. Yet in the logistic part of 2018, several age groups do. Household members aged between 25-34, 35-44 and 55-64 are found to have lower odds of adopting zero insulation measures than those aged between 45-54. Moving to the negbin parts, a significant positive effect on the number of insulation measures adopted is found for the age groups 25-34 and 35-44 in the 2012 models. For the 2012 and 2018 homeowner model, household members aged 75 or older were found to have significant lower odds of adopting a larger number of insulation measures. This also applied for homeowners aged between 55-64, in 2018 specifically. Hence, since no consistent evidence regarding the effect of age on insulation adoption was found, both sub-hypothesis H4a and H4b are rejected.

The fifth hypothesis, *'insulation measures are more likely to get adopted in owner-occupied housing than in rental properties (H5)'*, could solely be tested for the 2012 household model. From its logistic part, it can be concluded that owner-occupied households have significant and substantial lower odds of adopting zero insulation measures than households living in social housing and private rental housing. Conversely, owner-occupied households thus have higher odds of adopting an insulation measure than tenants. Yet, when assessing the model's negbin part, no significant differences between the effect of tenure types on the number of adopted insulation measures can be noticed. The fifth hypothesis can therefore partially be confirmed; owner-occupied households are more likely to adopt an insulation measure at all, yet do not significantly differ from rental households in the number of insulation measures adopted.

The sixth and final hypothesis stated that '*households part of a homeowner association are less likely to adopt insulation measures (H6)'*. In the logistic parts of the three models, HOAs do not demonstrate to significantly affect the adoption of insulation. In the negbin parts, however, households part of HOAs have significantly lower odds of adopting a larger number of insulation measures. This results in the last hypothesis to be partially confirmed; HOAs do not seem to significantly correlate with households not adopting any insulation, yet households part of such associations do appear to be less likely to adopt a larger number of insulation measures.

Table 23

Zero-inflated negative binomial model on insulation adoption among homeowners (2018)

Logistic part of the models

Variables	Odds ratio 2012 household	Odds ratio 2012 homeowner	Odds ratio 2018 homeowner
Income (1,000 euros)	0.996	1.000	0.999
Capital (10,000 euros)	1.003	1.004	1.002
Education (ref = Lower)			
Intermediate	0.939	1.233	1.661
Higher	0.807	0.935	1.776
Age (ref = 45-54)			
17-24	0.528	0.376	0.346
25-34	0.985	0.853	0.345**
35-44	0.886	1.060	0.460*
55-64	0.849	0.879	0.518*
65-74	0.772	0.926	0.772
≥75	1.367	1.085	0.520
Tenure type (ref = social housing)			
Owner-occupied	0.079***	n/a	n/a
Private rental	0.980	n/a	n/a
Homeowner association (ref = no)	1.707	1.670	1.259
Construction year (ref = >1995)			
≤ 1930	0.038***	0.029***	0.068***
1931-1959	0.027***	0.027***	0.016***
1960-1980	0.027***	0.023***	0.021***
1981-1995	0.065***	0.109***	0.099***
Likely to move (ref = no)	1.075	0.832	1.179

Negative binomial part of the models

Variables	Odds ratio 2012 household	Odds ratio 2012 homeowner	Odds ratio 2018 homeowner
Income (1,000 euros)	1.003	1.003	1.003*
Capital (10,000 euros)	0.998	0.999	1.001
Education (ref = Lower)			
Intermediate	0.993	1.093	1.271*
Higher	1.005	1.081	1.189
Age (ref = 45-54)			
17-24	1.279	1.536	1.334
25-34	1.429*	1.378*	1.152
35-44	1.284*	1.326*	1.084
55-64	0.973	0.923	0.784*
65-74	1.004	1.018	0.943
≥75	0.912	0.514*	0.573*
Tenure type (ref = social housing)			
Owner-occupied	0.967	n/a	n/a

Private rental	0.946	n/a	n/a
Homeowner association (ref = no)	0.509***	0.482***	0.549***
Construction year (ref = >1995)			
≤ 1930	0.641*	0.634*	0.872
1931-1959	0.586**	0.630*	0.759
1960-1980	0.510***	0.516***	0.679*
1981-1995	0.271***	0.360***	0.404***
Likely to move (ref = no)	0.912	0.876	0.916
Number of observations	4,749	2,791	2,841

Note. *** p<0.001, ** p<0.01, * p<0.05.

7. Discussion

7.1 Diffusion curves and insulation gaps

The analyses on insulation diffusion curves, foregone benefits and adoption influences contributed to a better understanding on the diffusion of insulation measures among Dutch households. The diffusion curve analysis demonstrated that the average degree of insulation has generally been increasing over the years. Yet, it also indicated that the rate by which these measures are diffusing has been decreasing more prematurely as diffusion theories would predict. This an interesting finding, suggesting that a significant part of Dutch households persistently renounces insulation and hence, does not enjoy subsequent benefits. While diffusion curves could only be examined up until 2018, analysing the diffusion of insulation measures for more recent years would be valuable for assessing whether this declining growth is still present.

Additionally, the diffusion curve analysis indicated the presence of substantial differences in the insulation degrees of Dutch dwellings. Such an 'insulation gap' for instance appeared between dwellings built prior to 1981 and dwellings built hereafter. While initial differences could be explained by the first municipal insulation requirements for new-build dwellings during the second half of the 1970's (Cornelisse et al., 2021), an insulation gap has remained over the years after. Similarly, apartments and social rental dwellings are found to have lower average insulation degrees than other types of dwellings and tenure. In contrast to the influential diffusion perspectives (e.g., Rogers, 2003), these insights show that diffusion curves are not solely suitable for analysing successful innovations ex-post. Since epidemic diffusion models are argued to be most suitable for examining innovations of which the total potential market is known (Tidd, 2010), which is argued to often be the case for EE measures, the diffusion of such innovations can also be examined ex-durante. By analysing the ongoing diffusion of EE measures, the diffusion process can be better understood and subsequently influenced. This shows that understanding how diffusion unfolds over time is still valuable and could also contribute to overcoming the survivorship bias present in contemporary diffusion models, as criticised by Geroski (2000).

7.2 Evaluation of foregone benefits

In the foregone benefits analysis, it was subsequently examined what natural gas (cost) savings could have been achieved if insulation measures had diffused to a greater extent than indicated in the diffusion curve analysis. It was found that households could annually save between 336 and 542 m^3 of natural gas on average, resulting in 2.37 billion to 3.82 billion m^3 total annual natural gas savings considering seven million households. To stimulate the robustness of these findings, they have been evaluated with alternative estimations. A rough estimation by TNO showed that 5.5 billion m^3 natural gas could be saved annually if all Dutch dwellings were insulated to energy label 'B' (Faaij et al., 2022). In a more extensive analysis conducted by TNO and the Netherlands Bureau for Economic Policy Analysis, Mot et al. (2023) found that 1.7 billion m^3 of natural gas would be saved annually when the analysed 5.4 million Dutch dwellings were renovated according to a defined minimum insulation standard. Taking into account the differences in the scope of these studies and the targeted insulation levels, the findings of the foregone benefits analysis of this study are concluded to be within the margins of prior estimations.

The foregone benefits analysis has further shown that the average and total natural gas savings are substantially lower for dwellings built after 1995 than those of older dwellings. This finding can be explained by differences in the energetic quality of Dutch dwellings, as the first national insulation legislation was introduced in the beginning of the 1990's (Cornelisse et al., 2021). Therefore, the energetic quality of the dwellings built after 1995 is generally higher than that of older dwellings, as also demonstrated in the diffusion curve analysis, which would subsequently lower the benefit of additional insulation. Interestingly, while similar insulation degrees for dwellings constructed between 1981-1995 were found in the diffusion curve analysis, the estimated foregone benefits associated with these dwellings were substantially higher than those of dwellings built after 1995. This disparity can be explained by the limitation of using the WoON insulation degrees. These do not consider the insulation thickness nor materials, which is expected to differ substantially between dwellings built after 1995 and the dwellings built before. Similarly, while the diffusion curve analysis indicated an insulation gap for apartments and social rental dwellings as well, these dwellings were found to have the lowest average foregone benefits of all other dwelling and tenure types. These insights show that lower insulation degrees, as considered in the first analysis, do not necessarily translate into higher foregone benefits.

The average natural gas savings have been ranked for each combination of construction year class and dwelling type. Aside from the dwellings built after 1995, this ranking showed that the average foregone benefits were mainly dependent on the type of dwelling. Generally, average foregone benefits were relatively low for apartments and increased for mid-terraced dwellings. Semi-detached/end-terraced dwellings and detached dwellings were found to have the highest average foregone benefits. This finding makes sense, as these dwelling types generally have a higher energy consumption due to being larger in size and having more surface through which heat is lost to the environment. Despite this, the highest total natural gas savings could have been achieved by insulating all dwelling types built between 1960-1980. ±45% of the total potential natural gas savings could have been saved by insulating these dwellings, while insulating the detached dwellings with the highest average foregone benefits would have saved ±22%. Although average foregone benefits are lower, dwellings built between 1960-1980 represent a larger share of the Dutch housing stock. This finding indicates that the private benefits of adopting additional insulation are not perfectly aligned with the societal benefits and thus creates a trade-off. Prioritising the insulation of individual dwellings that would benefit the most from additional insulation would not lead to achieving the highest societal benefits, and vice versa. Lastly, private and social rental dwellings were found to have lower average and total natural gas than owner-occupied dwellings. This can be explained by rental dwellings often being apartments or mid-terraced dwellings and owner-occupancy being the most common tenure type in the Netherlands (CBS, 2022b).

7.3 Adoption influences and EEG explanations

Finally, adoption influences were analysed to further understand the diffusion of insulation in relation to EEG explanations. The adoption analysis showed that an insulation measure is substantially more likely to be adopted in dwellings built up until 1995, than in the dwellings built hereafter. This can be explained by the lower foregone benefits for households living in these dwellings, as substantiated in the previous subsection. Paradoxically, it was found that dwellings built after 1995 have a higher likelihood of having more different kinds of insulation measures adopted. This remarkable disparity remains unexplained in this study and requires further research. Another interesting finding is that the second control variable, i.e. households' likelihood to move, turns out to be insignificant which contradicts previous studies. Explanations for this might be that Dutch households are emphasising the short-term benefits of additional insulation or that households planning to move, specifically homeowners, are retrofitting their dwellings to increase their value.

The adoption analysis further substantiated that households living in social and private rental housing are considerably less likely than homeowners to adopt any insulation measure. On a similar note, households part of HOAs seem to have lower odds of adopting a larger number of insulation measures. These findings appear to indicate a principal-agent problem. Here, tenants and households part of HOAs can benefit from adopting additional insulation measures, yet cannot make these adoption decisions (fully) by themselves. As the incentives of the deciding party, i.e. landlords or HOAs, may be different from those of tenants and individual homeowners, this can lead to less insulation measures being adopted.

In addition to testing the principal-agent problem explanation for the EEG, this study empirically examined other potential explanations as well. Based on the households' disposable income and financial capital, the capital constraints explanation has been tested. In the analysis, neither income or capital were identified to significantly affect insulation adoption. This is an interesting finding, as it is not in accordance with adoption literature and the debate on EE measures widening socioeconomic gaps. Although no significant relations were found, it should be noted that this study does not rule out the possibility of capital constraints being present. It is for instance unclear whether households' insulation adoption was not restrained by capital constraints at all, or whether it was already stimulated by supportive financial policies. Moreover, while capital constraints are not indicated in the WoON 2012 and WoON 2018 datasets, they could have been present during more recent years, which were characterised by higher inflation and energy prices. For providing these contemporary insights, it would therefore be interesting to reconduct this research with data from WoON 2024.

By assessing the effect of household members' age and education level on insulation adoption, the presence of several other EEG explanations, e.g. imperfect information and bounded rationality, was indirectly explored. For the level of education, this study found no significant effect. While some age groups did demonstrate a significant effect on adoption, these results were rather inconsistent between and within the models. Age is therefore not regarded as a significant predictor. Yet, similar to the capital constraints explanation, this study does not disprove the related EEG explanations. As this research made use of secondary data, it was not possible to include variables that could test these explanations more thoroughly. While the relevancy of including age and education level has been substantiated by adoption literature and empirical findings, the validity of this study could be improved by including more specific variables.

Due to the research design of this study, numerous relevant EEG explanations and adoption influences could not be tested for. Social influences are an example of this. In sociological diffusion perspectives, social networks and influences are regarded as the foundation for the spread of new information (Rogers, 2003). Peer effects are a specific type of social influence and refer to the situation where the behaviour of an individual is affected by other members within a peer group (Wolske et al., 2020). Since learning spillovers and peer effects go hand in hand, and EEG literature suggesting that the waiting for such spillovers to occur can slow down adoption rates, it would be interesting to examine the influence of peer effects on insulation adoption. As of yet, peer effects have received little attention in relation to the adoption of EE measures and thus provide an interesting area for further research (Wolske et al., 2020). Similarly, this study was not able to thoroughly test the various behavioural or attitudinal factors and EEG explanations. Yet, these are particularly worth investigating, as it is argued that such factors are able to better predict households' energy-related adoption decisions than mere demographic variables (Kastner & Stern, 2015). To support future research on the adoption of EE measures, it would therefore be fruitful for the succeeding WoON surveys, and surveys alike, to measure attitudinal and social household factors more extensively.

Finally, due to this study's research design, the influences of macroeconomic factors on insulation adoption, e.g. energy prices and insulation costs, could not be tested for. Changes in these factors are however relevant to consider, as these would directly affect the costs and benefits that individuals, one way or another, evaluate in their EE decision-making processes. Such factors can for instance be included in further NPV models or in regression analyses explaining insulation adoption rates over time. However, since decision-making processes remain not fully understood, the presence of behavioural and modelling EEG failures should still be considered when conducting such analyses.

8. Conclusion and recommendations

Insulation is an energy-efficiency measure that significantly reduces households' gas and energy consumption, resulting in benefits for both society and individual households. Despite these benefits for households, a large proportion of Dutch dwellings is still, relatively, poorly insulated. The diffusion of insulation has not been thoroughly examined and there is little empirical evidence on the size and explanations for the discrepancy between predicted and observed adoption rates of insulation measures and other energy-efficiency technologies, i.e. the Energy Efficiency Gap. This study therefore quantitatively examined the diffusion of insulation measures among Dutch households through three analyses.

In the first analysis, diffusion curves were derived to provide more context on the diffusion of insulation measures and the decarbonisation efforts of households in the Netherlands. Based on systematically conducted nation-wide surveys on the energetic quality of the Dutch housing stock (KWR and WoON), the development of the roof, floor, window and facade insulation degree of households was examined. This analysis showed that from 1989 to 2018, the average degree of insulation has been increasing for these insulation measures. However, it was also found that the diffusion rate of these measures has been decreasing prematurely, suggesting that a significant part of Dutch households persistently renounces insulation and hence, does not enjoy subsequent benefits. By subdividing the insulation degrees into construction year classes, dwelling types and tenure types, this study further investigated the insulation diffusion patterns. This indicated the presence of insulation gaps; substantial differences in the insulation degrees of Dutch dwellings. Such an insulation gap for instance appeared between dwellings built prior to 1981 and dwellings built hereafter. Similarly, the average insulation degrees have been lower for households living in apartments and in social housing, compared to other dwelling and tenure types. These insights furthermore show that diffusion curves are not solely suitable for analysing successful innovations ex-post, but can contribute to a better understanding of ongoing diffusion processes.

In the second analysis, building on the diffusion curve analysis and Menkveld et al. (2020), it was subsequently examined what foregone benefits could have been achieved if insulation measures had diffused to a greater extent. Annually, households could have annually saved 336 to 542 m^3 of natural gas on average, and 2.37 billion to 3.82 billion m^3 in total, which is in line with alternative estimations. These foregone benefits have also been subdivided into construction year classes, dwelling types and tenure types. It was found that average and total natural gas savings are substantially lower for dwellings built after 1995 than of older dwellings, which can be explained by a, legislated, higher energetic quality for dwellings built since the 1990's. This showed that lower insulation degrees do not necessarily translate into higher foregone benefits, as dwellings built between 1981-1995 had relatively high insulation degrees and high foregone benefits. Average foregone benefits were found to be mainly dependent on the type of dwelling. Generally, average foregone benefits were relatively low for apartments and increased for mid-terraced dwellings. Semi-detached/end-terraced dwellings and detached dwellings were found to have the highest average foregone benefits. Despite this, the highest total natural gas savings could have been achieved by insulating all dwelling types built between 1960-1980, as they represent a larger share of the Dutch housing stock. This finding indicates that the private benefits of adopting additional insulation are not perfectly aligned with the societal benefits and thus creates a trade-off. Lastly, private and social rental dwellings were found to have lower average and total natural gas savings than owner-occupied dwellings. This can be explained by rental dwellings often being apartments or mid-terraced dwellings and owner-occupancy being the most common tenure type in the Netherlands.

In the third analysis, based on the WoON 2012 and WoON 2018, adoption influences were analysed at the level of households through zero-inflated negative binomial regressions. This analysis showed that households living in dwellings built after 1995 are substantially less likely to adopt an insulation measure at all, which can be explained by the identified lower foregone benefits for households living in these dwellings. Paradoxically, it was found that the same households living in the dwellings built after 1995 have a higher likelihood of having more different kinds of insulation measures adopted. This remarkable disparity remains unexplained in this study and requires further research. The adoption analysis did further substantiate that households living in rental housing are considerably less likely than homeowners to adopt any insulation measure. Moreover, households part of homeowner associations were found to be less likely to adopt a larger number of insulation measures. These findings appear to indicate a principal-agent problem, which could serve as an explanation for the EEG. Other variables that were included in the adoption influences analysis - household members' income, capital, age, education level and likelihood to move - were not found to significantly affect the adoption of insulation. This suggests that socio-demographic factors appear to play a less significant role in the uptake of insulation measures than housing factors seem to do. Related to energy poverty, it thus appeared that households living in such poverty have financially not been more constrained in the adoption of insulation measures than other households. Nevertheless, since recent years were characterised by higher inflation and energy prices, affecting energy poverty, further research is needed to examine the relationship between energy poverty and insulation adoption.

The results of the adoption influences analysis have been shown to be quite robust for different model specifications. However, it should be noted that some household factors related to EEG explanations could not be included in this study, in particular, the attitude, perceptions and social network ties of households. It is recommendable to include such variables in future (WoON) surveys, so the adoption of insulation measures as well as other energy-efficiency measures can be analysed in fuller detail. By analysing this, it can be examined whether housing factors and principal-agent problems still appear to hinder the adoption of insulation measures, or whether other factors significantly influence their adoption as well. Similarly, the influences of macroeconomic factors on insulation adoption, e.g. energy prices and insulation costs, could not be tested for. Such factors can be included in further NPV models or in regression analyses explaining insulation adoption rates over time. It should here be noted that, since decision-making processes remain not fully understood, the presence of behavioural and modelling limitations need to be considered when conducting such analyses.

Finally, several policy recommendations can be drawn based on the results of this study. By deriving diffusion curves, this study found that insulation diffusion rates have been declining rather prematurely. Policy makers are therefore recommended to use these insights for the evaluation of past and contemporary policies, to assess how the diffusion of insulation can be accelerated instead. Since households part of rental housing or homeowner associations appeared to be less likely to adopt additional insulation measures, it should particularly be investigated how policy measures can encourage landlords and homeowners associations to adopt additional insulation measures. Similarly, differing private and societal benefits of insulation can also lead to split incentives and should therefore be taken into account when stimulating insulation adoption among Dutch households and the transition towards a decarbonised residential sector.

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Appendices

Appendix A - Secondary survey data

Table A.1 provides an overview of the KWR and WoON surveys that were used in this study. When variables or data on the survey respondents were missing, these respondents were excluded from the respective analysis. Despite having contacted the Dutch Ministry of the Interior and Kingdom Relations, the first KWR survey (1983) could unfortunately not be accessed for Analysis 1.

Table A.1
Overview of the surveys used in this study

Survey	*No. of respondents*	*Type of analysis*	*No. of respondents used*
KWR 1989	26,631	1. Diffusion curves	26,631
KWR 1995	15,022	1. Diffusion curves	15,022
KWR 2000	15,002	1. Diffusion curves	15,002
WoON 2006 energy module	4,724	1. Diffusion curves	4,724
WoON 2012 market module	69,339	1. Diffusion curves 3. Adoption influences	4,790 4,749 / 2,791
WoON 2012 energy module	4,792	1. Diffusion curves 3. Adoption influences	4,790 4,749 / 2,791
WoON 2018 market module	67,523	1. Diffusion curves 3. Adoption influences	4,506 2,841
WoON 2018 energy module	4,506	1. Diffusion curves 2. Foregone benefits 3. Adoption influences	4,506 4,273 2,841

Appendix B - Operationalisation diffusion curve analysis

1. Insulation degree

In the KWR and WoON surveys from 1995 and onwards, the insulation degree of building surfaces (roof, floor, windows, facade) have been expressed on a scale from 0 to 100%, representing the percentage of the respective building surface that has been insulated. This scale has been retained in Analysis 1. An overview of the survey-specific insulation degree variables can be found in Table B-1.

Insulation degrees KWR 1989

In KWR 1989, the insulation degree was measured on an ordinal level (*not insulated; less than half insulated; more than half insulated; fully insulated*) for roofs, floors and facades, while the insulation degree for windows was not captured within a single variable. To still include the year 1989 in the diffusion curve analysis, three (sensitivity) computations have been performed, in which roof, floor and facade insulation degrees have been derived on a scale from 0 to 100% for dwellings from the KWR 1989 survey. Table B-2 provides an overview of the three methods applied to re-operationalise the ordinal insulation degrees of KWR 1989.

For the first method, the ordinal values 'less than half insulated' and 'more than half insulated' were replaced by 25% and 75%, respectively. In the second method, these ordinal values were respectively replaced by 33.3% and 66.7%. For the third method, these ordinal values have been substituted by the average insulation degrees of dwellings in the same insulation and construction year class from the KWR 1995 survey. Concretely, for each insulation type (roof, floor and facade) and construction year class (≤1930; 1931-1959; 1960-1980; 1981-1995), the weighted average insulation degree has been computed for two dwelling cohorts of KWR 1995; dwellings with insulation degrees from 1% to 49% and those with insulation degrees from 50% to 99%. These weighted averages can subsequently be substituted with the respective ordinal insulation degree of KWR 1989 dwellings.

When using the third method, it should be noted that dwellings' average insulation degrees have likely been higher in 1995 than in 1989. Nevertheless, the third method was still deemed as more robust than simply substituting the ordinal values with fixed percentages, without considering differences in construction years, and thus the energetic state of the dwellings. It has therefore been decided to apply the third method.

Missing insulation degrees

It should also be noted that a substantial share of households within the KWR and WoON surveys did not have an insulation degree assigned, particularly for roofs and floors. As it was unclear whether this data was simply missing or whether assigning an insulation degree was not possible (e.g., for apartments which have no roof or floor to be insulated), average insulation degrees have been computed through four methods.

For Method 1 and Method 4, missing insulation degrees were respectively substituted with 0% and 100%. This way, a lower limit and upper limit of average insulation degrees was estimated. For Method 2, missing insulation degrees within each survey were substituted with the weighted average insulation degree calculated for the other dwellings of the same construction year class. After substitution, weighted averages were recalculated accordingly. Lastly, in

Method 3, dwellings with missing insulation degrees were excluded from the analysis. An overview of the average insulation degrees computed through the four methods can be found in Table B-3.

The average roof and floor insulation degrees are found to be a few percentage points lower when estimated through Method 2 than when computed via Method 3. Since these differences are minimal and no dwellings are excluded using Method 2, the average insulation degrees computed through this method have been regarded as leading in this study. This way, results could be generalised to the entire Dutch housing stock.

2. Weighting factor

In the KWR and WoON survey, weighting factors were assigned to the participating respondents. Each weighting factor indicated the number of similar households/dwellings present in the Netherlands. The sum of the weighting factors thus approximated the total number of households and dwellings in the Netherlands. As a result, the findings of Analysis 1 are highly generalisable. For an overview of the survey-specific weighting factor variables, see Table B-1.

3. Construction year class

Five construction year classes have been used to examine the diffusion of insulation measures among Dutch dwellings over time: *≤1930; 1931-1959; 1960-1980; 1981-1995; >1995.* These construction year classes are in accordance with the operationalisation used in prior WoON studies and analyses (e.g., WoON 2006; Rovers & Tigchelaar, 2022). An overview of the survey-specific construction year variables can be found in Table B-1.

4. Dwelling type

In the diffusion curve analysis, four types of dwellings have been distinguished as well. These are: *detached dwellings, semi-detached / end-terraced dwellings, mid-terraced dwellings and apartments.* As the operationalisation of dwelling types differed among the KWR and WoON surveys, these variables have been re-operationalised (see Table B-4.

5. Tenure type

Lastly, the three common Dutch tenure types have been used in the diffusion curve analysis: *owner-occupied housing, private rental housing and social housing.* As the operationalisation of tenure types differed among the KWR and WoON surveys, these variables have been re-operationalised (see Table B-5).

Table B-1

Analysis 1 variables with the same operationalisation as KWR and WoON

Diffusion curve analysis variables	*KWR 1989*	*KWR 1995*	*WoON 2000*	*WoON 2006*	*WoON 2012*	*WoON 2018*
Insulation degree roof	isodak	isobdkx	isobdkx	isobdkx	isodak*	isobdkx
Insulation degree floor	isobg	isobbgx	isobbgx	isobbgx	isovloe*	isozvx
Insulation degree windows	*n/a*	isoglx	isoglx	isoglx	isoglas*	isoglx
Insulation degree facade	isogev	ibggplx	ibggplx	isobggx	isogev*	isobggx
Construction year	bjaar	bjaarw	bjaarx	bouwjaar	BOUWJAAR	bouwjaar
Weighting factor household	weegfac	wg95n_2x	weeg00_3	weeg06tv	weegfactor*	ew_huis

Note. * Variable derived and corrected by the former Energy Research Centre of the Netherlands (now part of TNO).

Table B-2

Re-operationalisation methods for the KWR 1989 insulation degrees

Ordinal insulation degree operationalisation KWR 1989	*Method 1*	*Method 2*	*Method 3*
1. Not insulated	0%	0%	0%
2. Less than half insulated	25%	33.3%	Construction year average
3. More than half insulated	75%	66.7%	Construction year average
4. Fully insulated	100%	100%	100%

Table B-3

Methods for computing average insulation degrees with missing values

Average insulation degrees		*Method 1: Missing = 0%*	*Method 2: Missing = constr. year average*	*Method 3: Missing = excluded*	*Method 4: Missing = 100%*
Roof	1989	40.4	49.1	51.9	62.5
	1995	41.2	49.3	51.3	60.9
	2000	51.2	61.1	63.5	70.6
	2006	62.2	73.6	76.4	80.8
	2012	63.6	76.9	80.2	84.3
	2018	67.9	82.0	85.6	88.6
Floor	1989	17.0	21.2	23.0	42.9
	1995	19.6	22.6	23.8	37.3
	2000	27.8	33.5	34.7	47.7
	2006	31.7	38.6	43.4	58.7
	2012	43.7	53.6	55.8	65.4
	2018	49.0	60.2	62.7	70.9
Window	1989	n/a	n/a	n/a	n/a
	1995	56.0	56.2	56.2	56.3
	2000	66.2	66.3	66.3	66.3
	2006	76.8	76.7	76.7	76.7
	2012	85.6	85.7	85.7	85.7
	2018	85.2	85.3	85.3	85.3
Facade	1989	43.1	43.6	43.6	44.2
	1995	42.4	42.4	42.4	42.5
	2000	50.2	50.2	50.2	50.2
	2006	55.4	55.4	55.4	55.4
	2012	70.6	70.6	70.6	70.6
	2018	72.9	72.9	72.9	72.9

Table B-4

Re-operationalisation of the dwelling type variable

Dwelling type variable	*KWR 1989*	*KWR 1995*	*WoON 2000*	*WoON 2006*	*WoON 2012*	*WoON 2018*
1. Detached	**esit =** 1. Vrijstaand	**typwon =** 1. Vrijstaand	**typwon =** 1. Vrijstaand	**vorm_eg =** 1. Vrijstaand	**vorm_eg5 =** 1. Vrijstaande woning	**vorm_eg5 =** 1. Vrijstaande woning
2. Semi-detached / end-terraced	**esit =** 2. Twee onder een kap; 3. Hoek-/eindwoning	**typwon =** 2. Hoek / twee	**typwon =** 2. Hoe/twee	**vorm_eg =** 2. Twee onder een kap; 3. Hoekwoning	**vorm_eg5 =** 2. 2 onder 1 kap; 4. Rijwoning hoek; 5. Rijwoning eind	**vorm_eg5 =** 2. 2 onder 1 kap; 3. Rijwoning hoek
3. Mid-terraced	**esit =** 4. Tussenwoning	**typwon =** 3. Tussen	**typwon =** 3. Tussen	**vorm_eg =** 4; Tussenwoning	**vorm_eg5 =** 3. Rijwoning tussen	**vorm_eg5 =** 4. Rijwoning tussen
4. Apartment	**btwem =** 2. Meergezinswoning	**typwon =** 4. Meergezins	**typwon =** 4. Meergez	**vorm =** 2. Meergezinswoning	**vormwo =** 2. Meergezins	**vormwo =** 2. Meergezins

Table B-5
Re-operationalisation of the tenure type variable

Tenure type variable	*KWR 1989*	*KWR 1995*	*WoON 2000*	*WoON 2006*	*WoON 2012*	*WoON 2018*
1. Owner-occupied	**bhv =** 3. Eigen woningbezit; 4. Aangekocht bezit	**bhvcw1 =** 1. Koop	**bhvcw1 =** 1. Koop	**huko3 =** 1. Koopwoning	**HUKO3WO =** 1. Koop	**eighuura =** 1. Eigenaar
2. Social housing	**bhv =** 1. Sociale huur	**bhvcw1 =** 2. Soc huur	**bhvcw1 =** 2. Soc. huur	**huko3 =** 2. Sociale huur	**HUKO3WO =** 2. Sociale huur	**wieverh =** 1. Woningcorporatie
3. Private rental	**bhv =** 2. Particuliere huur	**bhvcw1 =** 3. Part huur	**bhvcw1 =** 3. Part. huur	**huko3 =** 3. Particuliere huur	**HUKO3WO =** 3. Particuliere huur	**wieverh =** 2. Gemeente, provincie, waterschap, het Rijk; 3. Pensioenfonds, verzekerings-maatschappij, belegger; 4. Particulier persoon; 5. Familie; 6. Zorginstelling

Appendix C - Operationalisation adoption influences analysis

For the variables ‘construction year class’ and ‘tenure type’, the same (re-)operationalisation used for Analysis 1, as elaborated in Appendix B, has been applied in the analysis on adoption influences. The (re-)operationalisation of the additional variables included in Analysis 3 are elaborated on below.

Number of insulation measures adopted
The dependent variable, number of insulation measures adopted, has been derived from the WoON 2012 and WoON 2018 data. As the WoON surveys distinguished between multiple subtypes of insulation measures that could have been adopted during the preceding five years, these variables have first been re-operationalised into the four insulation measures emphasised in Analysis 1 (see Table C-1). Subsequently, a new count variable has been derived, indicating how many of the four distinct insulation measures have been adopted during the preceding five years.

Disposable household income & household capital
Disposable household income and household capital have both been included on a ratio scale in WoON 2012 and WoON 2018. In Analysis 3, the same operationalisation has been applied for these variables. For an overview of the survey-specific disposable household income and household capital variables, see Table C-2.

Education level
The level of education of the survey respondents has been expressed in different ordinal scales in WoON 2012 and WoON 2018. For Analysis 3, the same operationalisation as in WoON 2018 was applied. The concerning education variables of WoON 2012 have been re-operationalised, according to the Dutch Standard Education Index on which the education variables of WoON 2018 were already based (CBS, 2021). Table C-3 provides an overview of the re-operationalisation applied for Analysis 3.

Age
In WoON 2012 and WoON 2018, the age of the survey respondents has been divided into seven categories: *17-24; 25-34; 35-44; 45-54; 55-64; 65-74; ≥75*. In Analysis 3, the same operationalisation was applied for this variable. For an overview of the survey-specific age variables, see Table C-2.

Homeowner association
Whether a household was part of a HOA was captured within a binary variable in WoON 2012 and WoON 2018. In Analysis 3, the same operationalisation was applied for this variable. For an overview of the survey-specific HOA variables, see Table C-2.

Likely to move
In WoON 2012 and WoON 2018, households’ likelihood of moving was captured within an ordinal variable. For Analysis 3, these variables have been re-operationalised into a more suitable binary variable (see Table C-4).

Table C-1

Re-operationalisation of the adopted insulation measures variables

Insulation measures adopted	*WoON 2012*	*WoON 2018*
1. Roof insulation measures = 1, IF (otherwise = 0)	**BESMAA05** (binnenisolatie dak) = 1. Ja; **BESMAA06** (buitenisolatie dak) = 1. Ja	**typeisolat* =** 3. Binnenisolatie dak; 4. Buitenisolatie dak
2. Floor insulation measures = 1, IF (otherwise = 0)	**BESMAA07** (isolatie zoldervloer) = 1. Ja; **BESMAA8A** (isolatie begane grond vloer) = 1. Ja; **BESMAA8B** (isolatie andere vloer(en)) = 1. Ja	**typeisolat* =** 5. Isolatie zoldervloer; 6. Isolatie begane grond vloer; 7. Isolatie andere vloer(en)
3. Window insulation measures = 1, IF (otherwise = 0)	**BESMAA01** (Dubbelglas HR++) = 1. Ja; **BESMAA02** (Dubbelglas geen HR++) = 1. Ja; **BESMAA27** (Dubbelglas type onbekend) = 1. Ja	**enerzmaat** =** 1. Dubbelglas
4. Facade insulation measures = 1, IF (otherwise = 0)	**BESMAA04** (gevelisolatie) = 1. Ja	**typeisolat* =** 1. Spouwermuurisolatie; 2. Gevelisolatie

Note. * Value ranging from 1 to 9 (i.e. typeisolat1, typeisolat2, …). ** Value ranging from 1 to 7 (i.e. enerzmaat1, enerzmaat2, …).

Table C-2

Analysis 3 variables with the same operationalisation as WoON

Adoption influences analysis variables	*WoON 2012*	*WoON 2018*
Disposable household income	bestinkh_r	bestinkh_r
Household capital	vermhh_r	vermogh_r
Age	i_lfthkw7_r	i_lfthkw7_r
Homeowner association	ActVVE	vveactief

Table C-3

Re-operationalisation of education level

Education level household member	*WoON 2012*	*WoON 2018*
1. Lower education	**vltoplop =** 1. Lager onderwijs; 2. LBO; 3. MAVO, MULO, VMBO	**vltoplop3 =** 1. Laag
2. Intermediate education	**vltoplop =** 4. HAVO, VWO, MBO	**vltoplop3 =** 2. Middelbaar
3. Higher education	**vltoplop =** 5. HBO, Universiteit	**vltoplop3 =** 3. Hoog

Table C-4

Re-operationalisation of households' likelihood of moving

Likely to move	*WoON 2012*	*WoON 2018*
0. No (unlikely to move)	**verh =** 4. Niet verhuisgeneigd	**verh =** 4. Niet verhuisgeneigd
1. Yes (likely to move)	**verh =** 1. Verhuisgeneigd; 2. Huisv gevonden; 3. Gedwongen verhuizing	**verh =** 1. Verhuisgeneigd; 2. Huisv gevonden; 3. Gedwongen verhuizing

Appendix D - Results foregone benefits analysis

Table D-1
Foregone benefits without level 2 insulation measures

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
≤1930	318	216.89	312,963,140	213,440,861.35	588	984,114
Semi-detached/end-terraced	363	247.56	69,617,830	47,479,360.14	125	191,788
Owner-occupied	340	231.59	56,303,546	38,399,018.17	107	165,809
Private rental	562	383.10	5,497,323	3,749,174.18	7	9,786
Social housing	483	329.23	7,816,962	5,331,167.79	11	16,193
Apartment	221	150.65	78,342,767	53,429,766.79	203	354,663
Owner-occupied	255	173.91	27,268,455	18,597,086.62	90	106,937
Private rental	233	158.65	38,411,133	26,196,392.57	71	165,116
Social housing	153	104.54	12,663,178	8,636,287.60	42	82,610

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Mid-terraced	297	202.36	72,498,907	49,444,254.69	141	244,343
Owner-occupied	305	207.76	50,633,870	34,532,299.06	98	166,214
Private rental	377	256.98	13,858,271	9,451,340.74	12	36,779
Social housing	194	132.06	8,006,767	5,460,614.89	31	41,351
Detached	479	326.34	92,503,636	63,087,479.73	119	193,319
Owner-occupied	485	330.49	79,872,057	54,472,742.60	106	164,826
Private rental	451	307.84	12,534,703	8,548,667.26	12	27,770
Social housing	134	91.39	96,877	66,069.86	1	723
1931-1959	421	286.88	452,055,789	308,302,048.00	599	1,074,676
Semi-detached/end-terraced	517	352.89	135,091,645	92,132,501.59	159	261,084
Owner-occupied	516	351.72	94,921,115	64,736,200.67	113	184,055

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Private rental	571	389.42	5,047,045	3,442,084.39	4	8,839
Social housing	515	351.29	35,123,485	23,954,216.53	42	68,189
Apartment	336	229.49	115,725,395	78,924,719.41	188	343,914
Owner-occupied	278	189.29	28,661,944	19,547,445.94	77	103,267
Private rental	398	271.58	41,330,192	28,187,190.91	45	103,791
Social housing	334	227.90	45,733,259	31,190,082.56	66	136,856
Mid-terraced	364	248.20	110,086,251	75,078,823.07	164	302,492
Owner-occupied	362	247.03	64,975,020	44,312,963.87	100	179,383
Private rental	454	309.42	6,268,564	4,275,160.45	5	13,817
Social housing	355	242.38	38,842,667	26,490,698.74	59	109,292
Detached	545	371.83	91,152,498	62,166,003.94	88	167,187
Owner-occupied	591	403.23	84,805,222	57,837,161.70	85	143,433

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Private rental	267	182.23	6,347,276	4,328,842.24	3	23,754
1960-1980	466	317.91	1,057,036,208	720,898,694.11	1,386	2,267,653
Semi-detached/end-terraced	519	354.27	337,565,877	230,219,928.17	407	649,851
Owner-occupied	546	372.27	240,923,659	164,309,935.64	295	441,371
Private rental	677	461.70	20,785,449	14,175,676.27	15	30,703
Social housing	427	291.01	75,856,769	51,734,316.25	97	177,777
Apartment	308	209.83	191,387,270	130,526,118.31	355	622,059
Owner-occupied	339	231.19	46,812,230	31,925,940.91	79	138,092
Private rental	348	237.29	50,292,095	34,299,208.93	72	144,543
Social housing	278	189.44	94,282,945	64,300,968.47	204	339,424
Mid-terraced	439	299.64	317,613,501	216,612,407.95	434	722,914
Owner-occupied	442	301.49	203,608,739	138,861,159.91	287	460,581

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Private rental	489	333.54	25,312,423	17,263,072.70	21	51,757
Social housing	421	287.25	88,692,339	60,488,175.34	126	210,576
Detached	771	526.12	210,469,560	143,540,239.68	190	272,829
Owner-occupied	787	537.03	198,687,486	135,504,865.71	181	252,321
Private rental	575	392.00	11,765,798	8,024,274.00	8	20,470
Social housing	435	296.67	16,276	11,099.97	1	37
1981-1995	285	194.24	415,995,286	283,708,785.26	942	1,460,634
Semi-detached/end-terraced	345	235.06	145,022,466	98,905,321.56	275	420,766
Owner-occupied	369	251.83	124,530,093	84,929,523.32	228	337,253
Private rental	262	178.61	5,060,549	3,451,294.31	11	19,323
Social housing	240	163.96	15,431,824	10,524,503.93	36	64,191
Apartment	178	121.35	83,071,644	56,654,861.07	292	466,860

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Owner-occupied	197	134.44	17,999,640	12,275,754.54	86	91,311
Private rental	280	190.96	23,236,529	15,847,312.96	36	82,986
Social housing	143	97.52	41,835,474	28,531,793.57	170	292,563
Mid-terraced	271	184.69	110,330,509	75,245,407.07	244	407,411
Owner-occupied	278	189.27	73,275,482	49,973,878.97	161	264,034
Private rental	324	220.98	17,262,493	11,773,020.18	28	53,275
Social housing	220	149.82	19,792,534	13,498,507.92	55	90,101
Detached	468	319.47	77,570,668	52,903,195.57	131	165,597
Owner-occupied	466	317.82	75,997,451	51,830,261.61	129	163,080
Private rental	625	426.23	1,573,217	1,072,933.96	2	2,517
>1995	104	70.88	131,118,504	89,422,819.80	758	1,261,625
Semi-detached/end-terraced	122	83.29	35,063,542	23,913,335.63	160	287,114

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Owner-occupied	119	81.23	29,538,276	20,145,104.13	140	248,002
Private rental	141	96.30	1,599,275	1,090,705.52	5	11,326
Social housing	141	96.36	3,925,991	2,677,525.98	15	27,786
Apartment	73	49.71	34,788,566	23,725,801.89	308	477,308
Owner-occupied	101	68.60	17,794,599	12,135,916.39	123	176,903
Private rental	57	38.65	7,837,036	5,344,858.44	60	138,304
Social housing	56	38.53	9,156,931	6,245,027.05	125	162,101
Mid-terraced	96	65.30	27,582,016	18,810,934.64	151	288,066
Owner-occupied	102	69.63	22,449,894	15,310,828.02	116	219,875
Private rental	75	51.14	1,898,820	1,294,995.46	13	25,324
Social housing	75	51.44	3,233,301	2,205,111.15	22	42,867
Detached	161	109.85	33,684,381	22,972,747.64	139	209,137

	Average natural gas savings (m^3/year)	**Average natural gas cost savings (€/year)**	**Total natural gas savings (m^3/year)**	**Total natural gas cost savings (€/year)**	**No. of households included from WoON 2018 energy module**	**Represented no. of Dutch households**
Owner-occupied	162	110.28	33,684,381	22,972,747.64	138	208,319
Private rental	0	0.00	0	0.00	1	818
Total	**336**	**229.23**	2,369,168,927	1,615,773,208.52	4,273	7,048,702

Table D-2

Foregone benefits without level 3 insulation measures

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
≤1930	484	330.28	476,591,646	325,035,502.24	588	984,114
Semi-detached/end-terraced	552	376.53	105,885,197	72,213,704.39	125	191,788
Owner-occupied	536	365.61	88,886,752	60,620,764.87	107	165,809
Private rental	703	479.24	6,876,883	4,690,034.40	7	9,786
Social housing	625	426.30	10,121,562	6,902,905.12	11	16,193
Apartment	301	205.32	106,774,071	72,819,916.73	203	354,663
Owner-occupied	356	242.86	38,080,995	25,971,238.72	90	106,937
Private rental	307	209.27	50,664,556	34,553,227.34	71	165,116
Social housing	218	148.84	18,028,520	12,295,450.67	42	82,610
Mid-terraced	455	310.19	111,132,839	75,792,596.41	141	244,343

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Owner-occupied	470	320.86	78,197,308	53,330,563.75	98	166,214
Private rental	568	387.11	20,875,918	14,237,375.95	12	36,779
Social housing	292	198.90	12,059,614	8,224,656.71	31	41,351
Detached	790	539.05	152,799,538	104,209,284.71	119	193,319
Owner-occupied	815	555.87	134,341,645	91,621,001.60	106	164,826
Private rental	657	447.89	18,237,390	12,437,900.21	12	27,770
Social housing	305	208.01	220,503	150,382.90	1	723
1931-1959	625	425.98	671,252,736	457,794,365.92	599	1,074,676
Semi-detached/end-terraced	774	527.87	202,077,716	137,817,002.03	159	261,084
Owner-occupied	778	530.50	143,169,381	97,641,517.98	113	184,055
Private rental	943	643.14	8,335,315	5,684,684.69	4	8,839
Social housing	742	505.81	50,573,020	34,490,799.36	42	68,189

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Apartment	442	301.22	151,896,246	103,593,239.66	188	343,914
Owner-occupied	361	245.93	37,238,577	25,396,709.76	77	103,267
Private rental	519	354.08	53,885,903	36,750,185.57	45	103,791
Social housing	444	302.85	60,771,766	41,446,344.33	66	136,856
Mid-terraced	549	374.51	166,107,810	113,285,526.08	164	302,492
Owner-occupied	563	383.65	100,908,577	68,819,649.40	100	179,383
Private rental	631	430.38	8,719,138	5,946,451.99	5	13,817
Social housing	517	352.44	56,480,095	38,519,424.69	59	109,292
Detached	904	616.66	151,170,965	103,098,598.14	88	167,187
Owner-occupied	972	662.64	139,361,868	95,044,793.86	85	143,433
Private rental	497	339.04	11,809,097	8,053,804.28	3	23,754
1960-1980	766	522.46	1,737,195,109	1,184,767,064.53	1,386	2,267,653

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Semi-detached/end-terraced	866	590.36	562,531,854	383,646,724.56	407	649,851
Owner-occupied	912	621.79	402,403,531	274,439,207.83	295	441,371
Private rental	1047	713.86	32,137,431	21,917,727.75	15	30,703
Social housing	720	491.01	127,990,893	87,289,788.98	97	177,777
Apartment	453	309.02	281,862,451	192,230,191.69	355	622,059
Owner-occupied	526	358.58	72,605,950	49,517,257.77	79	138,092
Private rental	492	335.34	71,072,291	48,471,302.45	72	144,543
Social housing	407	277.65	138,184,210	94,241,631.48	204	339,424
Mid-terraced	734	500.83	530,877,208	362,058,255.99	434	722,914
Owner-occupied	739	504.11	340,447,404	232,185,129.67	287	460,581
Private rental	755	514.85	39,072,192	26,647,234.76	21	51,757
Social housing	719	490.21	151,357,612	103,225,891.57	126	210,576

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Detached	1327	904.71	361,923,596	246,831,892.29	190	272,829
Owner-occupied	1341	914.64	338,392,068	230,783,390.49	181	252,321
Private rental	1148	782.94	23,499,912	16,026,939.79	8	20,470
Social housing	845	576.29	31,616	21,562.00	1	37
1981-1995	522	356.27	763,021,940	520,380,962.87	942	1,460,634
Semi-detached/end-terraced	637	434.39	268,000,870	182,776,593.39	275	420,766
Owner-occupied	679	462.98	228,945,818	156,141,047.85	228	337,253
Private rental	499	340.20	9,638,670	6,573,573.03	11	19,323
Social housing	458	312.54	29,416,382	20,061,972.52	36	64,191
Apartment	307	209.08	143,121,462	97,608,837.35	292	466,860
Owner-occupied	340	232.10	31,075,247	21,193,318.38	86	91,311

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Private rental	413	281.50	34,252,730	23,360,361.88	36	82,986
Social housing	266	181.35	77,793,485	53,055,157.09	170	292,563
Mid-terraced	515	351.19	209,793,588	143,079,226.95	244	407,411
Owner-occupied	529	360.61	139,610,803	95,214,567.70	161	264,034
Private rental	617	421.02	32,888,712	22,430,101.54	28	53,275
Social housing	414	282.29	37,294,073	25,434,557.71	55	90,101
Detached	858	585.25	142,106,019	96,916,305.19	131	165,597
Owner-occupied	856	583.94	139,632,860	95,229,610.62	129	163,080
Private rental	982	670.04	2,473,159	1,686,694.57	2	2,517
>1995	137	93.61	173,177,386	118,106,977.34	758	1,261,625
Semi-detached/end-terraced	172	117.28	49,372,811	33,672,256.95	160	287,114
Owner-occupied	170	115.83	42,120,663	28,726,292.08	140	248,002

	Average natural gas savings (m^3/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m^3/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Private rental	175	119.24	1,980,192	1,350,490.97	5	11,326
Social housing	190	129.40	5,271,956	3,595,473.90	15	27,786
Apartment	73	49.60	34,716,418	23,676,597.21	308	477,308
Owner-occupied	100	68.42	17,746,990	12,103,446.96	123	176,903
Private rental	57	38.90	7,889,561	5,380,680.91	60	138,304
Social housing	56	38.20	9,079,867	6,192,469.34	125	162,101
Mid-terraced	125	85.16	35,971,706	24,532,703.52	151	288,066
Owner-occupied	132	89.87	28,972,568	19,759,291.64	116	219,875
Private rental	108	73.74	2,738,008	1,867,321.76	13	25,324
Social housing	99	67.79	4,261,129	2,906,090.12	22	42,867
Detached	254	173.21	53,116,451	36,225,419.66	139	209,137
Owner-occupied	255	173.66	53,046,118	36,177,452.40	138	208,319

	Average natural gas savings (m³/year)	Average natural gas cost savings (€/year)	Total natural gas savings (m³/year)	Total natural gas cost savings (€/year)	No. of households included from WoON 2018 energy module	Represented no. of Dutch households
Private rental	86	58.65	70,333	47,967.26	1	818
Total	**542**	**369,73**	**3,821,238,817**	**2,606,084,872.90**	**4,273**	**7,048,702**