A comparison of strategies for mitigation of lifecycle greenhouse gases from residential buildings in the United States

Peter Berrill
Yale University Graduate School of Arts and Sciences, peter.berrill@yale.edu

Follow this and additional works at: https://elischolar.library.yale.edu/gsas_dissertations

Recommended Citation

This Dissertation is brought to you for free and open access by EliScholar – A Digital Platform for Scholarly Publishing at Yale. It has been accepted for inclusion in Yale Graduate School of Arts and Sciences Dissertations by an authorized administrator of EliScholar – A Digital Platform for Scholarly Publishing at Yale. For more information, please contact elischolar@yale.edu.
Abstract

A Comparison of Strategies for Mitigation of Lifecycle Greenhouse Gases from Residential Buildings in The United States

Peter Berrill

2021

Buildings play a key role in determining global demand for energy and materials, and therefore have a major influence on anthropogenic greenhouse gas (GHG) emissions. This dissertation examines recent trends and future trajectories of energy demand and GHG emissions from residential buildings in the United States. Around 10% of residential GHG emissions in the United States come from material production and construction activities, a share that will increase as energy supply decarbonizes. Decarbonization of electricity generation has been the primary source of residential sector emission reductions since 2005. Demand side energy efficiency improvements have helped to reduce emissions, but compared to transformations in energy supply, their contribution has been minor. In recent decades, reductions in residential energy demand and emissions from energy efficiency and decarbonization were offset by population growth and increases in floor area per person.

The types of structures that provide housing services are an important determinant of energy demand and emissions. Both federal and local policies limit supply of multifamily and small-lot single-family structures. An analysis of changes in federal housing policies and their effects on housing construction of different types found that several changes in federal housing policies in the 1970s and 1980s reduced new construction of multifamily housing by 14 million units up to 2015. A separate analysis found that single-family houses consume substantially more energy than multifamily, and that older single family houses consume much more energy for space heating and cooling, while newer single-family houses consume more energy for non-thermal end-uses such as
lighting and appliances. Combining estimates of policy effects on housing construction by type, and the effects of house type on residential energy use, overall influences of policy changes on residential energy and GHG emissions in 2015 were estimated. Without the federal policy changes, total urban residential energy demand in 2015 would have been 4.6-8.3% lower, or 27-47% per affected household. Removing policy barriers and disincentives to supply of multifamily housing has large potential for reducing future energy and emissions.

Informed by these findings, a highly spatially disaggregated housing stock model was developed and applied to all counties in the United States to analyze scenarios with varying rates of stock turnover, rates of home energy renovation, shares of multifamily housing, and floor area distributions of new housing. An important novelty in this model is the identification of a natural vacancy rate specific to house type and region, and incorporation of a local flexible vacancy rate in housing stock projections. Representation of flexible vacancy rates is particularly important for projecting housing stock growth in regions with low or negative population growth. The housing stock scenarios compare GHG reductions from increased renovation vs increased rates of housing stock turnover, and find that increasing the turnover rate would increase overall residential sector emissions. Energy consumption per floor area is much lower in new buildings due to higher energy efficiency codes and standards, but new single-family houses are generally much larger, which limits the energy reductions from stock turnover. This outcome is very sensitive to the floor area characteristics of housing built in future decades, which in most scenarios are assumed to be unchanged from housing built in the 2010s. Removing houses larger that 3,000 ft² (279 m²) from new housing supply results in a 25% reduction in the average size of new single-family houses, and produces a 4% reduction in cumulative 2020-2060 emissions. Increasing the share of multifamily housing in new construction, or increasing the rate and depth of energy renovations to existing housing, would produce emission reductions of similar magnitude. Different decarbonization strategies will be optimal in different regions. Regions with older housing are less likely to
experience strong future growth, and will rely to a greater extent to renovations of existing housing. Regions with high projected stock growth have a much greater potential to reduce future sectoral emissions by building smaller and more multifamily housing. The single factor with the biggest influence on future residential emissions is the rate at which electricity decarbonizes. A more ambitious combination of efficiency and sufficiency measures in housing supply and renovation, combined with greater decarbonization of electricity supply and material production, is required to achieve sectoral targets consistent with the Paris Agreement or limiting climate change to 1.5-2°C.
A Comparison of Strategies for Mitigation of Lifecycle Greenhouse Gases from Residential Buildings in The United States

A Dissertation
Presented to the Faculty of the Graduate School of Yale University in Candidacy for the Degree of Doctor of Philosophy

by
Peter Berrill
Dissertation Director: Prof. Kenneth T. Gillingham
June 2021
## Contents

Acknowledgements ........................................................................................................... xiii

1  Introduction and Overview .......................................................................................... 1

2  Capital in the American Carbon, Energy, and Material Footprint ................................. 5

   2.1  Introduction ........................................................................................................... 6

   2.2  Method ............................................................................................................... 9

   2.3  Results ............................................................................................................. 13

   2.4  Discussion ....................................................................................................... 21

   2.5  Conclusion ..................................................................................................... 27

3  Drivers of change in U.S. residential energy consumption and greenhouse gas emissions, 1990-2015 .................................................................................................................. 28

   3.1  Introduction ....................................................................................................... 29

   3.2  Drivers of residential energy and GHG emissions ................................................. 31

   3.3  Data and Methods .......................................................................................... 33

   3.4  Results .......................................................................................................... 40

   3.5  Discussion ..................................................................................................... 44

   3.6  Implications for future residential energy use and emissions .......................... 46

4  Linking housing policy, housing typology and residential energy demand in the United States ................................................................................................................. 49

   4.1  Introduction ....................................................................................................... 50

   4.2  Methods and Data .......................................................................................... 54
A  Appendix to Chapter 2 ................................................................................................................................. 150
   A.1  Extensions to original USEEIO model impact assessment ................................................................. 151
   A.2  Preparation of capital flow matrix ..................................................................................................... 155
   A.3  Hypothetical Extraction of capital assets ............................................................................................ 159
   A.4  Influence of capital depreciation on capital footprints .................................................................... 161
   A.5  Additional results ................................................................................................................................. 162
   A.6  Description of scripts and data files .................................................................................................. 174
B  Appendix to Chapter 3 ................................................................................................................................. 175
   B.1  Description of End-Use decompositions for energy and GHG emissions ....................................... 175
   B.2  Note on update to RECS end-uses in 2015 ....................................................................................... 179
   B.3  Note on activity definition and effect of household size .................................................................. 180
   B.4  Supplementary Tables ....................................................................................................................... 183
   B.6  Supplementary Figures ....................................................................................................................... 184
   B.7  Change in drivers over study period ................................................................................................. 189
C  Appendix to Chapter 4 ................................................................................................................................. 201
   C.1  Supporting notes .................................................................................................................................. 201
   C.2  Supporting Figures ............................................................................................................................. 213
   C.3  Supporting Tables .................................................................................................................................. 224
D  Appendix to Chapter 5 ................................................................................................................................. 229
   D.1  Development of stock model from AHS surveys ............................................................................. 229
E  Appendix to Chapter 6 .................................................................................................................................. 242
E.1 Energy retrofits to pre-2020 building stock .......................................................... 242
E.2 Housing characteristics of new construction post-2020 ........................................ 256
E.3 Additional Figures ..................................................................................................... 259

Table of Figures
Figure 2.1 Carbon, energy and material footprints of investment in, and consumption of capital by aggregate sectors in 2012 ........................................................................................................ 15
Figure 2.2 Highest carbon, material, and energy footprints of detailed commodities in 2007, 2012. .................................................................................................................................................. 18
Figure 2.3 Contribution of capital assets to the CF of capital consumption sectors, 2012 .......... 24
Figure 3.1 Indexed growth in U.S. residential final energy, primary energy, and GHG emissions, 1990-2020 ................................................................................................................................................. 31
Figure 3.2 a) Residential final energy, b) primary energy, and c) GHG emissions by end-use, RECS survey years 1990-2015 ........................................................................................................................................ 40
Figure 3.3 Decomposition of changes in a) residential final energy, b) primary energy, and c) GHG emissions, 1990-2015 ........................................................................................................................................ 42
Figure 3.4 Decomposition of changes in residential GHG emissions 1990-2001-2015 from a) space heating, b) space cooling, c) domestic hot water, and d) other end uses ........................................ 44
Figure 4.1 Annual single-family housing starts as a percentage of total starts, 1959-2018 ........ 53
Figure 4.2 1959-2018 historical single- and multifamily starts, and modelled starts without federal policies PHM, TRA 86, and FIRREA ......................................................................................... 61
Figure 4.3 Effects of house type and cohort on urban residential energy end-uses in 2015 ....... 64
Fig. 4.4 Counterfactual urban housing stock and energy consumption, 2015. a) Actual and counterfactual 2015 urban housing by type. b) Actual and counterfactual urban energy consumption in 2015 by type. ........................................................................................................................................ 66
Fig. 4.5 Comparison of residential energy reductions per household in average post-1970 single-family housing ................................................................. 67

Figure 5.1 Schematic of inputs and outputs from housing stock model ......................... 76

Figure 5.2 Inflows (additions) and outflows (losses) from stock for three house types for each housing stock scenario ........................................................................ 84

Figure 5.3 Evolution of single-family and multifamily housing stocks by construction cohort for two scenarios ........................................................................ 85

Figure 5.4 Occupied floor area per capita in each housing stock scenario ...................... 86

Figure 5.5 a) Floor area inflows and outflows from construction and demolition, b) Cumulative GHG emissions from new residential construction for five housing stock scenarios .......... 87

Figure 5.6 Multifamily stock evolution by construction cohort for selected counties ........ 89

Figure 5.7 Concrete inflows and outflows in selected counties for five housing stock scenarios .90

Figure 5.8 Ratio of cumulative construction material outflows to material inflows, 2020-2060, for US counties ........................................................................ 91

Figure 6.1 Schematic overview of model ........................................................................ 104

Figure 6.2 Total annual emissions from residential energy use and construction for combinations of housing stock and renovation scenarios, 2020-2060, for a) Mid-case and b) Low RE Cost electricity decarbonization scenarios ................................................................. 106

Figure 6.3 Differences in 2020-2060 cumulative GHG emissions from residential construction and energy use in housing built pre-2020 post-2020 ................................................................. 108

Figure 6.4 Summary comparison of cumulative 2020-2060 residential emissions for housing stock, renovation, and electricity supply scenarios ........................................................................ 109

Figure 6.5 Comparison of projection stock growth and percent of housing stock built before 1960 in all states. ........................................................................ 110

Figure A.1: Overall approach for construction of the $UK$ matrix in three steps .............. 158

Figure A.2 Contribution of capital assets to the CF of capital consumption sectors, 2007 ....... 160
Figure A.3 Growth of US housing stock and depreciation

Figure A.4 Carbon, energy and material footprints of investment and consumption of capital by aggregate sectors, 2007

Figure A.5 Contribution of production sectors to footprints of consumption in 2012

Figure A.6 Contribution of production sectors to footprints of capital consumption in 2012

Figure A.7 2012 Carbon, Energy, and Material Footprints with capital impacts based on 2007/2012 satellite accounts

Figure A.8 Carbon, energy, and material footprints of consumption in 2007 and 2012, by contributions from physical flows

Figure B.1 (a-b) Alternative definitions of activity in residential IDA models, and implications for effect of household size

Figure B.2 Weather-adjusted a) Residential final energy, b) primary energy, and c) GHG emissions by end-use, RECS survey years 1990-2015

Figure B.3 Hierarchical structure of IDA model, example for space heating

Figure B.4 (a-d) Decomposition of changes in final energy for each end-use, 1990-2015

Figure B.5 (a-d) Decomposition of changes in primary energy for each end-use, 1990-2015

Figure B.6 (a-c) Disaggregation of final energy, primary energy, and GHG emissions for Other energy end-uses, 2015

Figure B.7 Regional changes in household population distribution, 1990-2015

Figure B.8 House type changes in household population distribution, 1990-2015

Figure B.9 Regional changes in occupied homes per person, 1990-2015

Figure B.10 Changes in U.S. population distribution by housing age cohort, 1990-2015

Figure B.11 Changes in main fuel used for space heating at national level, 1990-2015

Figure B.12 Changes in main fuel used for domestic water heating at national level, 1990-2015
Figure C.4 Comparison of residential GHG reduction strategies in each scenario for single-family homes a) in absolute terms and b) in percentage terms ................................................................. 216
Figure C.5 Average total floor area in new single-family (SF) and multifamily (MF) homes .... 217
Figure C.6 (a-c) Effects of house type and cohort on urban residential energy end-uses in 2015 for three income groups ........................................................................................................... 219
Figure C.7 (a) Absolute and (b) relative distribution of urban households into multifamily (MF) and single-family (SF) housing types by three income groups and three household size groups. .................................................................................................................................................................................. 220
Figure C.8 Age distribution of (a) space and (b) water heating equipment in urban multifamily (MF) and single-family (SF) homes in 2015 ................................................................. 221
Figure C.9 Percentage of owner-occupied homes with at least one home improvement project completed for energy efficiency reasons within past two years .............................................. 221
Figure C.10 (a,b) Differences in main space and water heating fuel by urban house type, RECS 2015 ................................................................................................................................................................................................. 222
Figure C.11 a) Regional changes in percentage of homes with space cooling equipment, 1990-2015, b) Differences in space cooling equipment ownership by house type ................................................. 223
Figure C.12 Average total floor area in single-family (SF) and multifamily (MF) homes in 2015 by three income groups and average among all income groups .......................................................... 224
Figure D.1 US total population projection for three Shared Socioeconomic Pathways and USCB 2017 projections ................................................................................................................................. 229
Figure D.2 Relative reduction in household size 2020-2060 ...................................................... 230
Figure D.3 Population projections by house type for the counties of Harrix TX, Providence, RI, San Juan, NM, and Marquette, MI ................................................................................................................. 231
Figure D.4 Stock addition rates vs occupied stock growth rates for single-family houses in the US and three Census regions ................................................................................................................................. 234
Figure D.5 Growth Factor vs Change in Vacancy Factor, Single-Family ........................................ 235
Figure E.11 Residential Code Adoption by State, as of September 2020 ........................................ 259
Figure E.12 Annual national average CO₂ intensity of electricity for two grid scenarios .......... 260
Figure E.13 Annual GHG emission from residential construction and energy use, every 5 years 2020-2060, with a) Mid-case and b) Low RE Cost electricity decarbonization, for the Baseline stock evolution with Advanced Renovation scenario ........................................................................ 261
Figure E.14 Summary comparison of cumulative 2020-2060 residential emissions for housing stock, renovation, and electricity supply scenarios. Results shown as comparative index .... 261
Figure E.15 Comparison of multifamily share of occupied housing units and residential energy per person in counties in Indiana (a-b) and Florida (c-d) .................................................................................. 262

Table of Tables
Table 2.1 Variable Equations and Descriptions .............................................................................. 12
Table 2.2 Carbon Footprint of Consumption, Capital Investment and Capital Consumption, 2012 (Mt CO₂-eq) for aggregate sectors. ........................................................................................................ 16
Table 2.3 Sectors with highest absolute capital CF (Mt CO₂-eq), and capital percentage contribution to total CF ................................................................................................................. 19
Table 2.4 GHG multipliers for 2007 and 2012 for the ten most intensive sectors in 2012, and seven further sectors relevant to production-based GHG emissions, indicating contributions from capital and direct emissions, in producers prices .......................................................................................... 20
Table 2.5 Sectors with highest proportional contribution of capital to CF, carbon multipliers, and total CF, for 2012 ......................................................................................................................... 21
Table 3.1 Features of selected IDA models of residential energy and/or GHG emissions, including study location, outcome metric being decomposed, choice of activity variable, and the main drivers identified ................................................................................................................................. 33
Table 3.2 Indices and subscripts used in the IDA decomposition equations ........................................ 38
Table 4.1 Coefficient estimates from linear regression models of single-family share (%) of total housing starts ................................................................................................................................................................. 60
Table 4.2 Coefficient estimates from linear regression models of energy end-uses in urban homes in 2015 (MJ) .................................................................................................................................................................................................... 62
Table 5.1 Model variables and superscripts .................................................................................................................................................................................................... 76
Table 5.2 Five housing stock scenarios defined by stock loss rates and MF population share. .... 82
Table 6.1 Five housing stock scenarios defined by stock loss rates and MF population share ... 101
Table A.1 Carbon multipliers of capital assets consumed, 2007 and 2012 ................................. 160
Table A.2 Sectors with highest absolute 2012 capital EF (PJ), and capital percentage contribution to total EF ........................................................................................................................................................ 167
Table A.3 Sectors with highest absolute 2012 capital MF (MT), and capital percentage contribution to total MF ...................................................................................................................................................... 168
Table A.4 Sectors with highest proportional contribution of capital to EF, energy multipliers, and total EF, for 2012 ........................................................................................................................................................ 169
Table A.5 Sectors with highest proportional contribution of capital to MF, material multipliers, and total MF, for 2012 ...................................................................................................................................................... 170
Table B.1 Average household appliance ownership and size/usage characteristics in urban single-family detached homes by cohort, 2015 ......................................................................................................................... 183
Table B.2 Average final energy demand (MJ) within ‘other’ end-uses in urban single-family detached homes by cohort, 2015 ......................................................................................................................................................... 183
Table C.1 Linear model of likelihood for home-owner single-family households to invest in energy efficiency, 2015, 2017 ........................................................................................................................................................................... 210
Table C.2 All coefficient estimates from regression models of energy end-uses in urban homes in 2015 (MJ) ........................................................................................................................................................................... 225
Table C.3 Average household appliance ownership and size/usage characteristics in urban single-family detached homes by cohort, 2015 .......................................................................................................................................... 226
Table C.4 Average final energy demand (MJ) within ‘other’ end-uses in urban single-family detached homes by cohort, 2015

Table C.5 Summary statistics of residential energy end-uses in urban homes, 2015 (GJ/year)

Table C.6 Average energy demand in urban houses in 2015, by house type and age cohort (GJ/year)

Table C.7 Average GHG intensity of energy end-uses in urban houses in 2015 by house type (kg CO$_2$-eq/MJ)

Table C.8 Coefficient estimates from linear regression models of energy end-uses in urban homes in 2015 (MJ), with income modelled as a fixed effect interacting with house type and cohort, rather than a continuous covariate

Table C.9 Difference in total, heated, and cooled floor area in urban homes in 2015, distinguished by household income group and house type

Table D.1 Housing stock loss rates for single-family (SF), multifamily (MF), and manufactured homes (MH) by Census region, age range, and vacancy status

Table D.2 Percentage of additions to stock that comes from sources other than new construction, by types and region

Table D.3 Percentage of losses that comes from demolition, by types and region

Table D.4 Linear Models of Stock Addition Rate (AR) for three house types

Table D.5 Linear Models of Stock Growth Factor (GF) for three house types

Table E.1 Annual renovation rates (probabilities) by Census Region (rows) for house type and equipment combinations

Table E.2 Probability of new heating equipment using heating fuels (rows), by previous heating fuel (columns)

Table E.3 Assumption of representative climate zone and projection of representative IECC code adoption by Custom Regions (Location Region) and selected state groups

Table E.4 Assumption of representative IECC code adoption by Climate Zone
Acknowledgements

There are a great many individuals who supported me and my doctoral research process directly and indirectly, and to whom I owe a great debt for helping to make this dissertation possible. I first mention my wonderful committee members. Edgar Hertwich has been the principle source of guidance throughout my doctoral studies. I first worked with Edgar in the final semester of my MSc studies, when he encouraged me to consider continuing my research in a doctoral degree. I thank Edgar for his insights, mentorship, and encouragement, which have had a profound influence on my development. I thank Karen Seto for her unique perspectives, challenging questions, and excellent reading recommendations. I thank Peter Yost, who has been a fountain of knowledge on all things related to residential energy efficiency, and historical developments in the sector. I thank Kenneth Gillingham, who assumed the responsibility of dissertation director midway through my studies, and who has been tremendously supportive, generous with his time and knowledge, and always to the point with candid and valuable feedback.

At the Center for Industrial Ecology, I feel extremely lucky to have crossed paths with so many great minds and personalities. A great strength of the Center is the ease at which PhD students can benefit from the knowledge and experience of those who are a few steps ahead, and in this regard I thank in particular Ranran Wang, Tomer Fishman, and Niko Heeren, for their advice and inputs. To all my fellow students and colleagues, particularly Reed Miller and Paul Wolfram with whom I shared the entire journey, I thank you for the many good times during and after work. I gained valuable teaching experiences during my doctoral studies, and I thank Edgar Hertwich, Peter Yost, Marian Chertow, and Narasimha Rao for their examples in teaching, from which I learned a great deal. For help with all manner of enquiries and requests, I thank Elisabeth Barsa, Timothy De Cerbo, Judy Crocker, and Veronica Taylor. For a lot of fun and respite from studies, I thank my friends at Yale Grad Rugby, and my accomplices in musical endeavors in Yale and New Haven.
I gratefully acknowledge the funding support which enabled me to complete my doctorate. My study and research was funded by a 5-year doctoral fellowship from the Yale School of the Environment. My work also received financial support from the Charles Kao fellowship, Yale Institute for Biospheric Studies, and the REMADE institute.

I greatly enjoyed research exchanges over two summers at Waseda University in Tokyo, and I convey deep gratitude to Yasushi Kondo and Shinichiro Nakamura for welcoming me to Waseda, providing me with methodological support, and entertaining me with enjoyable lunch conversations. I spent my final summer as a doctoral student as a research intern at the National Renewable Energy Laboratory. I thank Janet Reyna, Eric Wilson, and Tony Fontanini for hosting me at NREL, and greatly supporting the work in my final chapter.

Finally, I would like to recognize the contributions from my family. My mother Mairéad was the first person to show me how a PhD is earned, and her never-ending drive is an enduring inspiration. My father Peter exemplifies the lifelong learner, and I cannot think of a better example for anyone aspiring to a career in research or academia. I thank Naomi and Alessandro, Matthew, and Johnny for their ears and support, and a special thanks to my nephews Pietro and Teo who encouraged me at various steps along the way with works of art and musical performances. Finally I thank my wife Ibana, who is always there to offer reassurances and listen patiently to the most minute of details, and whose company made life in lockdown so much more enjoyable!
1 Introduction and Overview

Increases in greenhouse gas emissions, largely from human activities, have caused atmospheric concentrations of CO₂ to rise to levels past seen over 3 millions years ago, when average temperatures were over 3°C higher than today (de la Vega et al., 2020). Due to the rate at which climate systems equilibrate, we are not yet experiencing climate conditions so different to what humans have grown accustomed to in the Holocene. But it is clear that in order to remain in a climate regime that is comparable to what he have today, emissions of greenhouse gases must reduce rapidly and, as soon as possible, go to zero. In the research presented in this doctoral dissertation, I examine recent historic trends, drivers, and potential trajectories of greenhouse gas emissions from the residential sector in the United States. While the dissertation focuses only on the United States, findings from this research may be instructive for other regions that have high consumption of residential floor area per person and relatively low population growth projections.

In this dissertation, I address novel questions, and produce new findings that help to illuminate trends and policies affecting the level of energy consumption and greenhouse gas emissions in the United States. In Chapter 2, with co-authors T. Reed Miller, Yasushi Kondo, and Edgar Hertwich, I demonstrate the contribution of capital assets to environmental footprints of consumption for three environmental categories – greenhouse gas emissions, primary energy consumption, and primary material extraction (Berrill et al., 2020). The basic assumption is that the consumption of a capital asset by an industry (calculated by it’s annual depreciation) plays a role in the supply chain of that industry, just like other inputs to production. Inputs of capital assets to supply chains are commonly omitted from environmentally-extended input output-based environmental footprint calculations. This omission is inconsistent with life-cycle perspective calculations of environmental footprints of consumption, and physical life-cycle inventory methods which usually incorporate some basic description of long-lived industrial plant and equipment. This work built on estimates of capital
consumption for each (405) detailed industry group defined in the BEA’s input-output tables within our lab group (T. R. Miller et al., 2019), and extended the USEEIO model developed by the EPA (Y. Yang et al., 2017). Our paper shows that capital inputs play an important role in carbon, energy, and material footprints of consumption in the U.S., and that housing is the sector most affected by inclusion of capital inputs to consumption.

In Chapter 3, with co-authors Kenneth Gillingham and Edgar Hertwich, I calculate the relative contributions of different drivers of changes in residential energy demand and GHG emissions over the period 1990-2015 (Berrill et al., 2021b). For this paper we use index decomposition analysis to attribute changes in energy and emissions to changes in total residential population, distribution of population among Census Divisions, house types, construction age cohort, and main heating fuel, household size, conditioned floor area per house, energy intensity (per person, floor area, or household depending on energy end-use category), and weather conditions, using six Residential Energy Consumption Surveys for the years 1990, 1993, 2001, 2005, 2009, and 2015. We find that after population growth, reductions in household size, and increases in conditioned floor area per house (which combine to define increases in floor area per person) are the most prominent drivers of increases in energy and emissions. Drivers of reductions in emissions include fuel switching, energy intensity reductions, and cohort shifting (i.e. housing stock turnover). However, the main factor reducing primary energy demand is increases in efficiency of electricity generation, and the main factor driving reductions in residential GHG emissions over this period, by far, is decarbonization of electricity supply. In this paper we call for a bigger contribution to residential GHG reductions from demand size energy efficiency improvements.

In Chapter 4 with co-authors Kenneth Gillingham and Edgar Hertwich, I develop a model estimating the effects of federal housing policy changes in the 1970s and 1980s on new housing construction by type (single-family and multifamily) (Berrill et al., 2021a). We show that three policies, the Public Housing Moratorium (PHM) in 1973, the Tax Reform Act of 1986 (TRA 86),
and the Financial Institutions Reform Recovery and Enforcement Act (FIRREA) in 1989, reduced multifamily housing supply in the subsequent decades. Over the years 1973-2015, in a counterfactual without these policy changes, we estimate that 14 million homes would have been produced as multifamily rather than single-family. Coupling this counterfactual housing stock with a model of the influence of house type and cohort on energy end-use consumption (controlling for other effects), we estimate the effects of the policies on total urban residential energy demand and GHG emissions. We find that urban energy consumption and emissions could have been 5-8% lower in 2015 had the policy changes not been enacted. These findings motivates a call to equalize the playing field for entry of single- and multifamily housing to housing markets, which we expect would raise the multifamily share of new housing and help to reduce future energy and emissions.

In Chapter 5, with co-author Edgar Hertwich, I develop a housing stock model to project housing stock evolution by type and cohort from 2020 to 2060 in all 3,142 counties in the U.S. Besides the high spatial resolution, an important novelty of this model is the incorporation of a dynamic vacancy rate. Despite being a normal and necessary part of regular housing markets, changes in vacancy rates are excluded from housing stock models used to project future levels, inflows, and outflows from housing stocks. I use descriptions of past housing stock turnover from the longitudinal American Housing Survey, and a detailed description of the current housing stock from the American Community Survey to develop the model, which is then driven by an estimate of county-level population growth (Hauer, 2019) scaled to US Census Bureau population projections to 2060 (US Census Bureau, 2017a). The model is used to project locations of housing stock growth and decline, flows of floorspace and construction materials into and out of the housing stock, and GHG emissions associated with new construction for five stock scenarios. The scenarios demonstrate that an increase in multifamily housing, or restricting the size of new housing, would reduce average floor space per person, and reduce the material requirements and construction related emissions from housing stock growth. An increase in the stock turnover rate meanwhile
increases the residential floorspace per person, material requirements and emissions. We show that there exists substantial potential for local (within-county) demolition material re-use in new construction, to the extent that the materials are still fit for use.

In Chapter 6, with co-authors Edgar Hertwich and Janet Reyna, Anthony Fontanini and Eric Wilson from the National Renewable Energy Laboratory (NREL), I combine the housing stock model outputs and scenarios from Chapter 5 with scenarios of residential renovation and electricity grid decarbonization to estimate future trajectories of residential sector emissions from energy and construction sources. Both sufficiency (reduced floor area per person) and efficiency (reduced energy per floor area) strategies are considered. One question that this paper addresses is whether greater GHG reduction potential exists from renovating existing housing at a higher rate and to more stringent levels, or from increasing the rate at which older (less efficient) housing is replaced by newer housing. Relatively minor energy and energy related emission reductions occur from housing stock turnover, because greater efficiency in new housing is counterbalanced by increased floor area in new housing. When including consideration of the additional emissions from materials and construction activities, higher turnover rates are found to produce a net increase in emissions. On the other hand, reducing the size of new construction, increasing the rate and depth of renovations, increasing the share of population in multifamily housing, and increasing the rate at which electricity systems decarbonize are all found to have considerable potential for reducing residential sector greenhouse gas emissions. We recommend that policy decisions should focus on prioritizing these areas for reduction of GHG emissions from housing in the US. Much more ambitious deployment of these strategies will be required in order to achieve targets of the 2015 Paris Agreement, or limiting climate change to below 2°C.
2 Capital in the American Carbon, Energy, and Material Footprint

Please cite as:


Abstract

Stocks of fixed capital play a vital role in fulfilling basic human needs and facilitating industrial production. Their build-up requires great quantities of energy and materials, and generates GHG emissions and other pollution. Capital stocks influence economic production and environmental pollution through their construction and over subsequent decades through their use. We perform an environmental footprint analysis of total consumption, capital investment and capital consumption in the US for 2007 and 2012. In 2012, capital consumption accounted for 13%, 19%, and 40% of total carbon, energy, and material footprints respectively. Housing, federal defense, state and local government education and other services (including household consumption of roads), personal transport fuels and hospitals are the consumption sectors with largest capital footprints. These sectors provide fundamental needs of shelter, transport, education and health, underlying the importance of capital services. Endogenizing capital causes the biggest proportional increase to footprints of sectors with low environmental multipliers. This work builds upon existing input-output models of production and consumption in the US, and provides a capital-inclusive database of carbon, energy and material footprints and multipliers for 2007 and 2012.
2.1 Introduction

Fixed capital stocks play a vital role in all economies, providing the foundation for all kinds of consumption and production. They are a major contributor to environmental impacts both directly, through their production, and indirectly, through their use. Capital stocks facilitate almost every aspect of modern lives, fulfilling basic needs such as mobility and shelter, and providing structures, vehicles, machinery and technologies to industrial production and commercial activity. Large capital buildups require extensive industrial activity, involving material, energy, land and water requirements, generating greenhouse gas (GHG) emissions, air pollution, and many other environmental impacts (Z.-M. Chen et al., 2018; Müller et al., 2013; C.-J. Södersten et al., 2017). For decades after their deployment, capital stocks strongly influence how societies live, move, work, produce and consume, making the total impact of capital investments long lasting and far reaching (Pauliuk & Müller, 2014; Seto et al., 2016). Most visions of a more sustainable society require incrementally or radically different means of production (Robèrt et al., 2002) as well as different levels and types of consumption (Hertwich, 2005). To achieve the former, a lot of new capital will need to be deployed, for example to reduce the environmental intensity of buildings, transport networks, energy supply, and industrial production systems, etc. (Pauliuk & Müller, 2014; Wiedenhofer et al., 2015).

In this work we quantify contributions of capital stocks to life cycle environmental impacts of consumption (a.k.a. footprints) in the United States, using the framework of environmentally extended input-output (EEIO) analysis, focusing on carbon, energy, and material footprints. In this context, ‘capital’ refers to assets produced in prior years which deliver value as an input to production in the given accounting year. We advance the USEEIO model (Ingwersen et al., 2017; Srocka & Ingwersen, 2017; Y. Yang et al., 2017), which was developed to support the US Environmental Protection Agency’s sustainable material management goals. Several important novelties are demonstrated in the current work. The newly released benchmark Make and Use
tables for 2007 and 2012 are used as the basis of the IO model; capital inputs to production are endogenized using a high-resolution capital flow matrix; and environmental satellite accounts are updated to temporally match with the benchmark tables, increase the coverage of material extractions, and include direct emissions from household activities.

There are two major ways in which capital affects the environment, covering short and longer timescales. The first is in the formation of capital, through the direct resource use and emissions associated with production of an asset. Formation impacts can be further viewed from two temporal perspectives. First, as is standard in the system of national economic and environmental accounting (UN, 2014) and in most IO models, impacts are accounted for in the year in which they occur and ascribed to capital formation, i.e. the ‘investment’ component of final demand. Second, as is more standard in life cycle assessment (Frischknecht et al., 2007), environmental impacts of capital assets are allocated to the consuming industries, i.e. endogenized as inputs to production, thus transforming impacts of capital formation impacts to impacts of capital consumption. From this perspective, capital assets contribute to footprints of final consumption in a later year, of products which required those assets in their supply chain. The second major way that capital affects the environment is through how assets perform in facilitating industrial production or household consumption. The performance characteristics of a capital asset will determine the type and quantity of other intermediate inputs required by the capital consuming sector – so that capital acts as a ‘consumption coupler’ (Pauliuk & Müller, 2014). To produce electricity for instance, the input requirements and environmental implications will be very different if the capital asset employed is a gas turbine or a wind turbine. In this paper, we compare impacts of capital formation and consumption, we identify the sectors most affected by capital endogenization, and we discuss important sources of capital footprints.

With some notable exceptions (Z.-M. Chen et al., 2018; Lenzen & Treloar, 2004; Minx et al., 2011; C. J. H. Södersten et al., 2018; Suh, 2006; Weber & Matthews, 2008b), contributions of capital
inputs to production are often neglected in EEIO, leading to a systematic underestimation of footprints of consumption. This is a well-recognized issue within EEIO. Correcting for requires capital to be endogenized as an input to production. Lenzen and Treloar (2004) compared two approaches (‘augmentation’ and ‘capital flow matrix’) to endogenizing capital inputs for Australia, judging the capital flow matrix approach to be more accurate albeit more data intensive, and finding that capital inputs increased most GHG multipliers by 10-15%. Recent work has investigated the impacts of capital over time in multi-regional input output (MRIO) models. Chen et al. (2018) used the augmentation method to show how global emissions embodied in capital stock increased from 1995-2009, while Södersten et al. (2018), endogenized capital with a capital flow matrix approach for 1995-2015 finding that 30% of global GHG emissions are associated with the investment in capital goods, and that impacts of capital consumption varies considerably by country.

Several highly detailed EEIO models have previously been developed for the US (Suh, 2005; Weber & Matthews, 2008b; Y. Yang et al., 2017). Except for (Y. Yang et al., 2017), these models included capital as an endogenous input to production based on capital flow matrices published by BEA, most recently in 1997. Studies based upon these models have investigated a range of questions including how household carbon footprints vary by income level and demographics (Weber & Matthews, 2008b), the importance of food-miles to carbon footprints of food consumption (Weber & Matthews, 2008a) and role of services in US carbon footprints (Suh, 2006), but no work yet has looked at the role and contribution of capital in the US. The main contribution of the current study therefore is to examine the role of capital as it contributes environmental footprints the US, based on a newly constructed capital flow matrix (T. R. Miller et al., 2019). Our results identify the particular importance of housing domestic energy, private transport, and healthcare, and government consumption to capital related carbon, energy, and material footprints.

The two major questions addressed in this paper are as follows. What is the contribution of capital to the carbon, energy, and material footprints of consumption in the US in 2007 and 2012? Which
consumption activities have the largest absolute and proportional contribution of capital to their footprints? While addressing these questions we also identify the main types of assets and production sectors which contribute to capital footprints, providing a focus for reducing the footprints of capital consumption.

2.2 Method

We perform an environmental impact analysis of total consumption, and of capital investment and consumption in the US for the years 2007 and 2012, and show the magnitude and share of capital’s contribution to footprints of consumption. An EEIO model is developed which is based on USEEIO (Srocka & Ingwersen, 2017; Y. Yang et al., 2017), but distinct in a number of important regards. We use recently released benchmark tables (BEA, n.d.), and a newly created capital flow matrix (T. R. Miller et al., 2019) to endogenize capital inputs to production. We modify environmental satellite accounts to be temporally consistent with the IO tables, include additional timber and fossil fuels in material footprints, and include direct household GHG emissions. All input data files and scripts prepared for this research are available in an archived online repository (Berrill & Miller, 2019).

Table 2.1 summarizes the most important variables and equations used in the impact analysis. The technical coefficient matrices $A$ and $A^K$ (representing, respectively, the intermediate and capital inputs to production per unit output) were prepared using the industry technology construct, BEA Make and Use tables, and a capital flow matrix $U^K$ for 2007 and 2012. Annual tables of investments and depreciation of fixed assets by summary industry groups provided the main data source for creating $U^K$. Further details regarding the derivation of $U^K$ and $A^K$ are given in section 2 of the Appendix A and a full description is found in (T. R. Miller et al., 2019). In the US input-output tables private expenditures on durable goods, including personal vehicles, are accounted under personal consumption expenditures, not investments in capital assets. Therefore, aside from
housing, capital consumption here excludes household-owned durable goods. We add three new sectors to the original 405 detailed sectors\(^1\) to include impacts from GHG-emitting household activities. ‘Personal transport fuels’, ‘residential petroleum fuels’ (i.e. distillate fuel oil, kerosene, and LPG), and ‘residential natural gas’ sectors are created, which cover emissions from private/household combustion of petroleum products and natural gas. This addition allows us to include impacts from private fuel combustion within the model and link these activities to their fuel supply chains. Our approach for adding these sectors is described in more detail in Appendix A section 1. Except for the oil and gas extraction sector, we apply the domestic technology assumption (DTA) – meaning that imports are assumed to have been produced with the same input requirements and environmental coefficients as domestic products.

Environmental satellite accounts, and the resulting absolute/normalized matrices of direct sectoral environmental flows/coefficients, \(F\) and \(S\), are created following the approach of (Ingwersen et al., 2017), adapted to match emissions, extractions, and economic output in the years for which benchmark IO tables are published, 2007 and 2012. Source data for environmental flows are given in Appendix A. We add extractions of fuelwood and industrial roundwood to the material resource use indicator, based on USDA production data (Howard & Jones, 2016). We also include energy content per unit mass characterization factors for fossil fuels coal, oil and natural gas to incorporate the mass of fossil fuels in the material footprint calculations. This brings the material footprints calculated in this model closer in line with materials considered in the economy-wide material flow accounting (EW-MFA) (Fischer-Kowalski et al., 2011) and material footprinting literature (Wiedmann et al., 2015).

Equations (2-3) summarize the approach to calculate environmental multipliers \(M\) and \(M^K\), excluding and including capital inputs respectively, where \(I\) is an identity matrix. The \(^\sim\) accent

\(^1\) ‘Detailed sectors’ are equivalent to the BEA Detailed Industry Group (DIG) description in Miller et al (2019)
indicates transformation of a vector into a diagonal matrix. \( C \) is a characterization matrix for aggregating GHG emissions based on three different approaches used in IPCC Assessment Reports, aggregating renewable, non-renewable, and total primary energy extraction, and aggregating material footprints into material categories used in EW-MFA. Different Carbon Footprints (CF), Energy Footprints (EF), and Material Footprints (MF) are calculated using Equations (4-8). EF reflects primary energy extraction as a result of consumption activities. Primary energy extraction is allocated only to the appropriate extraction sectors for fossil fuels. Direct consumption of non-fossil energy sources (e.g. solar, biomass) is allocated to households or the appropriate industries based on detailed sector-specific consumption data (EIA, 2013, 2019a), and subtracted from total primary production of each source to avoid double counting. Remaining non-fossil energy\(^2\) is allocated to electricity, and with the exception of biomass, primary energy for non-fossil electricity is estimated based on the substitution method (Grubler et al., 2012), where 1 kWh of electricity is divided by the average efficiency of fossil electricity in the relevant year. For the US in 2012, with average efficiency of 35.9% for fossil generation, 1 kWh of renewable/nuclear electricity equates to 2.79 kWh or 10 MJ of primary energy.

\(^2\) Nuclear, geothermal, hydropower, wind, solar, biomass
Table 2.1 Variable Equations and Descriptions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Equation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C$</td>
<td>-</td>
<td>Characterisation matrix, converting emissions to impacts</td>
</tr>
<tr>
<td>$F$</td>
<td>-</td>
<td>Satellite account of sectoral emissions and extractions</td>
</tr>
<tr>
<td>$S$</td>
<td>$S = Fx^{-1}$</td>
<td>(1) Stressor matrix of emissions per unit economic output</td>
</tr>
<tr>
<td>$M_f$</td>
<td>$M_f = C_f S (I - A)^{-1}$</td>
<td>(2) Environmental multiplier for footprint $f$, excluding capital</td>
</tr>
<tr>
<td>$M^K_f$</td>
<td>$M^K_f = C^K_f S (I - (A + A^K))^{-1}$</td>
<td>(3) Environmental multiplier for footprint $f$, including capital</td>
</tr>
<tr>
<td>$d_f$</td>
<td>$d_f = M_f \tilde{y}^c$</td>
<td>(4) Environmental footprint $f$ of consumption</td>
</tr>
<tr>
<td>$d_f$</td>
<td>$d_f = M_f \tilde{y}^i$</td>
<td>(5) Environmental footprint $f$ of investment</td>
</tr>
<tr>
<td>$d_f^{ci}$</td>
<td>$d_f^{ci} = M_f \tilde{y}^{ci}$</td>
<td>(6) Environmental footprint $f$ of consumption and investment</td>
</tr>
<tr>
<td>$d_f^{cK}$</td>
<td>$d_f^{cK} = M^K_f \tilde{y}^c$</td>
<td>(7) Environmental footprint $f$ of consumption, including capital</td>
</tr>
<tr>
<td>$d^K_f$</td>
<td>$d^K_f = M^K_f \tilde{y}^c$</td>
<td>(8) Environmental footprint $f$ of capital consumption</td>
</tr>
<tr>
<td>$y$</td>
<td>$y = Ty^{pur}$</td>
<td>(9) Conversion between final demand for commodities in producers’ prices $y$ and purchasers’ prices $y^{pur}$</td>
</tr>
</tbody>
</table>

Environmental multipliers are converted into total footprints $d_f^c, d_f^i, d_f^{ci}$ and $d_f^{cK}$ by post-multiplying environmental multipliers $M_f$ and $M^K_f$ by final demand vectors $y^c$ or $y^{ci}$ (Equations 4-7). $y^c$ comprises personal and government consumption expenditures, excluding investments, imports and exports, and changes in inventories. $y^{ci}$ includes private and government investments in addition to consumption. The core difference between $d_f^{cK}$ and $d_f^{ci}$ is that $d_f^{cK}$ represents footprints consumption including impacts associated with capital inputs to production but excluding capital formation (i.e. a life cycle accounting perspective), while $d_f^{ci}$ represents impacts from consumption and investment, excluding capital inputs to production but including capital formation (i.e. the national economic and environmental accounting perspective). The impact of capital consumption...
alone $d_f^K$ is $d_f^{iK} - d_f^t$. Impacts $d_{cr}^a$ associated with consumption of capital asset $a$ are calculated using the hypothetical extraction method on the $A^K$ matrix, further described in SI section 3. Our analysis uses producers’ prices, which accounts for impacts from transport and trade sectors separately. To facilitate analyses using purchasers’ price consumption data, we created a transformation matrix $T$ to convert final demand in purchasers’ prices $y_{pur}$ to final demand in producer prices $y$ (Equation 9). $T$ is constructed based on tables of trade and transport margins for personal consumption expenditures in 2007 and 2012 (BEA, 2018c). Sectoral footprints and multipliers in purchasers prices are included in the supplementary Data File.

2.3 Results

Aggregate sector impacts

Figure 2.1 displays carbon, energy and material footprints associated with capital investment ($d_f^i$) and consumption ($d_f^K$) in 2012, first calculated at the detailed level of 408 sectors, then summed to 24 aggregate sectors. A comparable result for 2007 is shown in Figure A.4. The stacked bars distinguish the source of consumption/investment, e.g. federal-defense investment, or personal consumption. Some aggregate sectors with negligible footprints are omitted from Figure 2.1. Table 2.2 compares non-capital related consumption footprints $d_f^t$ with footprints of capital investment $d_f^i$ and consumption $d_f^K$, showing the contribution of capital to total footprints $d_f^{i}$ and $d_f^{K}$. Capital investments account for 15% of CF, 20% of EF, and 44% of MF ($d_f^{si}$) in 2012. Metal, vehicle and machinery manufacturing dominate CF and EF of capital investment. Non-residential construction (roads, buildings and other infrastructure) is a large component of all investment footprints. Residential construction, mining and fossil extraction, and scientific research are other aggregate sectors which stand out in one or more of the footprints of investment. From a consumption perspective capital contributed 13% of total CF, 19% of EF, and 40% of MF ($d_f^{K}$) in 2012. Capital consumption footprints reveal sectors which are dependent on capital inputs to production, e.g.
housing, government services, healthcare, and personal transport fuels. These capital consumption footprints sectors are analyzed further in the detailed results and discussion sections below.
Figure 2.1 Carbon, energy and material footprints of investment in, and consumption of capital by aggregate sectors in 2012
Table 2.2 Carbon Footprint of Consumption, Capital Investment and Capital Consumption, 2012 (Mt CO2-eq) for aggregate sectors.

<table>
<thead>
<tr>
<th>Aggregate Sector</th>
<th>Consumption</th>
<th>Capital Investment</th>
<th>Capital Consumption</th>
<th>Capital Consumption % of d⁻¹K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agri, Forestry, Fishing</td>
<td>80</td>
<td>0</td>
<td>0%</td>
<td>6</td>
</tr>
<tr>
<td>Mining, Fossil Extraction</td>
<td>0</td>
<td>94</td>
<td>100%</td>
<td>0</td>
</tr>
<tr>
<td>Electricity, Water</td>
<td>864</td>
<td>0</td>
<td>0%</td>
<td>24</td>
</tr>
<tr>
<td>Residential Construction</td>
<td>0</td>
<td>110</td>
<td>100%</td>
<td>0</td>
</tr>
<tr>
<td>Non-res. Cons.</td>
<td>0</td>
<td>258</td>
<td>100%</td>
<td>0</td>
</tr>
<tr>
<td>Food, Drink, Textile, Apparel</td>
<td>671</td>
<td>1</td>
<td>0%</td>
<td>43</td>
</tr>
<tr>
<td>Bio, Chem, Mineral Products</td>
<td>124</td>
<td>5</td>
<td>4%</td>
<td>22</td>
</tr>
<tr>
<td>Metal, Vehicles, Machinery</td>
<td>164</td>
<td>266</td>
<td>62%</td>
<td>30</td>
</tr>
<tr>
<td>Wholesale Trade</td>
<td>97</td>
<td>36</td>
<td>27%</td>
<td>17</td>
</tr>
<tr>
<td>Retail Trade</td>
<td>272</td>
<td>10</td>
<td>4%</td>
<td>46</td>
</tr>
<tr>
<td>Transport</td>
<td>269</td>
<td>37</td>
<td>12%</td>
<td>23</td>
</tr>
<tr>
<td>Delivery, Warehousing</td>
<td>5</td>
<td>0</td>
<td>0%</td>
<td>1</td>
</tr>
<tr>
<td>Information Industries</td>
<td>50</td>
<td>15</td>
<td>23%</td>
<td>25</td>
</tr>
<tr>
<td>Finance, Insurance</td>
<td>84</td>
<td>0</td>
<td>0%</td>
<td>32</td>
</tr>
<tr>
<td>Housing, Real Estate</td>
<td>59</td>
<td>52</td>
<td>47%</td>
<td>164</td>
</tr>
<tr>
<td>Science, Prof. Services</td>
<td>16</td>
<td>135</td>
<td>89%</td>
<td>4</td>
</tr>
<tr>
<td>Management</td>
<td>0</td>
<td>0</td>
<td>0%</td>
<td>0</td>
</tr>
<tr>
<td>Admin, Support, Waste</td>
<td>50</td>
<td>0</td>
<td>0%</td>
<td>3</td>
</tr>
<tr>
<td>Education</td>
<td>66</td>
<td>0</td>
<td>0%</td>
<td>12</td>
</tr>
<tr>
<td>Healthcare, Social assist.</td>
<td>384</td>
<td>0</td>
<td>0%</td>
<td>76</td>
</tr>
<tr>
<td>Arts, Entertain., Recreation</td>
<td>62</td>
<td>0</td>
<td>1%</td>
<td>13</td>
</tr>
<tr>
<td>Accomm., Restaurants</td>
<td>249</td>
<td>0</td>
<td>0%</td>
<td>30</td>
</tr>
<tr>
<td>Repair, Personal services</td>
<td>92</td>
<td>0</td>
<td>0%</td>
<td>22</td>
</tr>
<tr>
<td>Government, Misc.</td>
<td>632</td>
<td>0</td>
<td>0%</td>
<td>186</td>
</tr>
<tr>
<td>Residential fuel</td>
<td>343</td>
<td>0</td>
<td>0%</td>
<td>10</td>
</tr>
<tr>
<td>Personal transport fuel</td>
<td>1,202</td>
<td>0</td>
<td>0%</td>
<td>55</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>5,836</strong></td>
<td><strong>1,019</strong></td>
<td><strong>15%</strong></td>
<td><strong>844</strong></td>
</tr>
</tbody>
</table>
Detailed sector impacts

Figure 2.2 shows total footprints $d^f_{ck}$ of detailed commodities for 2007 and 2012, for the fifteen commodities with highest footprints in 2007. Total CF decreased by 10%, EF by 5%, and MF by 18% in 2012 compared to 2007. The biggest single sources of CF and EF reduction between those years are residential electricity and natural gas, due to a decarbonizing electricity grid and a milder than usual 2012 heating season (EIA, 2019a). Lower carbon electricity also contributed to economy-wide CF reductions due to its importance to supply chains. Personal transport fuels and hospitals were two of the few activities whose footprints grew in 2012. Large footprints can be due to high multipliers $M^f_{ck}$ (e.g. residential natural gas, electricity), high consumption $y^c$ (e.g. government, housing, hospitals), or a combination of both (e.g. personal transport fuels).
Table 2.3 shows the twelve detailed sectors with highest CF of capital consumption in 2012 and 2007. Housing has by far the largest capital CF, followed by government, personal transport fuels, and hospitals. For personal transport fuels and electricity, despite capital contributions being sizable in absolute terms, they are a small percentage of total CF from that sector, due to much larger non-
capital emissions. The reduction in housing capital footprints in 2012 is discussed below. Similar results for EF and MF are shown in tables A.2-A.3 in Appendix A.

### Table 2.3 Sectors with highest absolute capital CF (Mt CO\textsubscript{2}eq), and capital percentage contribution to total CF. SL govt = state and local government

<table>
<thead>
<tr>
<th>Sector</th>
<th>Capital CF 2007</th>
<th>(% of total)</th>
<th>Capital CF 2012</th>
<th>(% of total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Owner-occupied housing</td>
<td>176.5</td>
<td>80%</td>
<td>126.7</td>
<td>77%</td>
</tr>
<tr>
<td>Federal govt (defense)</td>
<td>59.2</td>
<td>36%</td>
<td>58.5</td>
<td>37%</td>
</tr>
<tr>
<td>SL govt other services</td>
<td>51.9</td>
<td>13%</td>
<td>56.1</td>
<td>16%</td>
</tr>
<tr>
<td>Personal transport fuels</td>
<td>36.6</td>
<td>3%</td>
<td>54.6</td>
<td>4%</td>
</tr>
<tr>
<td>Hospitals</td>
<td>38.8</td>
<td>20%</td>
<td>40.1</td>
<td>18%</td>
</tr>
<tr>
<td>Tenant-occupied housing</td>
<td>46.1</td>
<td>90%</td>
<td>32.8</td>
<td>86%</td>
</tr>
<tr>
<td>SL govt education</td>
<td>31.7</td>
<td>15%</td>
<td>31.0</td>
<td>17%</td>
</tr>
<tr>
<td>Federal govt (nondefense)</td>
<td>29.0</td>
<td>47%</td>
<td>29.4</td>
<td>48%</td>
</tr>
<tr>
<td>Electricity</td>
<td>22.5</td>
<td>2%</td>
<td>20.2</td>
<td>2%</td>
</tr>
<tr>
<td>Limited-service restaurants</td>
<td>13.3</td>
<td>9%</td>
<td>12.6</td>
<td>9%</td>
</tr>
<tr>
<td>Pharmaceutical preparations</td>
<td>11.1</td>
<td>18%</td>
<td>11.8</td>
<td>24%</td>
</tr>
<tr>
<td>Wired telecomm. carriers</td>
<td>11.5</td>
<td>47%</td>
<td>10.6</td>
<td>36%</td>
</tr>
</tbody>
</table>

**Carbon multipliers**

Capital-inclusive carbon multipliers \(M_{CF}^K\) for 2007 and 2012 (both shown in kg CO\textsubscript{2} eq/2012USD producer prices)\(^3\) are listed in table 2.4, for the ten sectors with highest multipliers in 2012, and seven further sectors which are important to supply chain GHG emissions (figure A.5). The contribution of capital inputs and direct emissions to the total multiplier is shown. Most sectors with high multipliers have large direct emissions (e.g. cement, electricity), but for some sectors most emissions occur along the supply chain (e.g. animal products and cheese, with large supply chain emissions from beef cattle and dairy cattle respectively). Direct emissions account for 72-88% of multipliers for the seven most intensive sectors, while capital contributions are in the range

---

\(^3\) 2007 GHG multipliers are converted to impact per 2012USD using chain-type price indexes for gross output by industry (BEA, 2018a).
of just 1-5% for all sectors in table 4 except for mining and oil and gas extraction and refining. Comparing 2007 and 2012, the most notable change is the reduction of electricity’s GHG multiplier. We list all carbon, energy, and material multipliers for 2007 and 2012 in the supporting Data File with and without capital, in units of impact per USD producer prices (excluding trade and transport margins) and purchaser prices (including trade and transport margins, calculated as $M_{K,pur}^{} = M_{K,T}^{}$).

Table 2.4 GHG multipliers for 2007 and 2012 for the ten most intensive sectors in 2012, and seven further sectors relevant to production-based GHG emissions, indicating contributions from capital and direct emissions, in producers prices

<table>
<thead>
<tr>
<th>Sector</th>
<th>2007</th>
<th>(%) cap.</th>
<th>(%) dir.</th>
<th>2012</th>
<th>(%) cap.</th>
<th>(%) dir.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cement manufacturing</td>
<td>8.81</td>
<td>1%</td>
<td>84%</td>
<td>9.24</td>
<td>1%</td>
<td>88%</td>
</tr>
<tr>
<td>Residential natural gas</td>
<td>6.71</td>
<td>2%</td>
<td>73%</td>
<td>6.15</td>
<td>2%</td>
<td>83%</td>
</tr>
<tr>
<td>Electricity</td>
<td>7.29</td>
<td>2%</td>
<td>89%</td>
<td>5.26</td>
<td>2%</td>
<td>88%</td>
</tr>
<tr>
<td>Personal transport fuels</td>
<td>4.79</td>
<td>4%</td>
<td>74%</td>
<td>4.79</td>
<td>4%</td>
<td>73%</td>
</tr>
<tr>
<td>Dairy cattle and milk</td>
<td>4.46</td>
<td>2%</td>
<td>80%</td>
<td>4.60</td>
<td>2%</td>
<td>78%</td>
</tr>
<tr>
<td>Residential petroleum fuels</td>
<td>4.47</td>
<td>4%</td>
<td>72%</td>
<td>4.58</td>
<td>5%</td>
<td>72%</td>
</tr>
<tr>
<td>Lime and gypsum products</td>
<td>4.36</td>
<td>2%</td>
<td>78%</td>
<td>4.47</td>
<td>2%</td>
<td>82%</td>
</tr>
<tr>
<td>Beef cattle farming</td>
<td>4.41</td>
<td>2%</td>
<td>66%</td>
<td>4.40</td>
<td>2%</td>
<td>59%</td>
</tr>
<tr>
<td>Animal products (non-poultry)</td>
<td>2.65</td>
<td>3%</td>
<td>2%</td>
<td>2.60</td>
<td>3%</td>
<td>1%</td>
</tr>
<tr>
<td>Cheese</td>
<td>2.86</td>
<td>2%</td>
<td>2%</td>
<td>2.57</td>
<td>2%</td>
<td>1%</td>
</tr>
<tr>
<td>Grains</td>
<td>2.79</td>
<td>4%</td>
<td>64%</td>
<td>2.55</td>
<td>3%</td>
<td>66%</td>
</tr>
<tr>
<td>Waste and remediation</td>
<td>2.05</td>
<td>3%</td>
<td>77%</td>
<td>1.90</td>
<td>3%</td>
<td>79%</td>
</tr>
<tr>
<td>Truck transportation</td>
<td>1.59</td>
<td>5%</td>
<td>75%</td>
<td>1.59</td>
<td>5%</td>
<td>74%</td>
</tr>
<tr>
<td>Iron, steel, &amp; ferroalloys</td>
<td>1.78</td>
<td>4%</td>
<td>43%</td>
<td>1.57</td>
<td>5%</td>
<td>40%</td>
</tr>
<tr>
<td>Oil and gas extraction</td>
<td>1.35</td>
<td>17%</td>
<td>66%</td>
<td>1.32</td>
<td>21%</td>
<td>56%</td>
</tr>
<tr>
<td>Petroleum refineries</td>
<td>1.23</td>
<td>14%</td>
<td>20%</td>
<td>1.28</td>
<td>16%</td>
<td>18%</td>
</tr>
<tr>
<td>Other support for mining</td>
<td>0.57</td>
<td>14%</td>
<td>44%</td>
<td>0.72</td>
<td>17%</td>
<td>48%</td>
</tr>
</tbody>
</table>

Table 2.5 lists the twelve sectors with highest proportional input of capital to carbon multipliers and footprints in 2012. Tenant- and owner-occupied housing have the highest capital
contribution, and federal government non-defense also has high capital contribution. None other sectors in table 5 have high absolute capital or total CF. Because capital inputs increase most carbon multipliers by between 0.03-0.12 kgCO2eq/$, all of these sectors with high proportional capital inputs have carbon multipliers which are well below the economy average. Similar tables for energy and material multipliers are shown in App. A tables A.4-A.5.

Table 2.5 Sectors with highest proportional contribution of capital to CF, carbon multipliers, and total CF, for 2012

<table>
<thead>
<tr>
<th>Sector</th>
<th>Capital % of CF</th>
<th>Carbon multiplier (kg CO2eq/$)</th>
<th>Total CF (MT CO2e)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tenant-occupied housing</td>
<td>86%</td>
<td>0.09</td>
<td>38.1</td>
</tr>
<tr>
<td>Owner-occupied housing</td>
<td>77%</td>
<td>0.13</td>
<td>164.6</td>
</tr>
<tr>
<td>Independent artists, writers, and performers</td>
<td>69%</td>
<td>0.06</td>
<td>0.0</td>
</tr>
<tr>
<td>Sound recording industries</td>
<td>68%</td>
<td>0.11</td>
<td>0.6</td>
</tr>
<tr>
<td>Search, detection, navigation instruments</td>
<td>63%</td>
<td>0.18</td>
<td>0.0</td>
</tr>
<tr>
<td>Electromedical, electrotherapeutic apparatus</td>
<td>62%</td>
<td>0.23</td>
<td>0.6</td>
</tr>
<tr>
<td>Watch, clock, measuring devices</td>
<td>58%</td>
<td>0.20</td>
<td>1.1</td>
</tr>
<tr>
<td>Broadcast and wireless comms. equipment</td>
<td>57%</td>
<td>0.19</td>
<td>1.4</td>
</tr>
<tr>
<td>Telephone apparatus</td>
<td>55%</td>
<td>0.17</td>
<td>0.3</td>
</tr>
<tr>
<td>Federal govt (nondefense)</td>
<td>48%</td>
<td>0.18</td>
<td>61.4</td>
</tr>
<tr>
<td>Electronic computers</td>
<td>44%</td>
<td>0.11</td>
<td>2.0</td>
</tr>
<tr>
<td>Radio and television broadcasting</td>
<td>44%</td>
<td>0.17</td>
<td>1.1</td>
</tr>
<tr>
<td><strong>Economy Average</strong></td>
<td><strong>13%</strong></td>
<td><strong>0.49</strong></td>
<td><strong>-</strong></td>
</tr>
</tbody>
</table>

2.4 Discussion

*Analysis of results*

We now analyze the above results with a view to addressing the research questions posed in the introduction. First, what is the direct contribution of capital to carbon, material, and energy footprints? Depending on the year (2007/2012) and capital accounting perspective, capital investment contributes 17/15% of CF, 21/20% of EF, and 52/44% of MF, and capital consumption represents 12/13% of CF, 18/19% of EF, and 43/40% of MF. From either national accounting
(formation) or life cycle (consumption) perspectives, capital constitutes a substantial contribution to total footprints. Our estimates of economy-wide capital contributions to CF are on the lower side of the 13-16% range calculated for the US by Södersten et al. (2018) and comparable to the 10-15% increase range for Australia (Lenzen & Treloar, 2004). Higher footprints from capital investment compared to capital consumption corroborates findings by Chen et al. (2018) and Södersten et al. (2018), and can be explained to large extent by the fact that total capital stock generally continues to grow, so that capital investment usually exceeds depreciation matrix (T. R. Miller et al., 2019).

Second, which consumption activities have the largest absolute contribution of capital to their footprints? At a detailed level, housing, federal government defense, state and local government education and other services (in our model including household use of road networks), personal transport fuels and hospitals are the consumption activities with largest capital, energy, and material footprints (tables 2.3, A.2, A.3). These activities are key to satisfying fundamental human needs such as shelter, transport, health and education, underscoring the importance of capital in modern societies. While housing footprints are lower in 2012 due to lower levels of residential investment between 2007-2012 (discussed below), consumption of housing still has the largest capital related footprints. Personal transport fuels have notably higher energy and carbon capital footprints in 2012 due to the greater energy intensity of oil and gas extraction infrastructure. In figure 2.2 and table 2.3, we can observe some differences between sectoral capital footprints between 2007 and 2012. Most notable are reductions in capital footprints of housing, despite the total stock of housing being 3% higher in 2012 (USCB, 2019), caused by changes in environmental intensity (CS) of production and capital consumption (A) by housing sectors. The sum of capital inputs to housing (column sums of A) was $0.26 for every $1 of production in 2007, but only $0.21 in 2012. This is due to high levels investment in residential construction between 1997-2007 and much lower levels between 2008-2012, and the geometric depreciation approach to calculating capital consumption,
discussed further below. The change in technology also played a role, reducing the environmental intensity of capital consumed by housing in 2012 (table A.1, figure A.7).

To show what assets are involved in the largest capital footprints, figure 2.3 breaks down 2012 capital CF by asset type, for the twelve consumption activities with highest capital CF, all other sectors, and the economy-wide average. Non-residential construction and metal, vehicles and machinery contribute most to total capital CF. Construction assets are key contributors to housing (residential structures), state and local government (roads and nonresidential structures), hospitals (healthcare structures), and electricity (power/communication structures). Metals, vehicles and machinery are key components of the capital CF for sectors such as federal defense (aircraft and ships), hospitals and restaurants. Mining and fossils extraction assets are important for fossil fuel consuming sectors, especially personal transport fuels. Research is a key contributor to the capital CF of federal government and pharmaceuticals. Many of these assets have long service lives, particularly residential and nonresidential construction, and so the long-term effects of capital investments on future footprints (through capital consumption and capital as a consumption coupler) must not be underestimated. The carbon multipliers of the capital assets consumed in 2007 and 2012 are shown in App. A table A.1, and the contribution of assets to capital CF in 2007 is shown in figure A.2. figures A.5-A.6 in the Appendix show production sector contributions to capital and total footprints. Electricity, truck transportation, fossil fuel extraction, and construction materials (iron and steel, cement) are major production sectors contributing to capital CF, while mining and extraction related sectors are the main production sources of capital and total EF and MF.
Figure 2.3 Contribution of capital assets to the CF of capital consumption sectors, 2012

Which consumption activities have the largest proportional contribution of capital to their footprints? Sectors with the lowest capital-exclusive environmental multipliers are the most likely to have a large proportional contribution of capital to capital-inclusive multipliers. In 2012, 90% of carbon, energy and material multipliers increased by between 0.03-0.11 kgCO2eq/$, 0.8-3.8 MJ/$, and 0.06-0.37 kg/$ respectively, after endogenizing capital inputs. Aside from housing and federal defense, sectors with highest proportional capital inputs are related to media and entertainment, specialized machinery and instruments, or communications (tables 2.5, A.4, A.5). All of these sectors have low multipliers with or without capital, and with the exception of housing and federal defense, relatively low overall footprints.

Data quality and assumptions

Here we discuss the implications of data quality and some assumptions which are important to our results. An important limitation of all IO models arises from sector aggregation, which in the US

---

4 90% range calculated by 5th and 95th percentiles of additions to environmental multipliers with capital.
tables is particularly relevant to the oil and gas extraction sector. Due to the composition of domestic oil and gas extraction in the US, the domestic technology assumption would assume oil and gas imports to be mostly natural gas, while most imported oil and gas is oil. We correct for this by including the economic and physical values of oil and gas imports when calculating fuel-specific energy coefficients of oil and gas extraction. The price differential of oil and gas per unit energy or mass also causes anomalies in energy and material footprints, so that footprints of natural gas are underestimated, and footprints of oil/petroleum products are overestimated (see EF and MF of personal transport fuels and residential gas in Fig 2.2). This is discussed further in Appendix A section 1.

A temporal issue regarding environmental impacts of capital consumption is the assumption that capital assets produced with the same technology \((A + A^4)\) and environmental intensity \((CS)\) of production as the given accounting year, for instance capital consumed in 2012 is assumed to have been produced with the 2012 environmental intensity of production. Müller et al. rationalize this approach as the “replacement value” of the capital in question (Müller et al., 2013). Chen et al. (2018) addressed this issue by assuming that capital depreciated in year \(t\) has the emissions intensity of the capital stock in year \(t-1\). A comprehensive resolution would involve a dynamic capital stock approach where capital assets are assigned the production technology and environmental intensity of their year of production (Pauliuk et al., 2014). This would require disaggregating capital consumption tables into years of production, and estimating environmental production intensities over many years, which was outside of the scope of this work. We perform a sensitivity analysis to test the influence of temporal variation in environmental intensities to our results, where we assume that capital consumed in 2012 has the environmental intensity \((CS)\) of 2007. Results of this sensitivity are discussed in Appendix A section 5. If all capital assets were produced with 2007 rather than 2012 environmental intensity, the CF, EF and MF of capital consumed in 2012 would
be 14%, 2%, and 31% higher respectively, leading overall CF, EF, and MF to be 2%, 0.3%, and 12% higher.

Another temporal issue is the use of geometric depreciation in the calculation of the consumption of fixed capital by BEA, which contrasts with the linear depreciation over the lifetime of an asset assumed in LCA. Geometric depreciation allocates higher shares of consumption of capital assets to the earlier years of their lifetime, resulting in the assets’ annual life cycle impact declining over time. In contrast, assets would be depreciated by the same amount each year under straight line depreciation. This issue is further discussed in section 4 of Appendix A.

Significance of capital

The inclusion of capital provides numerous benefits to EEIO analyses. A major benefit, made possible by the creation of a detailed capital flow matrix, is the ability to demonstrate emissions from production of specific capital assets and link them to the relevant consumption sectors, mirroring a life cycle approach. It allows different production and consumption activities to be more fairly compared, due to a more comprehensive consideration of inputs to production. We show absolute capital footprints to be especially large for certain types of consumption, including housing and government expenditures, and that capital has the biggest proportional effect on footprints of sectors with low environmental multipliers, such as housing, media and entertainment, specialized machinery and instruments, and communications. As economies transition to less environmentally intensive but more capital-intensive methods of production and consumption, capital will necessarily become even more important to environmental footprints. Electricity for instance will continue to see capital contributions grow in relevance as low carbon technologies gain larger market shares (Berrill et al., 2016).
2.5 Conclusion

We calculate carbon, energy and material footprints of total consumption and separately capital investment and consumption in the US for 2007 and 2012. Our results compare the system of national accounting (formation) and life cycle accounting (consumption) perspectives on environmental impacts of capital. Our model uses recently released benchmark IO tables, and a newly constructed capital flow matrix, and includes emissions from household fuel combustion and personal transport. Overall, capital consumption contributed 13%, 19%, and 40% to CF, EF, and MF, in 2012. From a formation perspective, capital investment made of 15%, 20% and 44% of CF, EF, and MF. Personal transport fuels, domestic energy use, state and local government education and other services, hospitals, and housing have the largest total footprints, while housing, federal defense, state and local government services (including household consumption of roads), personal transport fuels and hospitals have the largest footprints related to capital consumption. Capital consumption and associated footprints of housing were substantially reduced in 2012 due to sustained low levels of residential investment after 2007. Considering capital contributions to footprints will become increasingly important as the US economy becomes more capital intensive.
3 Drivers of change in U.S. residential energy consumption and greenhouse gas emissions, 1990-2015

Please cite as:


Abstract

Annual greenhouse gas emissions (GHG) from residential energy use in the United States peaked in 2005 at 1.26 Gt CO$_2$-eq/yr, and have since decreased at an average annual rate of 2% per year to 0.96 Gt CO$_2$-eq/yr in 2019. In this article we decompose changes in U.S. residential energy supply and GHG emissions over the period 1990-2015 into relevant drivers for four end-use categories. The chosen drivers encompass changing demographics, housing characteristics, energy end-use intensities, and generation efficiency and GHG intensity of electricity. Reductions in household size, growth in heated floor area per house, and increased access to space cooling are the main drivers of increases in energy and GHG emissions after population growth. Growing shares of newer homes, and reductions in intensity of energy use per capita, household, or floor area have produced moderate primary energy and GHG emission reductions, but improved generation efficiency and decarbonization of electricity supply have brought about far bigger primary energy and GHG emission reductions. Continued decline of residential emissions from electrification of residential energy and decarbonization of electricity supply can be expected, but not fast enough to limit climate change to 1.5°C warming. U.S. residential final energy demand will therefore need to decline in absolute terms to meet such a target. However, without changes in the age distribution, type mix, or average size of housing, improvements in energy efficiency are unlikely to outweigh growth in number of households from population growth and further household size reductions.
3.1 Introduction

Residential buildings make a substantial contribution to global primary energy demand and greenhouse gas (GHG) emissions, and may be one of the easiest energy end-use sectors to decarbonize (Lucon et al., 2014). The primary energy required for residential energy services is determined by the *useful* energy demand (influenced by service level, occupant behavior and characteristics of the ‘passive device’, e.g. the building shell), *final* to useful energy efficiencies of conversion devices (such as space heaters), and *primary* to final energy efficiencies of final energy supply (e.g. fossil energy extraction and refining, electricity generation) (Cullen & Allwood, 2010). GHG emissions associated with residential energy use are determined by the primary energy demand, and the GHG intensity of each primary energy source.

There are various points along the energy supply chain where action may be taken to reduce primary energy requirements. Cullen and Allwood (2010) estimate that due to compounding of conversion efficiencies along energy supply chains, efficiency gains nearer the point of use have more potential for system-wide energy savings than efficiency gains further up the supply chain. To reduce GHG emissions from buildings, ‘electrify everything’ summarizes a strategy of electrification of energy services and simultaneous decarbonizing of electricity generation (Mai et al., 2018; M. Miller, 2018). Although the logic of this approach to reduce GHG emissions is clear, studies on electrification are focused on scenario analyses in various regions including the US (Frisch et al., 2018; Langevin et al., 2019) China (Peng et al., 2018), Chile (Verástegui et al., 2020), and Europe (Heinen et al., 2018; Manteuffel et al., 2016). A common theme from such studies is the dependency of emission reductions on the rate of grid decarbonization, and on efficiency factors of alternative heating systems. Meanwhile, empirical studies of whether electrification has already reduced residential or building sector emissions are lacking.
In Figure 3.1 we show changes in U.S. residential final and primary energy, and GHG emissions, from 1990-2020. The relative decoupling of GHG emissions from primary energy since 2007 demonstrates decarbonization of electricity supply. Since peaking at 1.26 Gt CO$_2$-eq/yr in 2005, residential GHG emissions have decreased at an average annual rate of around -2% per year to 0.96 Gt CO$_2$-eq/yr in 2019, with further reductions expected in 2020 (EIA, 2020b). This downward trend, although encouraging, remains well below the -7% annual reductions needed to limit climate change to 1.5°C warming (Höhne et al 2020).

This paper identifies the most prominent drivers of U.S. residential energy and GHG emissions over the period 1990-2015. Our analyses test the hypotheses that reductions in GHG intensity and residential fuel switching drove energy and emissions down, while smaller households and larger houses drove energy and emissions up. We use index decomposition analysis (IDA) to decompose changes in U.S. residential final energy, primary energy, and GHG emissions into drivers covering demographics, housing characteristics, and the energy and GHG intensity of energy demand and supply. It is the first analysis to decompose U.S residential energy and emissions at the end-use level, and the first to consider changes in household size, housing age cohort distribution and fuel switching as drivers. In section 3.2 we present a brief review of literature examining drivers of residential energy and emissions. In section 3.3 we describe the materials and methods used for our analysis. In section 3.4 we present and describe the main results, and in the remaining sections we discuss and interpret the results before concluding the article.
3.2 Drivers of residential energy and GHG emissions

In Table 3.1 we summarize a selection of IDA studies of residential energy or GHG by location, the outcome metric being decomposed, the activity variable, and the main drivers identified by each study. In IDA, ‘activity’ refers to a measure of the aggregate level of activity or service demand in a sector. It may be measured in economic output, or physical units - for example passenger- or tonne-kilometers for passenger or freight transport sectors (Xu & Ang, 2014). An important modeling choice in IDA models of residential energy is whether to define population or number of houses as the main activity variable (Xu & Ang, 2014). This choice can influence the modeled effects of changes in household size. If population is the activity variable, household size reductions will be identified as an upward driver of changes in the outcome, but if number of housing units is the activity variable, the same reduction in household size will be identified as a downward driver. We consider population a more appropriate choice of activity for residential IDA models than
number of houses, as population growth is a more convincing exogenous variable (further discussion on this point is found in Appendix B section B.3).

Two decompositions of final energy in the U.S. identified growth in the number of houses and average floor area per house as the main upward drivers of energy demand, with reductions in intensity (energy/floor area) the main downward driver (EIA, 2015; Hojjati & Wade, 2012). Regression models of residential energy in the U.S. largely agree on the importance of house type, size, and age in determining final energy demand or GHG emissions at the household level (Goldstein et al., 2020; Kaza, 2010; Tso & Guan, 2014). Analyses at high spatial resolution report less energy consumption in urban areas with higher percentages of multifamily and smaller homes, more energy consumption in suburban, sprawling areas (Ewing & Rong, 2008; Min et al., 2010), and more energy consumption in states with lower average household size and higher proportions of older buildings (Salari & Javid, 2016). The importance of household size as a determinant of aggregate residential demand has been long recognized (Jiang & O’Neill, 2007; O’Neill & Chen, 2002), and has been highlighted recently in the context of continued declining household sizes globally (Ellsworth-Krebs, 2019; Ivanova & Büchs, 2020), but the direction of this effect identified by IDA studies is mixed (Table 3.1), as it depends on the choice of activity variable. On the role of building stock turnover, several studies using building stock based energy models (Breunig et al., 2018; Fazeli et al., 2016; Reyna & Chester, 2017) find that lower turnover rates impede energy demand reductions from more efficient new housing. No IDA model that we are aware of has considered changing age profile of buildings as a driver of change in residential energy demand.
<table>
<thead>
<tr>
<th>Study</th>
<th>Location</th>
<th>Outcome Metric</th>
<th>Activity</th>
<th>Upward drivers (excl. Activity)</th>
<th>Downward drivers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hojjati and Wade (2012)</td>
<td>USA</td>
<td>FE</td>
<td>House</td>
<td>FA/house</td>
<td>Intensity</td>
</tr>
<tr>
<td>Nie and Kemp (2014)</td>
<td>China</td>
<td>FE</td>
<td>Pop.</td>
<td>Appliances, FA/cap</td>
<td></td>
</tr>
<tr>
<td>Xu and Ang (2014)</td>
<td>Singapore</td>
<td>FE (elec.)</td>
<td>Pop.</td>
<td>↓HHS</td>
<td>FA/house</td>
</tr>
<tr>
<td>EIA (2015)</td>
<td>USA</td>
<td>FE</td>
<td>House</td>
<td>FA/house</td>
<td>Intensity</td>
</tr>
<tr>
<td>Kurniawan et al (2018)</td>
<td>Indonesia</td>
<td>GHG</td>
<td>Pop.</td>
<td>GDP/cap</td>
<td>Intensity</td>
</tr>
<tr>
<td>Shigetomi et al (2018)</td>
<td>Japan</td>
<td>GHG</td>
<td>House</td>
<td>Intensity</td>
<td>↓HHS, Cohort</td>
</tr>
<tr>
<td>Balezentis (2020)</td>
<td>Lithuania</td>
<td>FE, GHG</td>
<td>Pop.</td>
<td>↓HHS, FA/house</td>
<td>Intensity</td>
</tr>
</tbody>
</table>

Note: FE = final energy, elec. = electricity, Pop. = population, HHS = household size, FA = floor area. Intensity is defined as outcome metric divided by a scaling factor, e.g. household, population, floor area, or income. All studies except Balezentis (2020) report the activity variable as an upward driver. Upward drivers correlate with an increase in energy/emissions, while downward drivers correlate with a decrease.

### 3.3 Data and Methods

Final energy consumption and housing characteristics data are obtained from six Residential Energy Consumption Surveys (RECS) from 1990 to the most recently published survey for 2015 (EIA, 2019d). Choosing 1990 as our starting year allows us to track the evolution of households in housing built from 1990 onwards in our decomposition of housing cohorts described below.

Primary energy consumption by residential end-use is calculated by combining RECS information with electricity generation efficiency by fuel from the State Energy Data System (SEDS) (EIA, 2019e), and Monthly Energy Review (MER) (EIA, 2020b). The supply-side (MER, SEDS) and demand-side (RECS) surveys from EIA differ in their estimates of total residential energy consumption. The supply side surveys produce better estimates of total demand, and are more comparable across years (EIA, 2018b), and so we scale RECS estimates to match supply-side estimates of total residential final energy consumption per fuel type and by Census division. To calculate GHG emissions and primary energy, we use CO$_2$, CH$_4$, and N$_2$O emissions factors for
fossil fuel combustion (Subpart C—General Stationary Fuel Combustion Sources, 2009), and calculate electricity GHG intensities and primary energy factors based on the generation fuel mix and electricity generation losses in each division and year (EIA, 2019e). Aside from direct emissions from electricity generation, GHG emissions from energy supply chains are not included in the analysis. Primary energy for non-fossil electricity is calculated in SEDS using the physical energy content method for nuclear, and the substitution methods for renewables (Grubler et al 2012, p. 142). Our definition of primary energy demand in this context is primary energy use (or fossil heat equivalent) at the point of conversion. It is not a cumulative energy demand calculation, which would include energy for fuel extraction, refining, processing, and distribution (Arvesen & Hertwich, 2015).

In Figure 3.2, we present final energy demand, primary energy, and GHG emissions by end-use for selected years 1990-2015. Weather adjusted versions of these figures are shown in Fig B.2. Space heating is the largest source of final energy demand, making up about 50% of the total each year. However, space and water heating become less important, and electricity dominated space cooling and other end-uses become more important when looking at primary energy and GHGs, due to the higher primary energy requirements and GHG intensity of electricity. In 2015, Other end-uses accounted for around 28% of final energy and 37% of GHG, while space heating contributed 47% to final energy and 36% to GHG.

We use an additive log mean divisia index (LMDI)-I multilevel-parallel IDA model (Ang & Zhang, 2000) to decompose changes in final energy, primary energy, and GHG emissions associated with four residential energy end-uses; space heating, space cooling, domestic hot water, and all other end-uses (see Appendix B Figure B.6 for a disaggregation of energy and emissions from other end-uses in 2015). Our model is multi-level, meaning that we analyze changes within hierarchically disaggregated sub-groups of the data (SI Fig B.3). Multi-level models are useful for analyzing the effects of changes in distribution of population between different categories, such as geographic
region, or age cohort of housing. Among the classes of IDA models, LMDI-I is better suited to multi-level models, as it produces estimates for sub-groups that can be aggregated in a consistent manner, while the decompositions leave no residual term at the subcategory level (Ang, 2015; Ang & Liu, 2001). IDA models are informative in ranking the importance of different drivers over time and allocating changes in the outcome variable to coincident changes in the explanatory variables. Limitations of IDA include assumptions of unit proportionality between driver and outcome (York et al., 2003), absence of measures of statistical significance, and assumptions of independence between drivers (O’Neill & Chen, 2002). For an IDA model to produce meaningful results, two considerations are worthy of attention. First, it is crucial to define drivers that can be reasonably assumed to influence the outcome through some plausible mechanism. Second, where possible, defining drivers that are less likely to be interdependent should be best practice.

Decomposing individual end-uses allows flexibility in incorporating driving factors applicable to each end-use (Xu & Ang, 2014). For instance, we incorporate changes in conditioned floor space as a driver of space heating and cooling, but disregard that driver when analyzing changes in domestic hot water or other end-uses. Avoiding incorporation of drivers which do not influence the outcome also avoids interdependence between drivers, as inclusion of such a driver will create two driving factors which are strongly inversely correlated. Equations 1-4 describe decompositions of final energy for each end-use, with all terms defined in Table 3.2. For primary energy and GHG, we add an extra term ($X_E$ and $X_G$ respectively) to each equation, to enable decomposition of changes in total primary energy demand and GHG emissions for each end-use into changes in electricity generation efficiency and GHG intensity of electricity in each Census division, in addition to other drivers (see equations B1-B8). The attribution of changes in energy and GHG by end-use into the drivers is described further in the supplementary information and detailed in equations B9-B31.

We define population as the activity variable, and the population effect describes changes in energy and GHG outcomes due to changes in total household population. Regional effects are calculated
based on changes in the population distribution among the nine Census divisions (New England, Mid Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific). Type effects are based changes in the population distribution among five types of housing within each division; single family detached and attached, multifamily low-density (units in buildings with 2-4 units) and high-density (5+ units), and manufactured housing. Cohort effects are due to changes in population distribution (within each division-type segment) between housing of six age cohorts spanning houses built pre-1950 to houses built from the 1990s onwards. Fuel effects are due to changes in distribution of population by main fuel used for space/water heating (natural gas/liquified petroleum gases, fuel oil/kerosene, electricity, or other), within each division-type-cohort subset. Household size effects are based on changes in the inverse of average household size within each division-type-cohort-fuel subset. Conditioned space effects are due to changes in average household heated floor space for space heating (m$^2_{\text{heat/house}}$), and the percentage of houses owning air-conditioners for space cooling. End-use intensity effects are based on changes in the intensity index defined by the weather-adjusted outcome variable (final/primary energy, GHG) per heated floor area for space heating, per house with air-conditioning for space cooling, per person for domestic hot water, and per house for other energy.

Changes in the primary energy and GHG indices ($X_E$ and $X_G$, included in the primary energy and GHG decomposition equations B1-B8) are used to calculate the electricity efficiency and GHG intensity effects. Weather effects capture differences in space conditioning and water heating due to difference in in heating degree days (HDD) and cooling degree days (CDD) in each Census division from their 30-year average. This allows us to control for the influence of weather fluctuations, and thereby provide better estimates of the other driver effects. Changes in drivers over the study period are visualized in Appendix section B.6.
Decomposition of final energy for space heating, end-use 1:

\[ E^1 = \sum_i \sum_j \sum_k \sum_l P \frac{p_{lj} p_{ijk} n_{ijkl} a_{ijkl} e_{ijkl}^1}{p_{li} p_{ij} p_{ijkl} n_{ijkl} a_{ijkl} e_{ijkl}^1} \times R \times T \times C \times F \times H \times S \times I^1 \times W \] (1)

Decomposition of final energy for space cooling:

\[ E^2 = \sum_i \sum_j \sum_k P \frac{p_{lj} p_{ijk} n_{ijkl} a_{ijkl} e_{ijkl}^2}{p_{li} p_{ij} p_{ijkl} n_{ijkl} a_{ijkl} e_{ijkl}^2} \times R \times T \times C \times H \times S \times I^2 \times W \] (2)

Decomposition of final energy for domestic hot water:

\[ E^3 = \sum_i \sum_j \sum_k \sum_l P \frac{p_{lj} p_{ijk} n_{ijkl} a_{ijkl} e_{ijkl}^3}{p_{li} p_{ij} p_{ijkl} n_{ijkl} a_{ijkl} e_{ijkl}^3} \times R \times T \times C \times F \times I^3 \times W \] (3)

Decomposition of final energy for all other uses:

\[ E^4 = \sum_i \sum_j \sum_k P \frac{p_{lj} p_{ijk} n_{ijkl} e_{ijkl}^4}{p_{li} p_{ij} p_{ijkl} n_{ijkl} e_{ijkl}^4} = R \times T \times C \times H \times I^4 \] (4)
Table 3.2 Indices and subscripts used in the IDA decomposition equations

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Summary</th>
<th>Unit of measurement/Example/Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>Population</td>
<td>National household population</td>
</tr>
<tr>
<td>N</td>
<td>Houses</td>
<td>Number of housing units</td>
</tr>
<tr>
<td>A</td>
<td>Conditioned floor area</td>
<td>Heated square foot per house for space heating; number of houses with AC for space cooling</td>
</tr>
<tr>
<td>E</td>
<td>Final energy consumption</td>
<td>MJ/yr</td>
</tr>
<tr>
<td>E’</td>
<td>Weather-adjusted final energy</td>
<td>MJ/yr</td>
</tr>
<tr>
<td>i</td>
<td>Subscript for Census Division</td>
<td>$P_i$ is population in division 5 (South Atlantic)</td>
</tr>
<tr>
<td>j</td>
<td>Subscript for house type (1-5)</td>
<td>$P_{i,j}$ is population in single-family detached type</td>
</tr>
<tr>
<td>k</td>
<td>Subscript for Age Cohort (1-6)</td>
<td>$P_{i,j,k}$ is population in houses built in 1980s</td>
</tr>
<tr>
<td>l</td>
<td>Subscript for heating fuel (1-5)</td>
<td>$P_{i,j,k,l}$ is population using primarily natural gas for space heating</td>
</tr>
<tr>
<td>R</td>
<td>Regional index</td>
<td>Distribution of national population among nine Census divisions</td>
</tr>
<tr>
<td>T</td>
<td>Type index</td>
<td>Distribution of Census division population among house types</td>
</tr>
<tr>
<td>C</td>
<td>Cohort index</td>
<td>Distribution of population among construction cohorts, for each division and house type</td>
</tr>
<tr>
<td>F</td>
<td>Heating fuel index</td>
<td>Distribution of population by main fuel used for space/water heating, for each division, house type, and cohort</td>
</tr>
<tr>
<td>H</td>
<td>Household Size index</td>
<td>Average number of occupied houses per person for populations segments by division, house type and cohort, and main heating fuel ($E'$ only)</td>
</tr>
<tr>
<td>S</td>
<td>Conditioned space index</td>
<td>Heated/cooled floorspace index for populations segments by division, house type</td>
</tr>
</tbody>
</table>
type and cohort, and main heating fuel ($E^j$ only), defined as

$S_1$ (heated m²/house) – average heated floor area per house within population segment

$S_2$ (houses with AC/all houses) – portion of houses owning AC within a population segment

| I     | End-use Intensity index | Final energy end-use intensity index:
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I¹ ($E'^1$/heated m²) for space heating</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I² ($E'^2$/house with AC) for space cooling</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I³ ($E'^3$/person) for hot water</td>
<td></td>
</tr>
<tr>
<td></td>
<td>I⁴ ($E'/house$) for other end-uses</td>
<td></td>
</tr>
</tbody>
</table>

| W     | Weather index | Ratio of actual final energy per end-use to weather adjusted final energy per end-use (i.e. an estimate of what final energy demand would have been with 30-year average weather) |

| X_E   | Primary Energy Index | Ratio of primary energy calculated using current primary energy factors for electricity to primary energy calculated using 1990 primary energy factors for electricity. |

| X_G   | GHG Index | Ratio of GHG emissions calculated using current GHG intensity of electricity generation to GHG emissions calculated using 1990 GHG intensity of electricity generation. |
3.4 Results

In Figure 3.3 we show changes in final and primary energy and GHG emissions decomposed into their relevant drivers. After population growth, the two most important upward drivers are reductions in household size and increases in conditioned space. Reductions in end-use intensity and cohort changes are the dominant sources of reductions in final energy. Reductions in end-use intensity reflect changes in energy or emissions per floor area/person/house (depending on the end-use), and may result from appliance and envelope efficiency improvements, or behavioural change. Cohort effects are due to changes in the distribution of population between housing of different age cohorts, and reflect lower energy consumption in newer houses.

The dominant drivers of primary energy and GHG emissions reductions are improvements in the efficiency of electricity generation, and reductions in the GHG intensity of electricity generation, respectively. Compared to these supply side effects, demand side reductions from cohort changes and changes in end-use intensity are relatively minor. Additional smaller reductions in final energy are driven by changes in population distribution between house types and Census divisions. Direct reductions from fuel switching are non-existent for primary energy, and small for GHG, despite substantial final energy reductions from fuel switching. This is likely due to electricity being more...
(primary energy and GHG) intensive than fossil alternatives at the time of switching (c.f. Fig B.24-B.25).

To demonstrate how drivers differ between end-uses and over subperiods, in Figure 3.4 we decompose changes in GHG emissions by end-use for 1990-2001 and 2001-2015. Reductions in household size drove substantial increases in GHG from other end-uses, space heating, and cooling. Increases in conditioned space was a prominent upward driver for both space heating and cooling, especially before 2001. Cohort changes are a prominent and consistent driver of energy and GHG reductions from space heating, suggesting that newer houses require much less energy to heat. Cohort changes interestingly do not drive GHG reductions for any of the other end-uses. Reductions in electricity GHG intensity are the second biggest driver of reductions in space heating GHG over the full period, and the dominant source of GHG reductions for all other end-uses. This effect is most impressive for other end-uses (incorporating lighting, refrigeration, appliances and cooking, etc., Fig. B.6), and has clearly been concentrated in the latter years of the study, with almost no effect before 2001.

Fuel switching for space and water heating differed by region, with displacement of fuel oil and by natural gas in North-Eastern regions (New England and Mid Atlantic), and displacement of natural gas by electricity in southern regions (East and West South Central, South Atlantic). These fuel switches have on the whole reduced GHG emissions from space heating, but increased GHG emissions from water heating. The Region effect shows that higher population growth in warmer regions reduced GHG from space heating, but increased GHG from space cooling. Changes in the population distribution among housing types have been too small to cause large changes in energy or GHG emissions. Due to a change in the allocation of electricity to different end-uses between 2009 and 2015 (EIA, 2018b), 1990-2015 growth in energy/emissions from space and water heating are likely overestimated, and growth in energy/emissions from other end-uses underestimated. This should not influence the relative importance of drivers (further discussion in Appendix B.2).
Figure 3.3 Decomposition of changes in a) residential final energy, b) primary energy, and c) GHG emissions, 1990-2015. “Elec Eff.” refers to the electricity efficiency effect based on changes in the Primary Energy Index $X_E$. 
a) Decomposition of changes in space heating GHG, 1990-2001-2015

1990: 359 Mton (+0.42% p.a.)
2001: 376 Mton (-0.01% p.a.)
2015: 375 Mton

b) Decomposition of changes in space cooling GHG, 1990-2001-2015

1990: 106 Mton (-2.1% p.a.)
2001: 133 Mton (-3.75% p.a.)
2015: 139 Mton

c) Decomposition of changes in domestic hot water GHG, 1990-2001-2015

1990: 133 Mton (+0.91% p.a.)
2001: 147 Mton (+0.94% p.a.)
2015: 168 Mton
3.5 Discussion

Our results confirm our hypotheses regarding the effects of reductions in household size, growth in conditioned floor area, and reductions in GHG intensity of electricity, while providing a mixed assessment of residential fuel switching. All else equal, changes in GHG intensity of electricity would have reduced annual GHG emissions by 24% of the 1990 level, 9-40 times more than any of the demand side measures identified. We quantify for the first time changes in U.S. residential energy and GHG emissions due to reductions in household size. The changes attributed to household size reductions equal 37% of the total increase in final energy, 28% of the total increase in primary energy, and 108% of the total increase in GHG. Our findings on the relationship between household size and residential energy and emissions concur with findings based on statistical modeling approaches (Fremstad et al., 2018; Ivanova & Büchs, 2020) and IDA studies which define population as the activity variable (Balezentis, 2020; Xu & Ang, 2014), but conflict with IDA studies which define housing as the activity variable (Shigetomi et al., 2018; Zang et al., 2017). Reductions in household size and increases in floorspace per house can explain the trends of growth in residential floor area per capita, recognized as a critical driver of increases in residential energy and GHG
emissions (Ellsworth-Krebs, 2019; Hertwich et al., 2020). Growth in heated floor area per house in single-family and manufactured homes (Fig B.15), and growth in the percentage of households owning space cooling equipment have driven growth in energy and emissions from space heating and space cooling, respectively. The average size of new single-family homes may have peaked in 2015 (Figure B.23), but it is too early to say whether this reversal of the historic trend will be temporary or longer lasting. Increases in percentage of houses using cooling equipment were stronger in the earlier years of our study period, and as access to cooling approaches saturation in most regions, this is expected to be a less important driver of increased energy and emissions in the future. However, larger houses, an increase in the percent of household floorspace that is cooled, and warmer weather could still drive future increases in cooling demand.

The effects of fuel switching were zero for primary energy and minor for GHG emissions. Considering the effects of fuel switching on space heating emissions by region, switching to electricity resistance heating will in most cases create a short-term increase in emissions (until electricity decarbonizes further) while switching to electric heat pumps is much more likely to produce an immediate reduction in GHG emissions (c.f. Fig B.24, B.25). Even if it results in a short-term increase in emissions, fuel switching to electricity increases the amount of energy which can be decarbonized in subsequent years through electricity decarbonization. The GHG benefits of ‘electrifying everything’ have so far been minor, but larger future reductions can be expected given the increased rate of decarbonization, and increased market share of heat pumps. Prioritizing the adoption of heat pump water heaters can also be of great help in providing more immediate and cost effective GHG reductions through electrification (Langevin et al., 2019). Most gas storage water heaters (which make up almost half of water heater sales) have a final-to-useful efficiency range of just 58-66%, while instantaneous gas water heaters achieve efficiencies of over 82%, electric resistance water heaters over 90%, and heat pump water heaters over 200% (EIA, 2017).
Comparing emissions by end-use, ‘other’ energy end-uses make up the largest contribution to overall residential GHG emissions. This is important to remember when modeling and comparing strategies for reducing residential energy and emissions. Due to high electrification levels, future GHG from other end-uses will continue to decline in line with GHG intensity of electricity, but this decline may be outweighed by population/household growth, and growth in intensity of use. Newer appliances have become more efficient over time (EIA, 2017), but newer homes also tend to have more and larger appliances that are used more often, which can outweigh the efficiency gains (Table B.1, B.2). The multifunctionality of newer electronic devices has potential to reduce both total number of appliances and energy consumption by product communities, but this effect is not yet evident for personal electronics (Ryen et al., 2014, 2015).

### 3.6 Implications for future residential energy use and emissions

In the introduction we note that there are multiple points along energy supply chains to reduce primary energy and/or GHG emissions. It is clear from Figure 2 that efficiency gains and decarbonization of electricity supply have been the dominant factors limiting growth of residential primary energy and GHG emissions in the United States. While we may expect this to continue, limitations to the rate of further reductions in GHG intensity of electricity should be considered. Deep decarbonization of electricity in the United States is not part of existing mid-range projections. EIA’s Annual Energy Outlook baseline scenario projects that the combined share of U.S. electricity generated by coal and gas to reduce from 61% in 2019 to 50% in 2050, with national average carbon intensity of electricity decreasing from 0.39 to 0.25 kg CO₂/kWh (EIA, 2020a). The Mid-Case scenario from NREL’s ‘standard scenarios’ outlook is more optimistic, forecasting coal and gas to fall to 33% of generation, and carbon intensity to become 0.18 kg CO₂/kWh by 2050 (Cole et al., 2019). These developments are in the right direction, but insufficient and inconsistent with climate stabilization goals requiring halving of emissions between 2020 and 2030, or net-zero emissions by 2050 (Otto et al., 2020). To meet more ambitious targets for the rate of emissions
reductions, the U.S. residential sector cannot rely so heavily on supply side electricity decarbonization; demand side solutions will need to play a larger role through reducing residential final energy demand.

There is a large technical and economic potential for energy demand reduction through technology upgrading, with building envelope improvements and increases in electric heat pumps in particular having a large potential to reduce final energy demand for space and water heating (Langevin et al., 2019; E. Wilson et al., 2017). Substantial further reductions in final energy demand would result from decreasing the size of new housing, higher rates of stock turnover enabling more new housing, and increases in the portion of population living in multifamily house types (Berrill et al., 2021a). All of these changes could be encouraged by relaxing or removing the many regulatory deterrents to multifamily, smaller, and new housing which exist at federal (A. F. Schwartz, 2015) and local (Gray & Furth, 2019; Gyourko et al., 2019) levels, allowing markets to respond to increased demand for house types consistent with smaller households. Household size will likely continue to decline for at least the next two decades (McCue, 2018), causing household growth to outpace population growth. Increases in appliance efficiency can support demand side emission reductions from other energy use, but efficiency improvements are limited by the rate of appliance stock turnover (Ryen et al., 2015), and could be counterbalanced by household growth, and greater overall appliance ownership and use. Behavioral change can contribute to reducing future energy demand, but is difficult to influence through policy (excepting incentives for efficient technology adoption) and may have to come about through greater cultural diffusion of efficiency and sufficiency attitudes towards energy use and conservation (Marghetis et al., 2019; Wolske et al., 2020).

Electrification and decarbonization will help to reduce U.S. residential sector GHG emissions, but to meet climate targets such as 1.5 °C of warming, energy demand reductions from other sources are needed. In existing houses, envelope retrofits and increased uptake of efficient equipment and
appliances will be required. For future changes to the housing stock, policies which remove regulatory barriers to new construction and multifamily housing could encourage faster replacement of older housing stock with more efficient housing (Berrill et al., 2021a). Combining the potential of demand-side reductions with electrification and decarbonization in this way would bring ambitious climate targets within reach.
4 Linking housing policy, housing typology and residential energy demand in the United States

Please cite as:


Abstract

Residential energy demand can be greatly influenced by the types of housing structures that households live in, but few studies have assessed changes in the composition of housing stocks as a strategy for reducing residential energy demand or greenhouse gas (GHG) emissions. In this paper we examine the effects of three sequenced federal policies on the share of new housing construction by type in the US, and estimate the cumulative influence of those policies on the composition of the 2015 housing stock. In a counterfactual 2015 housing stock without the policy effects, 14 million housing units exist as multifamily rather than single-family, equal to 14.1% of urban housing. Accompanied by floor area reductions of 0-50%, the switch from single- to multifamily housing reduces energy demand by 27-47% per household, and total urban residential energy by 4.6-8.3%. This paper is the first to link federal policies to housing outcomes by type and estimate associated effects on residential energy and GHG emissions. Removing policy barriers and disincentives to multifamily housing can unlock a large potential for reducing residential energy demand and GHG emissions in the coming decades.
4.1 Introduction

Background

Energy efficiency is frequently suggested as a strategy for reducing primary energy demand and greenhouse gas (GHG) emissions, reducing the need for negative emissions technologies to achieve climate change mitigation targets (Grubler et al., 2018). Buildings in particular have been identified as a demand sector with high potential for energy efficiency (Bardhan et al., 2014), a potential which is often underexploited (Gillingham & Palmer, 2014). Although structural characteristics such as building type (i.e. detached, attached, multi-unit, etc.) are acknowledged to be important determinants of energy demand in residential buildings (Estiri, 2014; Ewing & Rong, 2008), a change in the relative abundance of less energy intensive structural typologies in housing stocks is rarely considered as an energy efficiency or GHG mitigation strategy. Previous studies have evaluated a wide range of social benefits and costs of various housing policies, but there are exceedingly few assessments of the potential for housing policy to reduce residential energy or GHG emissions.

This study provides a novel perspective on the possibilities for energy and GHG reductions in the residential sector. Specifically, we measure the influence of three federal policies from the 1970s and 1980s on the single-family and multifamily share of new housing construction, estimate the cumulative effect of those policies on the type composition of urban housing stocks in 2015, and generate four scenarios of how this affected residential energy and emissions.

Policy influence on housing and residential energy

There is a broad literature assessing the influence of local housing and land-use restrictions on housing markets, and impacts on worker mobility and productivity urban sprawl and segregation, and housing supply and affordability (Barrington-Leigh & Millard-Ball, 2015; Been et al., 2019; Glaeser & Gyourko, 2003; Gyourko & Molloy, 2015; Hsieh & Moretti, 2019; Lens & Monkkonen,
Some studies assessed the effects of local restrictions (including single-family/low-density zoning or minimum lot-size restrictions) on housing outcomes by type, finding that they disproportionally suppress multifamily construction (Jackson, 2016; Pendall, 2000), and limit supply of multifamily and small-lot single family housing below what unrestricted housing markets would produce (Chakraborty et al., 2010; Gray & Furth, 2019; Knaap et al., 2007). Local land-use restrictions can change over time and vary enormously across jurisdictions. In aggregate terms they appear relatively stable in recent years; two independent attempts at measuring the extent of such restrictions found that overall local regulatory intensity has not changed considerably since the 1990s (Gyourko et al., 2008, 2019; Pendall et al., 2018). Studies assessing federal policy impacts on housing and related outcomes are less common (Dipasquale & Cummings, 1992; Glaeser & Shapiro, 2003), but because federal policies apply equally throughout the US and change less frequently, their effects on national housing outcomes can be readily investigated.

Federal housing policies in the US provide high levels of support for homeowners, and less support for renters (Landis & Reina, 2019; Mudrazija & Butrica, 2017). This translates into greater support for single-family households, as most homeowners live in single-family homes and most renters live in multifamily homes (A. F. Schwartz, 2015). The high fraction of homes that are single-family detached may help in understanding why US residential energy use per capita (SI Fig. 3) and floor space per capita is high by international standards (Ellsworth-Krebs, 2019). Compared to the 62% of US housing that is single-family detached (EIA, 2018a), Japanese housing is 55% single-family detached (Statistics Bureau of Japan, 2019), while EU27, German, and UK housing is 34%, 29%, and 25% single-family detached, respectively (Hirt, 2016).

If policy can influence housing outcomes by type, then there may be an indirect effect on residential energy consumption and GHG emissions, to the extent that housing typology influences energy demand. Analyses of household energy consumption in the US consistently find that single-family detached houses consume more energy, after controlling for other variables including house size,
climate, and income (Ewing & Rong, 2008; Tso & Guan, 2014). Estiri reports a large *indirect* effect of household size and income on residential energy, due to an increased propensity for households to choose larger and single-family detached housing as household size and income increases (Estiri, 2014). Ewing and Rong find more multifamily housing and lower household energy consumption in higher-density counties (Ewing & Rong, 2008). A scenario analysis by Goldstein and colleagues estimates that increased population density and a reduced share of single-family homes, on top of other energy saving and decarbonization measures, would be required for the US residential sector to meet its 2050 Paris Agreement target (Goldstein et al., 2020).

Federal policies affecting housing markets

Fig. 4.1 charts the historical single-family share of annual total (single-family plus multifamily) housing starts from 1959 to 2018 (United States Census Bureau, 2020). Three major federal policy events punctuate the figure, the Public Housing Moratorium (PHM) in 1973, the Tax Reform Act of 1986 (TRA 86), and the Financial Institutions Reform Recovery and Enforcement Act (FIRREA) in 1989. The PHM halted funding for all new public housing projects, excluding those devoted to elderly residency (Vale & Freemark, 2012). Public housing had been an important contributor to new housing construction in the US since the Federal Housing Acts of 1949 and 1954. These Housing Acts also had other influences on housing stocks and markets, through largescale demolition of buildings in city centers, and limiting access to mortgages in older and minority neighborhoods (A. F. Schwartz, 2015). Although federal funding for low-income housing continued through rent vouchers and community development block grants (“Public Housing Timeline, 1933–1993,” 2012; A. F. Schwartz, 2015), after PHM the federal government would no longer directly build and own new public housing. TRA 86 curtailed the availability of depreciation losses to lower income taxes, eliminated accelerated depreciation allowances for multifamily housing, and lowered the highest tier tax rates, reducing the value of depreciation allowances (A. F. Schwartz, 2015). Although the depreciation allowances had been made much more generous in
the Economic Cost Recovery Tax Act of 1981, after TRA 86 depreciation terms became much less generous than what existed before 1981 (Gravelle, 2000). In summary, TRA 86 altered effective tax rates in a way that made multifamily homes less attractive investments than single-family homes. In 1989, FIRREA bailed out institutions affected by the savings and loans crisis, and imposed new restrictions on the types and terms of loans that could be made, making access to capital much more expensive for multifamily compared to single-family investments (Dipasquale & Cummings, 1992) (Appendix C note 1). Housing markets may also be influenced by transport policies and infrastructure. Federal Highway Acts in the 1920s and 1950s brought about the construction of highways connecting city centers to suburbs, which may have contributed to the population decline of city centers (Baum-Snow, 2007) where multifamily housing is more common.

In this article we estimate the effects of the sequential implementation of PHM, TRA 86, and FIRREA on new housing construction by type, and we illustrate the influence of house types and age cohort on energy end-uses in 2015, while controlling for other major determinants of residential
energy demand. We create a counterfactual urban housing stock for 2015 by removing the effects of the federal policies and calculating the cumulative effect on the type composition of the housing stock. Our results suggest that policies affecting housing markets can support energy conservation and climate goals by removing disincentives and regulatory barriers to new and multifamily housing. This paper constitutes the first effort to link federal policies to residential energy demand and GHG emissions, and to estimate aggregate effects of house typology on residential energy demand and emissions at a national scale.

4.2 Methods and Data

**Housing starts model**

We develop a linear model of the single-family share of quarterly total housing starts (houses for which construction was started in each quarter) spanning 1971-2018. This model estimates the relationship between three federal policy changes, the PHM in 1973, TRA in 1986, and FIRREA in 1989, and the quarterly single-family share of housing starts, controlling for population growth, real GDP, 30-year mortgages rates, and seasonal effects. We use these results to estimate the share of housing starts by type in the absence of PHM, TRA86, and FIRREA. As existing local regulation and housing starts data do not support a time-series analysis of effects of local housing or land use policies on housing starts, local regulations on housing construction are not considered. Urban highway mileage and vehicle ownership per capita were considered as additional controls, but omitted from the final model (for further discussion on model development, see Appendix C note 2). Equation (1) summarizes the model, with macroeconomic and demographic covariate coefficients denoted as $\beta$, federal policy dummy variable coefficients denoted as $\gamma$, and $v_q$ denoting quarter-of-the-year fixed effects to capture seasonality. An observation $t$ in this analysis is a quarter.

$$SF.\text{Share}_t = \beta_1 \text{Population.\ Change}_t + \beta_2 \text{Real.\ GDP}_t + \beta_3 \text{30yrMortgage}_t +$$

$$\gamma_1 \text{Public.\ Housing}_t + \gamma_2 \text{TRA86}_t + \gamma_3 \text{FIRREA}_t + v_q + \epsilon_t. \quad (1)$$
30-year mortgage data are available starting in Q2 of 1971 (Freddie Mac, 2020), which defines the start date of our model. The PHM dummy is given the value of ‘0’ until Q4 of 1973, and ‘1’ from Q1 1974, as the public housing moratorium was announced in Q1 of 1973 and we assume that it took one year until new starts were affected by the moratorium, based on the likelihood that public housing starts in 1973 were funded by money committed before the moratorium was announced. TRA86, and FIRREA dummy variables are turned ‘on’ in Q1 of 1987 and Q4 of 1989 respectively, one quarter after they were signed into law. To the extent that the policy effects are independent of each other, our model estimates the independent effect of each policy. If the effectiveness of one policy is correlated with a previous policy, then our model estimates the effects of the second policy conditional on the first policy being implemented. The coefficient estimates for TRA86 and FIRREA should therefore be interpreted as the effects of those policies conditional on earlier policies being implemented. Historical population change data are calculated based on monthly total population estimates (US Bureau of Economic Analysis, 2020c). Data for single-family, multifamily, and total starts are taken from the USCB New Residential Construction publications (United States Census Bureau, 2020). Quarterly real GDP, is calculated by multiplying quarterly nominal GDP (US Bureau of Economic Analysis, 2020b) by quarterly price indexes for GDP (indexed to 2012 USD) (US Bureau of Economic Analysis, 2020a).

Development of counterfactual housing stock

The difference between the counterfactual and actual starts of each housing type in each year was used to inform a counterfactual 2015 national housing stock by type and age cohort (Fig. 4.2a, Fig. C.2). To reflect lower rates of completion of housing starts for multifamily than single-family, we adjusted the change in housing starts predicted by the housing starts model downward by 4.1%, the percentage difference in completion rates (U.S. Census Bureau, n.d.). We assume that the counterfactual starts made no change to the number of houses demolished each year of each type (App. C note 3). The number of additional multifamily units (and corresponding reduction in
single-family houses) adds up to a total alteration to the 2015 stock of 13.96 million homes. We assume that type changes are restricted to urban areas, as this seems more realistic.

The housing starts data are distinguished as single-family and multifamily (United States Census Bureau, 2020), while the energy consumption data splits single-family into attached and detached, and multifamily into units in buildings with 2-4 units and 5+ units. We convert the single-family/multifamily starts data into alterations of the stock by keeping the same ratio of more detailed housing types within single-family and multifamily.

**Modeling of energy end-uses**

We specify a linear model of urban household energy end-use consumption in 2015, drawing on data from the 2015 Residential Energy Consumption Survey (RECS) (EIA, 2018a). The four end-uses considered are space heating, space cooling, domestic hot water, and all other uses. Equation (2) summarizes the general formulation for end-use \( i \):

\[
\text{EnergyUse}_i = X_i \beta + \phi_i + \epsilon_i. \tag{2}
\]

Covariates included in \( X \) are household income (all end-uses), heating degree days (HDD, space heating and domestic hot water), household size (all end-uses), cooling degree days (CDD, space cooling only), heated floor area (space heating only), cooled floor area (space cooling only), and total floor area (domestic hot water and other end-uses). The \( \phi \) parameter contains house type-cohort fixed effects. Fixed effects are defined with 23 levels, based on combinations of building type (4 levels: single-family detached, single-family attached, multifamily low, and multifamily high), and construction age cohort (6 levels: <1950, 1950-69, 1970s, 1980s, 1990s, 2000+) with ‘multifamily high 2000+’ homes serving as the reference level. Multifamily low refers to units in buildings with 2-4 units, and multifamily high refers to units in buildings with 5+ units. We adopt these terms for brevity, but note that much of multifamily high is not necessarily high-density or high-rise; 27% of multifamily high units are in buildings with 5-9 units, and a further 25% are in
buildings with 10-19 units (US Census Bureau, 2020a). One possible concern with our specification of energy end-use models is selection of housing types based on preferences for certain characteristics. Households may choose to live in single-family homes due to preferences for larger space or other type-related characteristics. This could reduce the energy savings potential of a type switch if the characteristics of counterfactual multifamily homes (such as size) closely resembled single-family homes which they replaced.

To provide insight into how selection in housing type choice and housing characteristics could affect the results, we explored selection based on household income in one of our energy demand scenarios (CF1), and a range of changes in floor area associated with type switch are represented in the scenarios. In CF1, we model changes in energy end-use consumption separately for three income groups. Specifically, we specified a variant of our end-use model where income was removed from \( X \) and included in an expanded \( \varphi' \) parameter describing type-cohort fixed effects for low (annual income < $40,000), mid ($40,000 - $100,000) and high (> $100,000) income households. The fixed effects in this case are defined with 71 levels, based on combinations of four building type, six age cohorts, and three income groups. Further information about model development is found in App. C note 4.

**Energy and GHG emissions in housing stock counterfactuals**

We calculate four scenarios of urban residential energy demand in 2015, reflecting different assumptions of how selection effects influence which households may move to multifamily, and how the average size of affected multifamily units may change. As mentioned above, one way selection could play a role is if households of different incomes demand both different housing types and characteristics. In the first counterfactual (CF1) we represent the possibility of substantial selection by income: we assume that 65% and 35% of the households exchanging single-family for multifamily are low-income and mid-income respectively. Energy demand is calculated by applying income-group-specific type-cohort effects \( \varphi \) to the changes in housing stock by cohort.
and type. This representation of selection is motivated by empirical analysis (Estiri, 2014) and RECS data (Figure C.7, Table C.9) suggesting a strong role for household income in determining house type and floor area. CF1 also incorporates floor area preferences of single-family households, by assuming that households that moving to multifamily consume the same floor area as they consumed in a single-family house.

In the second scenario (CF2) we do not specify the income groups of households who move; the energy demand reductions are instead based on type-cohort effects for average households $\varphi$, after controlling for income. We again assume that households moving to multifamily consume the same floor area as they consumed in a single-family house, and household income remains unchanged.

In counterfactuals CF3 and CF4, we model the effect of the type switch for average households as in CF2, but relax the assumption of constant floor area. Instead, we estimate that moving from single- to multifamily housing is accompanied by a floor area reduction of 30% (of average single-family floor area) in CF3, and 50% in CF4. In these scenarios, the appropriate floor area regression coefficient for each end use (Table 2) is multiplied by the floor area reduction and applied to the multifamily houses added in the stock counterfactual. A complete description of the scenario energy calculations is provided in App. C note 5.

To calculate GHG emissions associated with final energy demand for each end-use and house type, we use direct emissions factors for fuel combustion (Subpart C—General Stationary Fuel Combustion Sources, 2009), and calculate electricity GHG intensities based on electricity fuel mix and generation losses, aggregating state data (EIA, 2019e) to Census Divisions (Table C.7). Calculating GHG intensities by Division is a simplification, as electricity grid regions do not follow Division boundaries, and there is much trading of electricity between grid regions. However, RECS data do not indicate locations of households at greater resolution than Census Division, so we could not use GHG intensities for specific grid regions. End-use GHG intensities differ by house type due to different energy carrier shares (e.g. electricity delivers a higher share of space heating in
multifamily homes), and differences between electricity GHG intensities between regions where single-family and multifamily homes are more prominent. To calculate reductions in GHG emissions associated with counterfactual housing stocks, we multiply the final energy reduction per end-use and house type by the corresponding end-use GHG intensity.

4.3 Results

Housing stock and construction under counterfactual federal policy

Our housing starts model estimates indicate that all of the federal policies considered are associated with increases in the single-family share of housing starts (Table 4.1) after controlling for demographic and macroeconomic factors. While recognizing that the effects of subsequent policies may depend on earlier ones, the PHM has the largest policy effect, and is associated with increasing the single-family share of quarterly starts by 18 percentage points, while TRA86 and FIRREA are associated with increases of the single-family share by 5-6 percentage points. Higher mortgage rates correlate with lower single-family shares, suggesting a stronger incentive to purchase a home with lower interest rates. Higher population growth is associated with a greater share of single-family homes. Higher GDP is associated with lower shares of single-family housing, contradicting positive correlations between GDP per capita and floor space per capita (Moura et al., 2015). While the identified GDP effect might be consistent with positive associations of GDP and urbanization (M. Chen et al., 2014), and more multifamily housing in urban areas (EIA, 2018a), GDP is included simply as a control for macroeconomic activity in our model, and we do not interpret this coefficient as a causal effect (App. C note 3).
Table 4.1 Coefficient estimates from linear regression models of single-family share (%) of total housing starts
Newey-West robust standard errors are shown in parentheses

<table>
<thead>
<tr>
<th>Percent Single-family</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>PHM</td>
<td>18.06*** (2.36)</td>
</tr>
<tr>
<td>TRA 86</td>
<td>5.84*** (1.19)</td>
</tr>
<tr>
<td>FIRREA</td>
<td>5.18* (2.96)</td>
</tr>
<tr>
<td>ΔPopulation</td>
<td>0.022* (0.009)</td>
</tr>
<tr>
<td>Real GDP</td>
<td>-0.006*** (0.002)</td>
</tr>
<tr>
<td>30yr Mortgage Rate</td>
<td>-1.11*** (0.27)</td>
</tr>
<tr>
<td>Seasonal FE</td>
<td>Y</td>
</tr>
</tbody>
</table>

Observations 191
R² 0.737

*p <0.10  **p <0.05, ***p <0.01

Figure 4.2 shows historical single- and multifamily housing starts, and predictions of housing starts in the absence of PHM, TRA86, and FIRREA. To generate our predictions, we assumed that housing starts would follow the trend estimated by the model without the effects of those policies. The counterfactual quarterly single-family shares were multiplied by quarterly starts for all housing. The model suggests that housing starts would have followed a trend of decreasing single-family share without the influence of the three policies considered (Fig. C.3), producing 13.96 million more multifamily units since 1974, exerting a sizeable influence on the current make-up of US housing.
Results of our household energy end-use models are shown in Table 4.2. Space heating is strongly correlated with heating degree days (HDD), heated floor area, and income. Higher space cooling use is associated with higher cooling degree days (CDD), cooled floor area, and income, but effects are weaker than for space heating. Unlike space heating, the coefficient for household size is significant and positive, although small. Domestic hot water demand is strongly correlated with household size; significant coefficients also exist for income, climate, and house size, but are of smaller magnitude. Other energy end-uses are correlated with household size, income and house size, with income having stronger effects on ‘other’ end-uses than on any other end-use.
Table 4.2 Coefficient estimates from linear regression models of energy end-uses in urban homes in 2015 (MJ)

<table>
<thead>
<tr>
<th></th>
<th>Space Heating</th>
<th>Space Cooling</th>
<th>Water Heating</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH Income</td>
<td>51.25***</td>
<td>5.46**</td>
<td>13.48***</td>
<td>56.37***</td>
</tr>
<tr>
<td></td>
<td>(9.57)</td>
<td>(2.10)</td>
<td>(2.60)</td>
<td>(5.78)</td>
</tr>
<tr>
<td>HH Size</td>
<td>-518</td>
<td>152*</td>
<td>4,265***</td>
<td>1,980***</td>
</tr>
<tr>
<td></td>
<td>(281)</td>
<td>(61)</td>
<td>(76)</td>
<td>(170)</td>
</tr>
<tr>
<td>HDD</td>
<td>7.66***</td>
<td>0.90***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.05)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDD</td>
<td></td>
<td>4.21***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.07)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heated Area</td>
<td>10.01***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooled Area</td>
<td></td>
<td>2.12***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Area</td>
<td></td>
<td></td>
<td>0.21</td>
<td>3.61***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.11)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>Type-Cohort</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>FE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
<td>4,393</td>
</tr>
<tr>
<td>R²</td>
<td>0.549</td>
<td>0.570</td>
<td>0.496</td>
<td>0.284</td>
</tr>
</tbody>
</table>

*p <0.05, **p <0.01, ***p <0.001

Dependent variables are annual energy consumption for the four energy end-uses. Coefficients reflect the modelled effects of each variable on each energy end-use, measured in MJ. Income is measured in thousand 2015 USD, household size in number of householders, HDD and CDD in °F-day, and floor area in square-foot. HH = household, HDD = heating degree day. CDD = cooling degree day. FE = fixed effects. Type-Cohort FE are show in Table C.2 and displayed in Fig. 4.3.

The fixed effect coefficients for the house type and age-cohort combinations are shown in Figure 4.3. These results clearly demonstrate that single-family houses use far more energy for space heating. This is especially the case for older single-family homes. Within each cohort, single-family detached houses require 13-39 GJ more space heating annually than multifamily high units. Energy for space cooling follows the same pattern, higher in single-family and older houses, but the magnitude is much smaller, with single family homes requiring 3-4 GJ more space cooling within each cohort.

Single-family houses also use more energy for hot water, but the differences are relatively small, and there is no clear age-cohort trend, reinforcing the importance of household size above other characteristics in determining demand for hot water. Single-family detached homes use 5-10 GJ
more energy for other end-uses, compared to multifamily high homes of the same cohort. The cohort effect is reversed in this case for single-family detached homes; greater energy use for other end-uses in newer homes is likely due to trends in appliance use and ownership. Newer single-family detached homes tend to have more TVs, refrigerators, lights, and appliances, particularly homes built in 1990s and 2000s (Tables C.3, C.4).

In summary, single-family detached houses use more energy than multifamily homes for all end-uses, but especially space heating. Newer single-family detached homes are characterized by greater appliance ownership and greater other energy use, while for heating and to a lesser extent cooling, older homes require considerably more energy. Increasing floor area correlates with increased energy consumption for all end-uses, most notably space heating. Increases in income also correlate with higher energy use, especially for other end-uses and space heating.
Figure 4.3 Effects of house type and cohort on urban residential energy end-uses in 2015. Effects are coefficient offsets by type-cohort to the reference of Multifamily high-density homes built 2000+, and are estimated by the linear models summarized in Table 2. Heavier markers are used for effects which are significant at $p<0.05$.

Residential energy demand in counterfactual housing stocks

We now demonstrate scenarios of reductions in residential energy use under a housing stock counterfactual resulting from removing the cumulative effects of three federal policies, PHM TRA 86, and FIRREA from new housing construction. Fig. 4.4 (a) shows the actual and counterfactual post-1970 urban housing stock by type in 2015. In the counterfactual stock, 13.96 million houses (14.1%) are multifamily rather than single family. Fig. 4.4 (b) shows four scenarios of energy consumption in the counterfactual stock, compared to actual consumption. The increase in
multifamily housing reduces total urban residential energy by 356 PJ (4.6%) in CF1, 385 PJ (5.0%) in CF2, 514 PJ (7.0%) in CF3, and 645 PJ (8.3%) in CF4. Results per-household in Figure 4.5 show the lower and upper bounds of the percentage energy reduction from our scenarios for the average single-family household. Assuming no floor area reduction, energy is reduced by over one quarter (27% in CF1, 28% in CF2), with the more substantial selection effect by income (CF1) having a minimal effect on energy reductions. Including floor area reductions of 30% and 50% brings the percentage energy reductions to 40% (CF3) and 47% (CF4) per household, respectively. Over half of the reductions are from space heating in every scenario. We compare the range of reductions from a type switch with modelled energy savings from individual and combined energy efficiency measures in US single-family detached housing (E. Wilson et al., 2017), and find reductions from the type switch to be considerably larger.

GHG emission reductions in each scenario by energy end-use are shown in Fig. C.4, and range from 1.9 tons CO$_2$-eq (21.5%) reduction per affected house in CF1, to 3.8 tons CO$_2$-eq (44%) in CF4. Due to the higher GHG intensity per unit final energy, ‘other end-uses’ figure more prominently in the GHG savings, with comparable reductions to those from space heating. Although the effects of typology changes take time to accrue, there is clearly substantial potential for energy and GHG reductions from a policy environment which encourages more multifamily housing.
Fig. 4.4 Counterfactual urban housing stock and energy consumption, 2015. a) Actual and counterfactual 2015 urban housing by type. b) Actual and counterfactual urban energy consumption in 2015 by type. CF1 assumes only low and mid-income (LMI) households switch from single-family to multifamily. CF 2 assumes average households switch from single-family to multifamily, after controlling for income. CF1 and CF2 assume households switching to multifamily have no change in floor area. CF3 and CF4 assume floor area in counterfactual multifamily homes is reduced to 70%/50% of average single-family floor area. Cohorts before 1970 and manufactured homes are unaffected by the counterfactual, and omitted from the figure.
Fig. 4.5 Comparison of residential energy reductions per household in average post-1970 single-family housing. CF1 shows reductions for low-mid income households, CF2-CF4 for average households controlling for income effects. CF1, CF2 assume no change in floor area when exchanging single-family for multifamily, CF3 and CF4 add floor area reductions of 35% and 50%. Scenarios are compared with efficiency strategies in US single-family detached homes modelled by Wilson et al. (E. Wilson et al., 2017), VSHP = variable speed heat pump, 'economic elec. saving’ refers to implementing all electricity efficiency upgrades with positive NPV. Basis for % reductions is average single-family home affected by the housing stock scenario.

4.4 Summary and Discussion

Single-family homeownership is often described as part of the American Dream (Hirt, 2016), and this is reflected in policies at federal and local level that disproportionately assist home-owning single-family households. This policy preference is at odds with climate mitigation. Changing housing policy to be more encouraging of multifamily housing could support reaching GHG reduction targets, such as those set by the Paris Agreement. Our analysis finds substantially lower energy consumption in newer homes and multifamily homes. Lower energy consumption in newer homes is likely due to improved building standards and residential building energy codes, which were introduced in the 1980s and have steadily become more stringent over time (Hewitt, 2017). Older homes tend to have higher air leakage (Chan et al., 2013), and are more likely to have vented attics, less insulation, and less energy efficient windows (NREL, 2020; E. Wilson et al., 2017).
Suspected mechanisms for lower energy requirements in multifamily homes include structural characteristics including less externally exposed area (Obrinsky & Walter, 2016), higher urban heat island effects (Ewing & Rong, 2008), and higher thermal mass. Multifamily homes are also more likely to have newer space and water heating equipment (Figure C.8), and are far more likely to use electric-based heating (Figure C.10), which is more efficient (in final to useful energy conversion) than natural gas heating (EIA, 2017) which is more common in single-family.

Moving beyond a comparison of physical characteristics and energy consumption of housing types as they currently exist, it is helpful to consider how housing markets, housing characteristics, and the share of housing types might evolve in a policy environment that was less focused on supporting home-ownership of mostly single-family homes. Based on current correlations of household income, house type choice, and floor area demand, it is likely that an increase in the share of multifamily households would increase the average income and floor area consumption of multifamily households. Energy efficiency adoption may also be affected by a higher share of multifamily homes, but the overall impact is unclear. Among home-owners, single-family and high-income households are more likely to invest in energy efficiency (US Census Bureau, 2020a), but this group of households also has the highest energy consumption (App. C note 7). Potential changes in the average floor area of multifamily will be more likely to determine the overall energy savings.

Concrete steps that can be taken at the federal level to support multifamily housing include equalizing federal taxes and subsidies for owned and rental housing, and equalizing access to finance for multifamily and single-family investors (SI note 8). In addition to reducing the large difference in federal subsidies for homeowners and renters, increased support for rental housing could help reduce the number of very low income households who need, but do not receive, rental housing assistance (Landis & Reina, 2019). Many scholars question the benefits of home-ownership policy targets (Francisco, 2019; Glaeser & Shapiro, 2003) and alternative approaches
exist. For example, Germany has less emphasis on home-ownership, rental contracts which allow for indefinite leases, and greater scope for recourse against unsatisfactory landlords, resulting in a higher fraction of multifamily housing and renter households, and long average leases (Muellbauer, 2018). Barriers to multifamily housing also exist at the local level, where multifamily properties are often subject to higher effective property taxes (Goodman, 2006), and numerous land-use regulations restrict supply of multifamily housing (Chakraborty et al., 2010; Jackson, 2016; Knaap et al., 2007; Pendall, 2000). In addition to allowing increased supply of multifamily construction, relaxing local land-use regulations would also increase the rate of new housing construction generally (Been et al., 2019; Gyourko & Molloy, 2015), which would aid in replacing or renewing the houses with highest potential for energy reduction – older single-family houses. Greater support for multifamily housing could complement approaches to pricing carbon, as carbon prices which raised gasoline prices would likely incentivize denser urban development (Creutzig et al., 2015).

Our estimates of energy and GHG savings are based on a major alteration to the share of housing types in the 2015 urban housing stock. Other housing and demographic trends will have important influences on residential energy demand in coming decades. Growth in average floor area and reductions in household size have been important upward drivers of per capita residential energy demand since 1990 (Berrill et al., 2021b). Climate change, stronger population growth in warmer areas, and increasing adoption of air-conditioning (AC) have also increased demand for cooling. AC ownership is currently similar for housing types in the warmest regions, and slightly higher in single-family housing in cooler regions (Fig. C.11). Due to saturating AC ownership, current trends suggest the biggest societal driver of future cooling will be increases in cooled floor area per house, which would be smaller with greater shares of multifamily housing. The evolution of housing stocks by housing type and other characteristics (most notably age and size) will be of great relevance to future residential energy demand and GHG emissions in the US, and is a promising area for future work.
In this paper we provide evidence suggesting that US federal housing policy changes have encouraged construction of single-family housing and suppressed multifamily housing, increasing residential energy demand and GHG emissions. Increasing the multifamily share of housing can be expected to produce energy large savings, even with no change of household income or floor area. Policies that suppress demand and restrict supply of multifamily housing thereby directly obstruct a large potential for residential GHG emission reductions. Housing policy can support climate policy by removing barriers and disincentives to multifamily housing.
5 Material flows and GHG emissions from housing stock evolution in US counties, 2020-2060

*Peter Berrill, Edgar G. Hertwich*

Abstract

The evolution of housing stocks determines demand for construction materials and energy, and associated emissions of greenhouse gasses. Although construction of new housing can reduce energy intensity of housing stocks, emissions occur during material production and construction activity. In this paper we develop a housing stock model for all counties in the United States, incorporating flexible vacancy rates, which endogenously influence stock outflows and inflows. We project stocks of three house types (single-family, multifamily, manufactured housing) and ten construction cohorts for all counties in the United States, for the period 2020-2060. In five scenarios differentiated by stock turnover rates, population share by house type in each county, and floor area characteristics of new houses, we estimate inflows and outflows of housing units, floorspace and construction materials, and greenhouse gas emissions associated with material production and construction activities. Increasing the stock turnover rate increases future residential floorspace per person, material requirements, and emissions. Increasing the multifamily share of population and new construction, or eliminating the construction of very large new homes reduces future floorspace per person, material requirements, and emissions. Our results demonstrate the potential for local re-use of demolition materials in new construction.
5.1 Introduction

Buildings are a major contributor to anthropogenic greenhouse gas (GHG) emissions. The extent to which emissions can be reduced from construction and operation of buildings will play a key role in determining the feasibility of achieving ambitious climate change mitigation targets (Krausmann et al., 2020). The evolution of building stocks over time through construction and demolition induces demand for new material production, produces construction and demolition waste, and generates GHG emissions from material production and construction activities. Evolution of building stocks can reduce emissions from building energy use, as newer buildings are generally more efficient than buildings that are removed from the stock (Berrill et al., 2021a). Building stock models that project total stock levels, demolition and construction flows are widely used for estimating material stocks and flows (Lanau et al., 2019), and in some cases energy and GHG emissions from construction and operation of buildings (Hertwich et al., 2020; Roca-Puigros et al., 2020). The role of vacancies in building stock models, and their relation to construction, demolition, and related material flows, have until now received little attention in building stock models. This is a pertinent area for developing and improving the validity of building stock models. For example, regions with populations decline are likely to see vacancy rates increase (Deilmann et al., 2009; Wuyts et al., 2020), areas with high vacancy rates to begin with are likely to have less demand for new construction, while areas with low vacancy rates are likely to have higher demand for new construction (Zabel, 2016).

In this paper, we describe the development and application of a housing stock model for US counties, and project the evolution of the US housing stock by county over the period 2020-2060. We incorporate dynamic, county-specific vacancy rates in our model, and using historical survey data we estimate region and house type-specific ‘natural vacancy rates’ which housing stocks tend towards. Drawing on the observed and natural vacancy rates in each timestep, we develop novel approaches to modeling stock additions and losses. The application of the model to all 3,142 US
counties enables estimation of housing stock evolution, construction and demolition related material flows, and emissions at a local level. The high spatial resolution estimation of material flows can be used to demonstrate potential (or lack thereof) for circular re-use of construction materials locally. We demonstrate results of housing stock and material flows, GHG emissions associated with new construction, and the progression of residential floor space per person for five housing stock scenarios. The scenarios investigate the embodied material and GHG implications of different strategies with potential to reduce and energy consumption in US housing: increasing the share of multifamily housing, reducing the share of older buildings through increased rates of stock turnover, and reducing the average size of newly-built housing.

5.2 Representation of vacancy in existing research

Research on housing markets in economics has yielded evidence for the existence of natural vacancy rates, which in rental markets can be defined as the vacancy level where rent is at its long term equilibrium (Rosen & Smith, 1983). More generally, vacant housing can be understood as the result of a housing search process by households with varying preferences within a heterogenous housing stock (Wheaton, 1990; Zabel, 2016). Hwang and Quigley (2006), the first to include vacancies as an input to economic housing supply models, showed that lower vacancy rates are likely to persist in more heavily regulated housing markets. More recently, Zabel (2016) specified a model for changes in housing supply including vacancy rates, and found that vacancy above the natural rate has a downward effect on new housing construction, while vacancy below the natural rate has an upward effect on new construction. These economic studies provide some evidence and explanation for non-zero vacancy rates in normal housing markets, and also important indications of relationships between regulations, vacancy rates, and housing supply. Unlike dynamic stock models produced for material flow analyses (Lanau et al., 2019) however, these models focus only on housing supply, and do not disaggregate net stock growth into additions and losses.
In balanced housing stock-flow models used in industrial ecology and material flow analysis, vacancy rates have rarely been incorporated. Most often vacancy is disregarded completely, something that can lead to infeasible negative inflows in cases of negative stock growth (driven by population decline), as acknowledged by (Deetman et al., 2020). Vásquez et al. (2016) address this issue by adjusting their estimates of in-use stock by subtracting vacant floor area arising from declines in population or reductions in floor area per person, but they do not account for ‘market vacancies’ that exist in housing stocks. Deilmann et al. (2009) generated scenarios describing additions losses to stock in eastern and western Germany to 2050, highlighting the increase in vacancies that would occur in regions with declining population unless loss rates also increased. Roca-Puigròs et al. (2020) incorporate three occupancies states (stock used daily, stock used temporarily, vacant stock) in their description of the Swiss housing stock, but vacancy rates did not change over time, or play a role in determining stock inflows or outflows. For the Japanese city of Kitahyushu, Wuyts et al. (2020) use qualitative approaches to understand the phenomenon of vacant housing stock by district, and present a rationale for when urban mining should be considered to retrieve materials from vacant buildings. Reviewing these different considerations and treatments of vacancies in different strands of research, it is apparent that no housing stock model has yet incorporated changeable vacancy rates which endogenously influence demand for new housing, or losses from the housing stock.

5.3 Data and Methods

We develop a bottom-up housing stock model for US counties, classifying housing typologies by type (single-family, multifamily, manufactured housing), construction cohort, and vacancy status (occupied/vacant). The principal data sources used for model development are longitudinal ‘sample case history’ datasets spanning 1985-2017, indicating movement of housing units in and out of the housing stock (US Census Bureau, 2017c), and the corresponding American Housing Survey (AHS) microdata from which the sample case histories were produced (US Census Bureau, 2020a).
The sample case history files, and the ‘components of inventory change’ reports based on these data, demonstrate that a substantial portion of housing units moving in and out of the stock comes from sources other than new construction and demolition. Between 2011-2013 for instance, just 30% of ‘losses’ from stock were from demolition or disaster (Eggers & Moumen, 2011), with much of the remaining 70% coming from houses changing to non-residential uses, becoming damaged and thus unfit for habitation, or mobile/manufactured homes moving out from the site where they were last surveyed. Over the same period, 63% of ‘additions’ to the housing stock were from new construction, with other major sources of additions including conversions from non-residential to residential use, recovery from temporary losses (such as buildings that had previously been uninhabitable being repaired and brought back into the housing stock), and mobile homes moving into new sites. In these surveys, a housing unit is only considered to be ‘part’ of the total (occupied plus vacant) housing stock if it is physically fit for habitation, and available for residential use, i.e. not currently used for a non-residential purpose.

In this paper, we first model stock evolution considering additions to and losses from stock from all sources, using historical regional loss rates by house type, age, and vacancy status from AHS surveys. We then estimate how much of the stock additions and losses come from construction and demolition respectively, based on average historical relationships between construction and additions, and demolition and losses. Further details on model development can be found in the Appendix D. Figure 5.1 shows a schematic diagram of the model inputs and outputs, and Table 1 details the variable names and superscripts used in the equations that follow.
The starting point for our model is calculation of the occupied stock $S$ by house type, based on total population, population share by type, and average household size by type (Eq. 1).
We use population projections for US counties from Hauer, who projected US county population to 2100 based on a blended cohort-change differences and cohort-change ratios model (Hauer, 2019) for five shared socioeconomic pathway (SSP) scenarios (O’Neill et al., 2017). We adapt Hauer’s SSP2 (“middle of the road”) projection to 2060, scaled first to the US Census Bureau mid-range population projection (US Census Bureau, 2017a) (Figure D.1) and again to actual US resident population on July 1, 2020 (US Census Bureau, 2020c), to bring the projections in line with more up to date US population level and projections. We estimate changes in national average household size based on data from McCue (2018), and apply the same proportional reduction in household size to all house types (Figure D.2). For counties that experience growth in multifamily population share two of our scenarios (described below), we assume no change in household size by house type, as the increase in multifamily housing will already produce reductions due to the smaller average household size in multifamily housing. Initial data of household size and population share by house type in each county is from a combination of 1-yr and 5-yr population and occupied housing unit estimates for 2019 from the American Community Survey (ACS) Tables B25033 and B25127 (US Census Bureau, 2021). This estimation is elaborated further in Appendix D.1.6.

In the second step we estimate losses from the housing stock based on annual loss rates, which are summarized in Table D.1. Loss rates are converted from the per age-range specification to per age-cohort in each time step, and total loss flows ($L$) per house type and age cohort are then calculated based on existing stock ($S$) by type, cohort, county, and vacancy, and corresponding loss rates ($LR$) (Eq.2), assuming that average loss rates per Census region apply for SF and MF housing, and that national average loss rates apply for MH.

\[
L^t.c.k.v.y = S^t.c.k.v.y \times LR^t.c.r.v.y
\]
By adding an age-related dependency to loss rates, our modeling of decay of existing building combines the ‘lifetime’ and ‘leaching’ approaches described by Roca-Puigroès et al. (2020). The introduction of vacancy-dependent loss rates is a novelty of this model, and is motivated by the large differences in loss rates observed for occupied and vacant units; vacant units are much more likely to leave the stock than otherwise comparable occupied units (Table D1).

Next we calculate additions to stock, with separate formulations depending on whether occupied stock growth (OSG) in a model year is positive or negative. Positive and negative OSG generally correspond to positive and negative population growth, but reductions in household size can also generate positive OSG even in the case of zero or marginally negative population growth. In existing housing stock models, it is usually assumed that there will be no new additions to stock if the occupied stock does not grow in excess of stock losses. Our analysis of AHS data finds that this is not necessarily the case, at least at national and Census Region levels, where additions to stock occur even in times of negative OSG (Fig. D.4). This can be explained by demand for new housing existing within a region even if the occupied stock in the region as a whole declines. We use a linear model (Table D.4) to estimate the addition rate ($AR$) based on the OSG rate in cases of negative OSG. We then use this estimate of $AR$ multiplied by the total stock to calculate additions to stock $A_{-OSG}$ (Eq. 3).

$$A_{-OSG}^{t,k,y} = \overline{AR}^{t} \times S^{t,k,y}$$ (3)

For cases of positive OSG, we calculate annual additions to stock $A_{+OSG}$ as the sum of total stock growth and losses (Eq. 4), where total stock growth ($TSG$) equals the product of OSG, a ‘natural’ vacancy factor ($VF_n$), and a stock growth factor ($GF$).

$$A_{+OSG}^{t,k,y} = TSG^{t,k,y} + L^{t,k,y} = (\overline{GF}^{k,y} \times VF_n^{t} \times OSG^{t,k,y}) + \sum_{c,v} L^{t,c,k,y}$$ (4)

In Eq. 4 the natural vacancy factor $VF_n$ is equal to total stock divided by occupied stock, and is equivalent to $(1-V_n)^{-1}$, where $V_n$ is the natural vacancy rate. The $GF$ term is a factor which will
increase or decrease the level of stock growth (and additions to stock) in order to move the stock back towards the natural vacancy rate. For example, if vacancy rates are below the natural rate, \( GF \) will be greater than 1, which will cause the vacancy rate to decrease. If vacancy rates are above the natural rate, \( GF \) will be less than 1, causing the vacancy rate to increase. We specify a linear model to estimate \( GF \) as a linear function of changes in the vacancy factor (Fig. D.5-D.7). Because excess stock growth will tend to increase vacancy rates and vice versa, there is a very strong linear relationship observed historically between \( GF \) and change in \( VF \) (Table D.5). We then estimate the value of \( GF \) in each model year based defining change in \( VF \) as half of the difference between the actual vacancy factor in that year, and the natural vacancy factor, i.e. \( 0.5 \times (VF_n - VF) \). This specification determines that, in growing stocks, vacancy factors and (vacancy rates) will tend gradually towards the exogenously determined natural level. If the housing stock is already at the natural vacancy rate, \( GF=1 \) and \( TSG \) is simply the product of \( VF \) and \( OSG \).

Our estimates of the natural vacancy rates and factors for each house type and Census Region are estimated as the mean of values calculated from AHS data 1985-2019, with vacancy rates averaging approximately 10%, 15%, and 20% for single-family, multifamily, and manufactured housing respectively, with some variation around these levels for different Census Regions (Figure D.8). To describe the initial condition of the housing stock in 2020, we calculate vacancy rates by type, cohort, and county using data on occupied and total housing stocks from ACS Tables DP04 and B25127 (US Census Bureau, 2021). The total stock by type for the beginning of the next timestep \( y+1 \) is calculated as shown in Eq. 5, and vacancy factors are calculated as total stock divided by occupied stock, as shown in Eq. 6.

\[
S^{t,k,y+1} = S^{t,k,y} + A^{t,k,y} - L^{t,k,y} \tag{5}
\]

\[
VF^{t,y+1} = \frac{S^{t,k,y+1}}{S^{t,k,y=0,y+1}} \tag{6}
\]
In order to calculate material flows associated with additions and losses to stock, we first convert additions and losses into new construction and demolition. The portion of additions to stock coming from sources other than new construction varies by region and type, but additions from new construction tend to be around 85% of total additions (Table D.2). For demolition, we assume based on AHS sample case history rates that on average 35%, 20% and 50% of SF, MF, and MH losses from stock are due to demolition or disaster, which would determine the outflow of materials to reuse or waste treatment. The resulting estimates of material outflows are very sensitive to this conversion of total loss rates to demolition rates. The rates that we adopt are slightly higher than the average percentages in AHS data (Table D.3), as we assume that many of the houses that leave the stock for reasons other than demolition will likely be demolished in subsequent years, and therefore actual demolitions in a given year will include some houses which left the stock in previous years (which wouldn’t be picked up by AHS statistics of housing demolitions). Some remaining houses which leave the stock may never be demolished while materials are still usable, leading to ‘dissipative flows’ of building materials which cannot be recovered (Jelinski et al., 1992).

Estimates of average floorspace per house type and cohort by county are based on floorspace characteristics by Core-Based Statistical Areas (CBSA) from the AHS 2017 survey. Details for converting from CBSA to county resolution are given in Appendix D.1.7. With the exception of the Reduced Floor Area scenario described below, average floorspace by house type for housing built in the 2010s is assumed to be reflective of average floorspace in future cohorts (Fig. S10). Combining the occupied floorspace outputs with population estimates by county, we can calculate evolution of floorspace per person (m²/cap). Calculating floorspace per person as a model output contrasts with the approach taken in most housing stock models, where floorspace per person is an exogenously assumed model input reflecting service level (Hertwich et al., 2020; Müller, 2006; Roca-Puigròs et al., 2020). The approach taken in our model, where floorspace per person is a model output, facilitates the identification of different aspects of stock dynamics that are likely to
determine future growth of floorspace per person, as well as identifying strategies that can be pursued to limit this growth. We use floorspace per house distributions by type and cohort to convert construction inflows and demolition outflows into floorspace inflows and outflows. We obtain data of material intensities (kg/m²) of new residential construction in the US for seven major construction materials (steel, concrete, cement, aluminium, glass, wood, and copper) from databases and recent publications of material intensity for different structure types (Heeren & Fishman, 2019; Marinova et al., 2020; Pauliuk et al., 2020). GHG intensities of each of material production are estimated from a variety of sources (Hasanbeigi et al., 2016; Jones, 2019; Nilsson et al., 2017; Pauliuk et al., 2020), and assumed to decline moderately to 2060. Carbon intensity of construction activities (on-site transport and energy use) per m² new construction are estimated based on emissions from direct energy and transport inputs to residential construction (Berrill et al., 2020) divided by total residential floorspace added in 2012 (US Census Bureau, 2019, 2020b). These construction activity emission intensities are also assumed to decline moderately to 2060.

Five scenarios of housing stock evolution are generated along dimensions of population share by house type, housing stock loss rates, and average size of new housing (Table 5.2). The scenarios reflect housing stock strategies that may be adopted to reduce direct energy demand and emissions, and the effects of these scenarios on energy consumption and emissions is the focus of future research. In this paper we demonstrate housing and material flows, and related emissions, for each scenario at a local and national level. In a Baseline scenario, population share by house type is assumed to remain constant throughout the projection period. In a High Turnover scenario, we increase the loss rates from Table D.1 by a factor 1.5, which is equivalent to reducing average lifetime for all housing by one third. In cases of positive OSG, this will directly produce higher addition rates through the description of addition in Eq. 4. For negative OSG, we apply the factor of 1.5 to the additions estimated in Eq. 3. In a High MF scenario, we increase the share of population living in MF by 0.25 percentage points (p.p.) per year in counties whose population grows by at
least 5% over 20 years between 2020-2040, and 2040-2060. The *High Turnover & High MF* scenario simply combines the loss rate and population share assumptions of scenarios 2 and 3. For the High MF scenarios, we do not incorporate the exogenous reduction in household size per each house type, as reduction in population-wide household size will instead result from higher population shares in MF house types with lower household size. In a *Reduced Floor Area* scenario, we redefine the floor area characteristics of any house falling into the 3,000-3999 sqft and 4,000+ sqft bins such that these houses are instead in the 2,000-2,499 and 2,500-2999 sqft bins (Fig. S12). This has the effect of eliminating construction of any new housing which exceeds a total floor area of 3,000 sqft (279 m²). To put this scenario in context of recent trends, between 25-30% of new single-family houses built in the 2010s were 3,000 sqft or larger (US Census Bureau, 2020b). To compare with the global convergence of residential floor area per person to an average of 30 m²/capita assumed in a Low Energy Demand (LED) scenario (Grubler et al., 2018), or a US-specific interpretation of LED in which floor area reduces to 40 m²/capita (Hertwich et al., 2020), a household would require 7-9 inhabitants to justify living in a house with 3,000 sqft.

*Table 5.2 Five housing stock scenarios defined by stock loss rates and MF population share. High multifamily increases apply only to counties with growing population*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss Rate</td>
<td>Historical rates by region</td>
<td>1.5 * Historical rates by region</td>
<td>Historical rates by region</td>
<td>1.5 * Historical rates by region</td>
<td>Historical rates by region</td>
</tr>
<tr>
<td>MF Population</td>
<td>2020 share by county</td>
<td>2020 share by county</td>
<td>Increase 0.25 p.p. per year</td>
<td>Increase 0.25 p.p. per year</td>
<td>2020 share by county</td>
</tr>
<tr>
<td>Floor Area Distribution</td>
<td>Same as 2010s</td>
<td>Same as 2010s</td>
<td>Same 2010s</td>
<td>Same 2010s</td>
<td>No homes &gt; 3,000 sqft</td>
</tr>
</tbody>
</table>

82
5.4 Results

5.4.1 Aggregated National Results

Figure 5.2 shows annual additions and losses to stock, aggregated to the national level, from 2020 to 2060 for the five housing stock scenarios. In all scenarios, additions to stock are higher than losses, especially for single- and multifamily homes, reflecting expected stock growth. In the High Turnover scenarios we see much higher levels of stock losses and additions. In the High MF scenarios, MF inflows are substantially higher than in the Baseline, and become higher than SF additions in the late 2020s or early 2030s.
In Figure 5.3 we compare the evolution of SF and MF stocks in housing stock scenarios 1 and 4. With high stock turnover and high MF population, the total stock of SF houses grows to 103 million units by 2060, compared to 117 million units in the baseline scenario, from a 2020 stock of 94 million. The MF stock grows from 38 million units to 50 million (Baseline) or 64 million (high turnover and MF population) units by 2060. With higher stock turnover, we also see moderately faster decline of existing stock; pre-1960 housing declines from 27.3% of the total housing stock in 2020 to 14.4% in 2060 in scenarios 1, 3, and 5, and 11.9% in scenarios 2 and 4. These scenarios
demonstrate that even with a considerable increase in construction and demolition rates, over 10% of the housing stock in 2060 will be over 100 years old.

Figure 5.3 Evolution of single-family and multifamily housing stocks by construction cohort for two scenarios

In Figure 5.4 we show implications of the housing stock scenarios for residential floor area per person (m²/cap). In the Baseline scenario, we see steady growth of occupied floor area per person, from 60.2 m²/cap in 2020 to 69.1 m²/cap by 2060. This is because housing built from 2020 onwards is notably larger on average than the housing which leaves the stock (Fig. D.11). Speeding up the turnover rate in scenario 2 amplifies this trend, and floor space per person reaches 70.6 m²/cap by
Due to lower floor area per person in multifamily housing, increasing the multifamily share in scenario 3 attenuates the growth in floorspace per person, which grows to 64.4 m$^2$/cap by 2060. The lowest growth is in the Reduced Floor Area scenario, in which floor area per person stabilizes at 62.2 m$^2$/cap from 2040 onwards.

![Floor area per capita by housing stock scenario, 2020-2060](image)

**Figure 5.4 Occupied floor area per capita in each housing stock scenario**

In Figure 5.5 we chart floor area inflows and outflow, and cumulative GHG emissions from material production and residential construction activities in each scenario. In the High Turnover scenarios (2 and 4), floor area inflows and related emissions are larger, due to the higher requirements for new housing construction. Cumulative 2020-2060 emissions from new construction are higher in High Turnover scenario 2 than Baseline scenario 1 by 1.2 Gt CO$_2$e, which is slightly higher than current annual emissions from residential energy use (EIA, 2020b). Despite the fact that more new housing units would need to be built in the High Multifamily scenarios, and slightly higher material intensity (kg/m$^2$) in multifamily buildings, emissions from new construction are lower if the multifamily share increases, due to the much lower average floor area per unit. Cumulative 2020-2060 emissions from new construction are lower in High Multifamily scenario 3 than Baseline scenario 1 by 0.4 Gt CO$_2$e. Further reductions in emissions from new
construction results from the Reduced Floor Area scenario, where emissions are 0.8 Gt CO$_{2e}$ lower than in the Baseline scenario.

![Graph showing floor area inflows and outflows from construction and demolition, and cumulative GHG emissions from new residential construction for five housing stock scenarios.](image)

**Figure 5.5 a)** Floor area inflows and outflows from construction and demolition, **b)** Cumulative GHG emissions from new residential construction for five housing stock scenarios

### 5.4.2 Selected County Results

We next compare stock model results for four counties, selected to demonstrate the granular nature of the model output, and illustrate a variety of local population and housing stock growth trajectories (Fig D.3). Harris County, TX (home to the city of Houston, TX) is a county with strong projected population growth. Providence, RI is a county with positive, but low projected population growth. San Juan County, NM, is a county expected to see major population decline, and Marquette County, MI is projected to have modest population decline.

We show the projected total stock of multifamily housing for each of these counties in Figure 5.6 in the Baseline scenario. In Harris County, strong population growth translates into large increases in housing from the new cohorts. In Providence county, we see modest additions of multifamily housing in the new cohorts (much more than additions in the 2000s and 2010s, but less than additions in the 20$^{th}$ century cohorts), but the total stock grows only slightly, and new construction occurs mostly to replace losses from the existing stock. Providence is notable for having a much
larger share of pre-1960 housing than the other counties shown here. This is characteristic of early-developed urban counties in the US, particularly those in the Northeast and Midwest. In San Juan, the population decline is so substantial that no construction of new multifamily (or indeed single-family) housing is estimated between 2020 and 2060. Despite the steady decline of the housing stock, population decline is more rapid still, and so the vacancy rates increase (Fig D.10). Finally, Marquette County shows a modest decline in housing stock, starting in 2030 when the population starts to decline. However, there are still non-negligible flows of new construction in future cohorts to make up for losses from the existing stock (and accommodate declines in household size). Regarding the relation of housing stock growth and vacancy rates (Fig D.10), in fast growing counties such as Houston, TX, vacancy rates approach the natural rate relatively quickly, and remain steady once the natural rate has been approximated. In slow growing counties, vacancy rates move toward the natural rate much more slowly. As our formulation for stock additions under negative OSG has no basis in natural vacancy rates, but is rather estimated based on the magnitude of the decline in occupied stock (Eq. 3), it is less clear that stocks would tend towards natural vacancy rates in declining counties. To address this, we adjust loss and addition rates if vacancy rates become very large or very small, as described in Appendix D.1.2. However, in some cases such as San Juan, NM, even with zero construction vacancy rates can still increase.
In Figure 5.7 we demonstrate concrete material inflows and outflows associated with construction and demolition for the four selected counties. Of these four counties, only Harris County, TX, has strong enough population growth to see the multifamily population increase in *High Multifamily* scenarios 3 and 4. In Harris County, there are higher material flows associated with *High Turnover* scenarios, and lower material flows associated with *High MF* scenarios, consistent with Figure 5.5.
For the other three counties, there is no difference in population or occupied housing shares between scenarios 1 and 3, or scenarios 2 and 4. In the growing countries, material inflows are much larger than the material outflows. In the declining counties, material inflows may be similar or still larger than outflows (e.g. Marquette County), or in the case of San Juan, material inflows are much lower than outflows. The *Reduced Floor Area* scenario shows the smallest inflows of concrete in each case. The magnitude of difference between scenarios 1 and 5 depends on the relative share of large (single-family) homes in the stock growth of each county.

![Concrete inflows and outflows](image)

*Figure 5.7 Concrete inflows and outflows in selected counties for five housing stock scenarios. In Providence, San Juan, and Marquette counties, population growth is not high enough to activate the high MF scenario, and therefore Scenarios 1 and 3 are the same, and Scenarios 2 and 4 are the same.*

90
The quantification of materials outflows at local level for bulky low-value materials such as concrete that are expensive to transport can be used to estimate potential for material re-use within a limited geographic area. To demonstrate how this re-use potential varies throughout the country, in Figure 5.8 we show the ratio of cumulative demolition rated material outflows to 2020-2060 cumulative construction related material inflows for all materials. We use a logarithmic scale on this graph to better capture the variation between counties. For the nation as a whole this ratio is around 0.38; more construction material inflows are demanded than what comes out from demolition. However, as can be seen, a large number of (bright colored) counties have outflows that are higher than inflows. The dark colored counties are generally higher growth counties. In such locations there will be ample opportunity for material reuse in new construction, as there will be a lot of new construction, but reuse of waste materials will be far from sufficient to supply the total materials needed. In bright colored counties, a large portion of new construction could make use of materials source from demolition activities, but overall new construction is lower.

Figure 5.8 Ratio of cumulative construction material outflows to material inflows, 2020-2060, for US counties
5.5 Discussion

Given the very long average lifetime of housing in the US (Ianchenko et al., 2020), and the slowdown in stock turnover observed in some areas due in part to stringent local regulations (Reyna & Chester, 2015), there may be some scope for increasing the rate at which new housing replaces old housing. The potential benefits of increased stock turnover for reducing energy related GHG emissions are however not immediately clear. Because the average size of new housing is larger than most of the older houses that will be replaced, Baseline floor area per person is expected to increase steadily in the coming decades (Fig. 4), and this trend would be accelerated by higher turnover rates. Further, higher turnover necessitates increased construction and higher material flows and related emissions. Increasing turnover by a factor 1.5 would produce a cumulative increase in construction related emissions of about 1.2 Gt CO$_2$e over the period 2020-2060. Whether the energy and GHG reductions associated with more efficient newer housing would outweigh the floorspace increases and additional construction-related emissions is an important question for future research. The high turnover scenario would produce higher opportunity for material re-use, as the number of redundant vacant units (in excess of the natural vacancy rate) would be reduced, and their materials would become available for potential re-use. We do not currently model GHG benefits from material recycling or re-use in this model, but this has been shown to have potential for reducing emissions from construction (Hertwich et al., 2020), and could be investigated at a local level using the model we have developed here. Emission reductions from circular re-use of materials are not guaranteed, and depend on the appropriate estimation of the recycling or re-use credit, local demand for re-use, and level of material transport required (Andersen et al., 2020). The county-level depiction of material inflows and outflows in this model would lend itself well to more detailed analyses of potential for circular material use at a local level.

Both increasing the share of multifamily population, and reducing the construction of large (>3,000 sqft) new houses have the potential to reduce emissions from new construction, and reduce floor
space per person, which would imply further reductions in emissions from energy consumption. In our high multifamily scenario, annual additions of multifamily housing become higher than additions from single-family sometime in the late 2020s. This would be a substantial departure from current trends, but could be feasible if momentum to remove restrictions on multifamily development existing in most jurisdictions of the US (Gyourko et al., 2019) continues to build. The Minneapolis 2040 plan was approved by the city council, and declares intent to abolish the city’s single-family zoning (City of Minneapolis, 2019). Even in California, infamous for stringent land-use and development restrictions (Murray & Schuetz, 2019; Quigley et al., 2005), cities are considering the removal of single-family zoning (Bliss, 2021). Aside from land-use restrictions, federal tax and finance regulations also encourage single-family over multifamily development (Berrill et al., 2021a), while local property taxes also tend to be higher for rental housing (Goodman, 2006), which are predominantly multifamily. Restricting the construction of new homes larger than 3,000 sqft may be a larger challenge than removing barriers to new multifamily. While many of the federal and local policy changes (e.g. de-zoning, removal of lot size and density limits) that would encourage smaller single-family construction (Gray & Furth, 2019) are the same as those which would permit more multifamily, there are other forces of household preference and market structure which likely play a role in the growth of very large single-family homes in new construction. More research is needed to determine the causes for the growth in size of new single-family homes, and feasible strategies which could limit continued construction of very large homes.

Developments in material stock and flow modeling have brought about increasing spatial resolution, particularly in studies that combine material flow analyses with GIS (Tanikawa & Hashimoto, 2009; D. Yang et al., 2020). Although the spatial resolution of our housing stock model is not as high as GIS-based studies, the geographical unit of US counties is still useful for comparing local-scale material inflows and outflows, and the potential for local material re-use without the need for long-distance transportation. The introduction of dynamic vacancy rates into housing stock
(and flow) models is a particularly important innovation. Vacancy rates influence housing stock losses (Table D.1), demand for new construction (Zabel, 2016), and the potential for material recovery through urban mining (Wuyts et al., 2020). Dealing with changeable vacancy rates is an inescapable requirement for modeling building stock evolution in regions with low or negative population growth (Deilmann et al., 2009). As most industrialized and post-industrial nations fit this population growth paradigm, and with declining fertility rates globally (Vollset et al., 2020), more explicit consideration of vacancy in housing stock model projections will grow increasingly relevant.

5.6 Conclusions

Energy and environmental analyses of housing stocks can benefit from a localized model of stock evolution, as many aspects related to environmental performance, including energy demand, and potential for material recovery and re-use have geographic dependencies. In this study we present a novel housing stock model for US counties incorporating dynamic vacancy rates, and disaggregating housing stocks by type and construction cohort. We estimate natural vacancy rates which vary by region and house type, and specify the model to gradually reduce discrepancies between actual and natural vacancy rates at the county level. Vacancy rates approach the natural level in growing counties at a rate which depends on the level of growth, while vacancy rates are less predictable in declining counties, and may continuously increase in cases of strong population decline.

Our scenario results indicate that a shift to more multifamily housing, and reducing the share of very large homes in new construction, would lower floorspace per person and reduce emissions associated with new construction. Increasing stock turnover on the other hand would exacerbate the growth in floorspace per person and increase emissions from new construction. To prevent growth in floorspace per person, higher increases in multifamily population share, or considerable
reductions (~40% or greater) in the average size of new single-family homes would be required.
We compare total material inflows and outflows from new construction and demolition by county.
These results can serve as a detailed data source for assessing the potential for local material re-use within the residential sector. Future work will consider the overall GHG implications of the housing stock scenarios including energy use. Increasing the share of multifamily and reducing the size of new single-family homes are strategies which can reduce the embodied environmental burdens of new construction.
6 Strategies for climate change mitigation in residential buildings: a lifecycle perspective

Peter Berrill, Janet L. Reyna, Anthony D. Fontanini, Eric J.H. Wilson, Edgar G. Hertwich

Abstract

Increasing recognition is given in recent literature to the prominence of aggregate and per-capita residential floor area in determining energy and material demand, and GHG emissions in the residential sector. Sufficiency-based approaches to climate change mitigation therefore prioritize reduction of residential floor area per capita. In this chapter we combine outputs from a high spatial resolution housing stock model with a residential energy simulation model with rich characterization of housing characteristics to project energy demand and greenhouse gas emissions in the contiguous United States from 2020 to 2060. We develop twenty scenarios to compare different strategies for reducing emissions in the US residential sector. Increasing the multifamily share of new construction, restricting the size of new construction, and increasing the rate and depth of renovations each have the potential to reduce cumulative emissions by 1-1.2 Gt CO₂ (3.5-4%). Faster decarbonization of electricity supply can reduce emissions by 4.4 Gt (14%). Increasing stock turnover results in a more energy efficient housing stock, in terms of energy use per unit floor area, but due to increased construction and growth in overall floor area, total emissions are higher. A more ambitious combination of efficiency and sufficiency measures in housing supply and renovation, combined with greater decarbonization of electricity supply and material production, is required to achieve sectoral targets consistent with the Paris Agreement or limiting climate change to 1.5-2° C.
6.1 Introduction

Decarbonization and energy efficiency in residential buildings will play a central role in efforts to reduce global GHG emissions. In the U.S., energy-related emissions from residential and commercial buildings are declining much faster than those from industry and transportation (EIA, 2020b), largely due to a higher share of electricity in the energy mix coupled with steady declines in GHG intensity of electricity generation. Improvements in residential energy efficiency have contributed a little to reductions in US residential emissions, but much less than the ongoing decarbonization of electricity supply (Berrill et al., 2021b). A major determinant of energy and material requirements in residential buildings is house size, or the per-capita floor area consumption (Berrill et al., 2021a; Hertwich et al., 2020; Huebner & Shipworth, 2017). A recent shift towards sufficiency (over efficiency) in some sustainability research argues for a sustainable consumption transition based on absolute reductions in energy and material use (Cohen, 2020). Applied to residential buildings, the sufficiency perspective supports a reduction in residential floor area consumption per person, to somewhere in the range of 15-40 m²/cap (Cohen, 2020; Grubler et al., 2018; Hertwich et al., 2020). Current average floor area consumption in the US is 67 m²/cap in single-family homes, 43 m²/cap in manufactured housing, 41 m²/cap in multifamily, and 60 m²/cap across all house types (c.f. Chapter 5). As the size of new single-family homes has grown continuously over the past century, achieving a measurable reduction in floor area consumption in the US would require a major transformation in the characteristics of newly built housing, a restructuring of household arrangements (i.e. increases in household size) and structural characteristics of existing housing (e.g. conversion large homes into multiple housing units), or some combination of these measures.
In this chapter we make a comprehensive assessment of US residential sector GHG emissions for twenty scenarios, considering emissions arising from material production and construction activities in addition to emissions from energy use. The scenarios compares different strategies aimed at reducing the energy and GHG intensity of the residential sector, some focused on limiting growth of floor area per capita through altering the characteristics of new construction, some based on faster decarbonization of electricity supply, and others focused on reducing energy intensity through retrofitting the existing stock or increasing construction of new more efficient housing. This last strategy stems from the recognition that the long lifetime of residential buildings in the US (Ianchenko et al., 2020), and the slowing rate of building stock renewal in some high-demand markets (Hsieh & Moretti, 2019; Reyna & Chester, 2015), allows older buildings with lower efficiency to remain in stock for a long time. Our starting hypotheses are 1) increasing the rate of housing stock turnover has a greater potential for reducing residential sector GHG emissions than increasing the retrofitting of existing buildings, and 2) increasing the supply of multifamily and smaller single-family housing is will greatly increase the feasibility of reducing residential emissions in line with climate stabilization targets.

### 6.2 Perspectives from literature

The question of whether greater energy or environmental benefits accrue from retrofitting buildings or demolishing and rebuilding has been debated for some time (Power, 2008). Numerous studies have tackled this question, with varying system boundaries and assumptions, such as the modelled or assumed energy performance of the retrofit buildings vs new buildings, the building lifetime/analysis period used to compare the alternatives, or whether analyses were performed on individual houses or entire housing stocks. It is thus easy to find contrasting recommendations from the literature. In a study of Belgian housing, Dubois and Allacker recommend that common subsidy schemes for renovations with minor energy savings be abolished, and that public funding be instead used to support deep renovations, and demolition and reconstruction (Dubois & Allacker, 2015).
In contrast, Palacios-Munoz and colleagues use a case study multifamily building in Spain to estimate lower lifecycle impacts from retrofitting as opposed to demolishing and building anew (Palacios-Munoz et al., 2019). Many studies addressing this question focus on a single building, or selected buildings in a single region (Ding & Ying, 2019; Feng et al., 2020; Palacios-Munoz et al., 2019), and don’t consider heterogeneity and scaling effects across national building stocks. Some studies report a carbon or energy ‘pay-back period’ after which new construction becomes lower impact than a renovation alternative (i.e. when the additional emissions from new construction are balanced by the reduced operational energy emissions from the new building compared to the renovated one). In a case study of older housing in British Columbia, Canada, Feng and colleagues report that new built houses have lower lifecycle emissions than renovated houses after 10-15 years (Feng et al., 2020). In a study of historic housing in Hangzhou, China, Ding and Ying find that replacing historic buildings with efficient new buildings would require 10-24 years for the GHG investment to be recovered (Ding & Ying, 2019). A review of literature aiming to compare lifecycle carbon footprints of refurbishment or replacement alternatives summarizes that "it is still not possible to conclusively determine which of the alternatives is preferred" (Y. Schwartz et al., 2018). Although literature is clear on the importance of building age on energy demand (Salari & Javid, 2016), and how regulations suppress new housing supply (Been et al., 2019; Hsieh & Moretti, 2019), no study that we are aware of assesses the influence of increased housing stock turnover on residential energy or GHG emissions, meaning that a comprehensive assessment of the “demolish and rebuild” approach for reducing energy and emissions in a national housing stock is still lacking.

A crucial part of this question is the carbon emissions from material production and construction activities. If new housing with higher efficiency than renovated housing could be built without any emissions, then increasing the rate of new construction would be a sure bet to reduce emissions. However, that is not the case. Berrill and colleagues show that housing is the sector in the US economy with largest carbon footprint of capital consumption (GHG emissions associated with the
use of capital assets), and that investment into new housing generated an annual carbon footprint of 0.11 Gt CO$_2$e in 2012, equal to 1.5% of economy-wide emissions, or 9% of emissions from residential energy use (Berrill et al., 2020). Some research warns that we may exceed emission restrictions associated with climate mitigation targets due to emissions associated with construction of new buildings and infrastructure alone (De Wolf et al., 2017; Krausmann et al., 2020). There is potential for material and resource efficiency strategies, such as use of lower carbon building materials and more intense use of building stocks (i.e. reduced floorspace per capita), to reduce emissions associated with growth of building stocks (Churkina et al., 2020; Hertwich et al., 2020). It is clear however that emission reductions from building newer more efficient housing should be considered alongside the initial increase in emissions generated by their construction. Recent studies contains more detailed descriptions of national building stock used to assess scenarios of building sector GHG emissions (Roca-Puigròs et al., 2020; Sandberg et al., 2021), but the incorporation of material and construction related emissions alongside emissions from energy use (e.g. Hertwich et al., 2020; Pauliuk & Heeren, 2020) is rare.

Residential energy efficiency in its broadest sense can describe not just improvements in technical performance of building shells and appliances, but also changes in consumer choice and behavior (Levesque et al., 2019; Wolske et al., 2020), lower floorspace consumption (Cohen, 2020; Grubler et al., 2018; Hertwich et al., 2020), and a shift towards more efficient building typologies (Berrill et al., 2021a). In U.S. housing, technical strategies with high potential for energy and emission reduction include adoption of more efficient space and water heating equipment, and more efficient building envelopes (Langevin et al., 2019; E. Wilson et al., 2017). Increasing the share of households living in multifamily housing also has a large potential for reducing energy and emissions (Berrill et al., 2021a; Goldstein et al., 2020). This can be considered one aspect more compact urban development, which has been shown to have large potential for energy savings in buildings (Creutzig et al., 2015; Güneralp et al., 2017) and transport (Ewing & Cervero, 2017).
6.3 Data and Methods

We estimate future occupied housing stocks in US counties from 2020-2060 using a housing stock model developed by Berrill & Hertwich (2021) (Chapter 5 of this dissertation) for five housing stock scenarios defined by assumptions regarding future housing stock loss rates, multifamily (MF) share of population, and size characteristics of new construction (Table 6.1). County population projections are adapted from the SSP2 projection by Hauer (2019), scaled to the mid-range scenario from the most recent Census Bureau population projections to 2060 (US Census Bureau, 2017a). In high stock turnover scenarios (2 and 4), stock loss rates are increased from historical levels by a factor 1.5. In high multifamily scenarios (3 and 4), the multifamily population share increases by 0.25 percentage points (p.p.) every year for counties whose population grows by at least 5% over twenty years. Two periods are defined (2020-2040; 2040-2060) to identify such counties.

*Table 6.1 Five housing stock scenarios defined by stock loss rates and MF population share*

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss Rate</td>
<td>Historical rates by region</td>
<td>1.5 * Historical rates by region</td>
<td>Historical rates by region</td>
<td>1.5 * Historical rates by region</td>
<td>Historical rates by region</td>
</tr>
<tr>
<td>MF Population</td>
<td>2020 share by county</td>
<td>2020 share by county</td>
<td>Increase 0.25 p.p. per year</td>
<td>Increase 0.25 p.p. per year</td>
<td>2020 share by county</td>
</tr>
<tr>
<td>Floor Area Distribution</td>
<td>Same as 2010s</td>
<td>Same as 2010s</td>
<td>Same as 2010s</td>
<td>Same as 2010s</td>
<td>No homes &gt; 3,000 sqft</td>
</tr>
</tbody>
</table>

For the years 2020-2060 we calculate occupied housing stock by type and construction cohort in US counties. These outputs are then used to estimate total residential energy consumption by energy carrier and end-use, by house type and cohort, in all counties in the contiguous US (excluding Hawaii and Alaska) every five years from 2020 and 2060, using the ResStock residential energy simulation model (NREL, 2021). This model, built on the OpenStudio/EnergyPlus building energy simulation engine, draws on an extremely rich description of US residential building characteristics at various geographical resolutions ranging from national to county and Public Use Microdata.
Areas (PUMAs), depending on the characteristic in question (NREL, 2021; E. Wilson et al., 2017). For our scenarios, we develop the building characteristic descriptions in ResStock to be reflective of the occupied housing stock in 2020, and then modify these characteristics to represent geographically-specific housing characteristics in four future cohorts (houses built in 2020s, 2030s, 2040s, and 2050s) depending on expected adoption of residential building energy codes by states (EIA, 2020c), and updates to federal energy appliance standards (Electronic Code of Federal Regulations, 2020). Building energy codes mostly apply to building envelope characteristics, such as insulation and infiltration levels, energy ratings of windows, etc., while the federal efficiency standards apply to energy consuming equipment and appliances such as space and water heaters, air-conditioning systems, etc. We also consider trends in housing and energy appliance characteristics that are not directly based on codes and standards, but more related to household preferences and energy and appliance prices, such increases in the electric share of final energy carriers used for space and water heating, increased use of heat pumps, and increased adoption of air-conditioning equipment. We base our assumptions on increased electrification of space and water heating on the assumed spread between prices for electricity and natural gas in Census Divisions over the next three decades (EIA, 2021). For housing built before 2020, we model two scenarios of envelope retrofits and equipment replacements, informed by historic renovation rates and characteristics by region and house type. Two renovation scenarios are considered, one based on historic rates, and a second with increased renovation rates and deeper renovations, including greater electrification and diffusion of heat pumps for space and water heating. Development of appliance and envelope efficiency characteristics for the two renovation scenarios is described and illustrated in Appendix E.1.

We calculate energy related GHG emissions using standard emission factors for combustion of fossil fuels (Subpart C—General Stationary Fuel Combustion Sources, 2009), and two scenarios (‘Mid-Range’ and ‘Low Renewable Energy (RE) Cost’) of GHG intensity of electricity from
NREL’s standard scenarios (Cole et al., 2019), to represent moderate and more rapid decarbonization of electricity (Fig. E.12). Trajectories of GHG intensity of electricity are implemented at the level of 18 regional transmission organizations (RTOs). We use material intensities (kg/m²) of new residential construction in the US for seven major construction materials (steel, concrete, cement, aluminium, glass, wood, and copper) defined databases and recent publications of material intensity for different structure types (Heeren & Fishman, 2019; Marinova et al., 2020; Pauliuk et al., 2020). GHG intensities of each of material production are estimated from a variety of sources (Hasanbeigi et al., 2016; Jones, 2019; Nilsson et al., 2017; Pauliuk et al., 2020), and assumed to decline moderately to 2060. Carbon intensity of construction activities (on-site transport and energy use) per m² of new construction are estimated based on emissions from residential construction sectors (Berrill et al., 2020).

Figure 6.1 summarizes the data inputs, assumptions and various components of the model, which produces outputs of annual energy consumption by end-use and fuel, GHG emissions associated with energy use and material flows and GHG from new construction, for housing stocks by type and cohort in each county. A more detailed description for the housing stock model is provided by Berrill & Hertwich (2021), and documentation for the ResStock energy simulation model is provided by Wilson et al., (2017) and in the online project repository (NREL, 2021).
Figure 6.1 Schematic overview of model

6.4 Results

In Figure 6.2 we show annual trends of GHG emissions for combined housing stock, renovation and electricity scenarios, including emissions from material production and construction, as well as emissions from energy use. A direct assessment of the relative merits of increased renovation vs faster demolition and rebuilding can be made by comparing the baseline, advanced renovation scenario against the high turnover, regular renovation scenario. From these results is it clear that increased renovation has more potential to reduce overall GHG emissions. The high turnover scenario actually shows increased emissions relative to the baseline. Scenarios incorporating
increased multifamily housing and reduced floor area have very similar total emissions trajectories, and these are the housing two stock strategies with greatest emissions reduction potential. A low RE cost electricity scenario would allow emissions to decrease much sooner, to lower levels. We indicate on these figures a 2030 intermediary target associated with limiting climate change to 1.5°C warming, requiring a halving of 2020 emissions by 2030 followed by more rapid reductions to achieve net-zero emission by 2050 (Otto et al., 2020; Rockström et al., 2017). We also indicate a 2050 goal represented by the US’s nationally determined contributions as part of the 2015 Paris Agreement, which targets an 80% reduction of US 2005 emissions by 2050 (UNFCC, 2015). As a basis for the Paris 2050 target, we calculated total residential emissions in 2005 by combining residential energy emissions (EPA, 2020) with emissions from investment in new housing in 2005, using data from Berrill et al. (2020). None of the scenarios considered come close to achieving the 1.5°C or Paris Agreement emission reduction targets.
Figure 6.2 Total annual emissions from residential energy use and construction for combinations of housing stock and renovation scenarios, 2020-2060, for a) Mid-case and b) Low RE Cost electricity decarbonization scenarios.
To help explain the diverging emissions projections in the stock and renovation scenarios, we turn to Figure 6.3, where we break differences in cumulative 2020-2060 emissions in each stock-renovation scenario compared to differences related to construction of new housing, energy use in pre-2020 housing, and energy use in new housing. All of the scenarios in Figure 6.3 are assessed with respect to the baseline with regular renovation, and all results are based on Mid-Case Electricity GHG scenario. In the high stock turnover scenarios, existing houses are removed faster, which explains the reduced emissions from energy use in pre-2020 housing. However, the higher turnover necessitates increased new construction, leading to higher emissions from construction, and higher emissions from energy use in post-2020 housing. The net change in GHG emissions depends on the balancing of these different factors. In high stock turnover scenarios (2 and 4), increased emissions from new construction and new housing outweigh emission reductions from existing pre-2020 housing. Higher stock turnover does reduce total emissions from energy consumption, due to higher efficiency in newer homes. However, this difference turns out to be quite small, and not at all large enough to make up for the additional emissions from new construction. We analyze this finding further in the discussion section.

Scenarios based on increased shares of multifamily housing (3) and smaller new single-family housing (5) are much more likely to generate emissions reductions, but for different reasons. Comparing the two stock scenarios with lowest emissions (scenarios 3 and 5, both with advanced renovation), the reduction in emissions from energy use in new housing are greater in the high multifamily scenario, suggesting that increasing the multifamily share is more effective at reducing energy related emissions than building smaller single-family homes. The reduction in emissions from construction is however greatest in the reduced floor area scenarios, illustrating that building smaller (single-family) homes has greatest potential to reducing construction emissions, as shown in Chapter 5. The combination of high turnover and high multifamily in scenario four was designed to test the potential increased replacement of older, energy intensive single-family housing with
new efficient multifamily housing. Under assumptions of either regular renovation or advanced renovation, these scenarios are very similar to the baseline scenarios, as the multifamily increase lowers emissions, but the higher turnover increases emissions by a similar amount. To put the differences in cumulative emissions into perspective, the high turnover, regular renovation scenario has almost 1 Gt GHG emissions more than the baseline regular renovation scenario (c.f. the net difference line), which is approximately equal to one year of current annual emissions (EIA, 2020b). Meanwhile, cumulative emissions in the high multifamily and reduced floor area scenarios with advanced renovation are more than 2 Gt lower than the baseline scenario with regular renovation.

In Figure 6.4 we summarize cumulative 2020-2060 GHG emissions for the five housing stock scenarios, two renovation scenarios, and two electricity supply scenarios. This figure illustrates that the high multifamily and reduced floor area scenarios have approximately equivalent emission reduction potential, and that greater emissions are possible from increasing the renovation in the
existing stock. Compared to changing the characteristics of new construction or renovating existing housing, increasing the rate of decarbonization of electricity has the greatest emission reduction potential (LowREC Electricity scenarios). The scenario with greatest reduction potential is the reduction floor area stock scenario with advanced renovation and Low Renewable Energy cost electricity supply, where emissions are 6.6 Gt (21%) lower than the baseline stock scenario with regular renovation and Mid-Case electricity supply. A version of Figure 6.4 demonstrating emission reductions relative to the baseline is shown in Appendix Figure E.14.

We finally demonstrate some results illustrating the relevance of future stock dynamics on the identification of local optimal strategies for reducing emissions from the housing stock. As indicated in Figure 5.6 of Chapter 5, different regions can have very different housing stock age profiles, as well as projected housing stock growth. The combination of these and other characteristics (including climate, housing type mix, etc.) can influence the identification of optimal emission reduction strategies. In Figure 6.5 we show projected housing stock growth (2020-2060) vs the share of 2020 housing that was built before 1960 for each US state and the District of Columbia (DC). What is immediately clear from this figure is that most states with high shares of older housing are less likely to experience significant stock growth in the next forty years. Conversely, states with higher projected stock growth tend to have lower shares of old housing.
Furthermore, most of the states fitting the “old housing, low-growth” pattern also have cold climates, and therefore have heating-dominated energy requirements. Strong implications for identification of high-potential emission reduction strategies in different states can be drawn from Figure 6.5. In “newer housing, high-growth” states such as Arizona, Florida, Texas, Utah, etc., the potential for emission reduction through prioritizing more efficient, smaller housing typologies is very substantial. On the other hand, in the “old housing, low-growth, cold-climate” states such as Rhode Island, Pennsylvania, Connecticut, Illinois, and Michigan, although improving the efficiency of new housing is definitely helpful, old housing will remain proportionally more prominent in the housing stocks, and much more of the emission mitigation potential will therefore lie in increasing the rate and depth of energy renovations to existing housing. This is especially true considering that house age has a far greater influence on space heating demand than any other end-use (Berrill et al., 2021a) (Chapter 4, Figure 4.3).

Figure 6.5 Comparison of projection stock growth and percent of housing stock built before 1960 in all states. Trend line linear model excludes the outlier of DC
6.5 Discussion

Based on the results shown, we firmly reject our first hypothesis that increasing stock turnover has a greater potential for reducing residential GHG emissions than retrofitting. While higher turnover does reduce emissions related to residential energy use (compare red and blue bars in scenario 2 results in Fig. 6.3), this reduction is minor. The crucial explanation for the limited reduction in energy and emissions from greater supply of new housing is the difference in floor area in new vs old housing. Growth in average size of new housing has been high through the mid-twentieth and early twenty-first centuries, and has primarily occurred in single-family homes (Appendix D Figure D.11). The average size of a new single-family home completed in 2015 was over 60% higher than in 1975 (250 m$^2$ vs 155 m$^2$) (US Census Bureau, 2020b). Although the growth in floor area of new homes appears to have peaked temporarily in the mid 2010s (US Census Bureau, 2020d), without a major transformations in new construction it is unlikely that new single-family homes will return to sizes observed of homes built in the early/mid twentieth century. Therefore, although new housing is much less energy intense per unit floor area than older housing, the size differential means that energy savings associated with increased stock turnover are limited. This finding fits with a multi-country analysis of the effects of increased residential energy efficiency when combined with larger homes sizes (Viggers et al., 2017). If the average size of new housing were to decrease, the GHG benefits of increased housing stock turnover would increase accordingly. If floor area of new housing by type does not decrease measurably, other options to reduce residential emissions through lowering floorspace per person including increased household sharing (Ivanova & Büchs, 2020) and increased shares of multifamily housing.

Given the prominence of single-family housing in the US housing stock, and the “American Dream” (Hirt, 2016), increasing the share of population living in multifamily housing may at first seem like an unworkable strategy. However, there are a large number of trends and direct policy levers which, if deployed, would make such a scenario less far-fetched. First of all, much U.S.
population growth in the coming decades is expected to take place in urban counties (Hauer, 2019), which tend to have higher share of multifamily housing (Fig. E.15). Thus, even without changing the population share by house type in each county, the locations of population growth would suggest a small growth in the national multifamily population share, unless all urban population growth occurs in ever-sprawling suburbs. The supply of new multifamily housing is however restricted in almost every region of the U.S through local land-use restrictions, such as zoning large parts of urban areas for single-family housing only, minimum lot size restriction, height and density limitations, etc. (Chakraborty et al., 2010; Gyourko et al., 2019). As our housing stock model results suggest, removal of restrictions might have limited effect on increasing multifamily supply in regions with low population growth (this has been shown to be the case when moderately removing some land-use restriction in Chicago, a city which is not growing (Freemark, 2019)). On the other hand, in growing regions there is empirical evidence for unmet demand for smaller-lot housing which does not satisfy local restrictions (Gray & Furth, 2019), and that removal of restrictions can change the number, location, and types of buildings brought to market in a relatively short time (Gray & Millsap, 2020). After Minneapolis’s decision to abolish single-family zoning (City of Minneapolis, 2019), other jurisdictions (e.g. Oregon state, cities of Berkeley and Sacramento, CA) are passing legislation to enact similar changes (Bliss, 2021). Not all efforts to reduce restrictions and increase supply have been successful; multiple attempts to increase housing supply by reforming land-use restrictions in the entire state of California (including Senate Bills 50, 827, and 1120) failed to gain approval of state legislature (Brasuell, 2020).

Barriers to multifamily housing also exist at federal levels. Equalizing federal tax and finance treatment for single-family and multifamily housing could increase supply of multifamily (Berrill et al., 2021a), while removing or restructuring the federal mortgage interest tax deduction would reduce subsidies and incentives for build large single-family homes (Glaeser, 2009). Policies more traditionally linked to residential energy efficiency also play an important role in the trajectory of
residential GHG emissions. Increasing energy efficiency through improved building energy codes and appliance standards are a straightforward and effective tool for reducing residential emissions (Kotchen, 2017; Mauer & DeLaski, 2020). Without much stronger diffusion of all-electric new homes and electrification renovations than we currently model in this chapter, fossil fuels will still deliver a sizable share of residential energy services through mid-century (Fig. E.13), and if that is the case, improving the efficiency of fossil consuming appliances is of great importance. Recent rollbacks of federal furnace and water heater appliance standards therefore represent very unfortunate, avoidable obstacles to residential sector decarbonization (Somberg, 2021).

A major determinant of future emissions from housing is the pace of decarbonization of electricity supply. Faster decarbonization can have a very large impact on reducing annual residential emissions, particularly in the short term. In order to meet the policy targets indicated by the US’s Paris 2015 nationally determined contribution, or a more ambitious aim of limiting climate change to 1.5°C warming, electricity supply will need to decarbonize even faster than the NREL Low Renewable Energy Cost scenario employed in this analysis, and residential energy supply will need to convert to electricity much sooner. Analyses of deep electrification in new construction, and additional combinations of the stock strategies (e.g. higher multifamily and reduced floor area) would therefore be very valuable extensions to the research presented here.

Emissions from material production and construction activity are another crucial part of future residential sector emissions, as their share of residential emissions will grow as energy related emissions decrease (Fig. E.13). In this analysis we don’t consider emission reductions which could be achieved by increasing the share of low carbon materials, or reduced emissions associated with higher levels of material recycling or re-use. Such strategies have demonstrated potential for emission reduction in national (Pauliuk & Heeren, 2020) and global analyses (Andersen et al., 2020; Churkina et al., 2020; Hertwich et al., 2020), and would be a promising avenue for future research with national or regional focus.
6.6 Conclusion

In this chapter we assess the GHG emission reductions potential in the US residential sector from altering the type, size and rate characteristics of new construction, increased rate and depth of energy renovation, and electricity decarbonization. Our results show that increasing stock turnover would not reduce emissions, due to increased construction related emissions, and because reductions in energy related emissions are limited by the differences in average floor area of new and older housing. Although newer houses are much more efficient, they are also much larger than older houses which are removed from stock.

In the endeavor to reduce GHG emissions to shift climate change trajectories to 2°C warming or lower (Höhne et al., 2020; Otto et al., 2020), it is imperative that each sector seizes the opportunities which are likely to maximize emission reductions. For the residential sector in the U.S., more rapid decarbonization of electricity, higher rates of deep energy renovations, smaller new single-family homes and higher shares of multifamily housing are the surest strategies to reduce emissions, in that order. The strategies we identify as having high emission reduction potential are all subject to policy influence, for instance through stronger regulation and pricing CO₂ emissions in electricity markets, through removal of federal and local regulatory barriers to new multifamily and smaller single-family housing, and through more ambitious federal appliance standards, state adoption of building energy codes, and local programs for improving energy efficiency in existing housing. In addition to identifying best strategies for reducing residential emissions as a whole, our results also support identification of location-specific best strategies, such as renovation in regions with old housing and low projected housing stock growth, and focusing new construction on smaller housing and more multifamily in regions with high projected growth. Greater adoption of sufficiency oriented strategies will require more than policy support. Public awareness and appreciation of sufficiency-based approaches to climate change mitigation will also be needed to encourage societal adoption of reduced floor space per person, and increase public support for policies which
encourage supply of smaller housing typologies. Only with meaningful scale-up of sufficiency and efficiency strategies in housing will external improvements, such as decarbonization of energy supply and material production, be sufficient to set the US residential sector on an emissions trajectory that has real potential mitigate extreme climate change.
7  Conclusion

7.1  Chapter summaries

The research chapters of this dissertation fit broadly into two groups. Chapters 2-4 describe environmental impacts coming from residential sector activities in recent years and decades, and investigate different policy, technical, and demographic influences on energy demand and GHG emission trends. Chapters 5 and 6 look to the future and project possible trajectories of residential energy and emissions based on scenarios of housing stock evolution with different type, size, and efficiency-related characteristics, and two scenarios of electricity GHG intensity. Chapter 2 demonstrates that construction of new housing makes up an important part of overall residential emissions; 9% and 14% in 2007 and 2012 respectively. It is likely that this share will grow in the future, as material production will struggle to decarbonize at the same rate or to the same extent as energy supply. As such, in prospective analyses of residential emissions it is important to consider emissions from new construction in addition to influences of new construction on energy demand and emissions.

Chapter 3 demonstrates that decarbonization of electricity supply is the primary reason that residential GHG emissions declined between 1990-2015. Residential emissions actually grew until 2005 and declined thereafter, once electricity GHG intensity started to decline in earnest. Some demand-side changes (efficiency improvements, stock turnover, fuel switching, etc.) also contributed to emission reductions, but on a much smaller scale than electricity decarbonization. After population growth, the two major trends behind growth of emissions were reductions in household size, and increases in conditioned floor area (incorporating both growth in heated floor area and increased access to air-conditioning equipment). Reductions in household size and increases in house size and AC ownership all contribute to increases of conditioned floor area per
person (m²/cap), which is identified in literature and in several sections of this dissertation as a key metric in determining residential energy demand and material requirements for new construction.

In Chapter 4, we link changes in federal policies to increases in residential energy and GHG emission through policy effects on housing supply by type, and influences of housing type on energy demand. Although changing the type mix of new housing that is built in a single year exerts only a small change to the energy-consuming characteristics of the entire housing stock, if such influences persist over years and decades, their cumulative effect can be considerable. Our policy counterfactual in Chapter 4 estimated that due to federal housing policies over the years 1973-2015, approximately 14 million housing units were built as single-family rather than multifamily. Strong correlations between house type and energy consumption imply that reversing these policy influences would reduce total urban residential energy use by 4-7%, or 25-47% per affected household. In order to begin to create a less energy and GHG-intensive housing stock, it is crucial to steer new housing supply towards more efficient typologies immediately. This chapter suggests that increasing the share of new housing built as multifamily would be very effective in doing so. On the other hand, any housing policy (federal or local) that incentivizes or encourages greater supply of single-family over multifamily homes is in direct opposition to policies and ambitions to mitigate climate change through reducing GHG emissions.

We develop a novel and localized housing stock model in Chapter 5 to demonstrate housing stock scenarios by house type for US counties, implementing different assumptions regarding the rate of stock turnover, multifamily population share, and floor area distributions of new housing. These scenarios are used to estimate material requirements and total GHG emissions embodied in new construction, and evolution of floor area per person. If floor area characteristics of housing built in the 2010s remain constant over the next four decades, floor area per person will rise steadily to 2060, primarily because newly built (single-family) homes are considerably larger than the older homes that leave the stock. This increase would be amplified by increasing the rate of stock
turnover. Two scenarios are elaborated that reduce emissions from new construction and attenuate the growth in floor area per person. These scenarios involve increasing the multifamily population share in counties with growing populations, or changing floor area distributions so that no new housing is larger than 3,000 sqft \((279 \text{ m}^2)\). Such changes would involve large shifts in policy and current housing characteristics trends. We discuss challenges surrounding these changes in the policy implications section of this conclusions chapter.

In Chapter 6 we extend the analyses of Chapter 5 to include energy and associated GHG emissions for the housing stock scenarios, and we expand the scenario descriptions to incorporate two levels of energy renovations to existing housing and two future electricity GHG intensity scenarios. The aim of this chapter is to assess the GHG mitigation potential of different technical strategies to decarbonize the US residential sector, and identify which strategies can bring about the greatest reductions. We address the open question of whether retrofitting existing stock or demolishing and rebuilding has greater potential for emission reduction. Considering emissions from construction and energy use, rebuilding faster will increase overall emissions. This will happen first of all because of the greater embodied emissions in new construction, but secondly because real efficiency gains (reduced \(\text{MJ/m}^2\)) in new housing are almost cancelled out by large floor area increases that occur when replacing older homes with new homes. Increasing the rate and depth of energy retrofits of existing homes is therefore a much more reliable strategy to reduce residential emissions than hastening the rate at which the housing stock turns over.

Changing the characteristics of new housing on the other hand does have potential for reducing emissions associated with construction and energy use in new housing. Increasing the percentage of population living in multifamily housing from 21\% to 29\%, over 40 years would reduce cumulative 2020-2060 emissions by 3\%, approximately the same reduction as increasing the renovation rate by factor 1.5. Reducing the floor area distributions in new construction so that no new home built from 2020 onwards exceeds a floor area of 3,000 \(\text{ft}^2\) would reduce the average size
of new single-family housing by 22%, and this change on its own could reduce cumulative 2020-2060 emissions by 5%. Similar to historical trends shown in Chapter 3, the single measure with greatest potential to reduce residential emissions over the next four decades is to increase the rate of electricity decarbonization. In the two electricity scenarios considered (from NREL’s “standard scenarios”), average national CO₂ intensity declines from a 2020 level of 347 kg CO₂/kWh to 250 CO₂/kWh in 2040 and 165 CO₂/kWh in 2050 (Mid-Case Scenario), or 125 CO₂/kWh in 2040 and 85 CO₂/kWh in 2050 (Low Renewable Energy Cost Scenario). The more ambitious decarbonization trajectory would reduce cumulative 2020-2060 emissions by 4 Gt CO₂, or 13%, a larger emission reduction than the high multifamily, advanced renovation, and reduced floor area strategies combined. Future extensions to the research demonstrated in Chapter 6 will consider more rapid growth of electricity as the predominant energy source in new homes.

7.2 Synthesis and Policy Implications

The finding that the greatest technical potential for decarbonizing the US residential sector lies in the electricity supply system corroborates research on the entire building sector in the US (Langevin et al., 2019), as well as suggesting a continuation of the prominent role of decarbonizing electricity supply illustrated in Chapter 3 (Berrill et al., 2021b). How to achieve more rapid decarbonization of electricity in the US is a question occupying many researchers (e.g. Cole et al., 2019; Joskow, 2020; Victor et al., 2018), and is not the focus of this dissertation. In the following paragraphs, I therefore focus discussion on the feasibility and challenges surrounding GHG mitigation strategies relating to evolving characteristics of the US housing stock. It is worth noting that decarbonization of energy supply will be much easier if demand-side improvements help to limit and reverse the growth of absolute energy demand (Grubler et al., 2018; C. Wilson et al., 2012).

The simplest way to reduce future emissions from residential construction and energy use is to reduce the growth of aggregate and per capita floor area consumption, either by increasing the share
of multifamily in new construction, reducing the average size of new single-family construction, or both. Minimum lot sizes that encourage larger homes are a common feature of local land-use restrictions (Gyourko et al., 2019; Gyourko & Molloy, 2015), while minimum home sizes may be stipulated in more restrictive local regulations (Desegregate Connecticut, 2021). Restrictions on maximum house size are much less common (a recent exception in Portland, OR is discussed below), and usually expressed through maximum floor area ratios (maximum allowable ratio of floor area to lot size) (LeSher et al., 2018). As floor area ratios are often accompanied by large minimum lot sizes, they rarely limit the construction of very large homes, but they do tend to limit the height of multistory buildings (Gyourko & Molloy, 2015). Attempting to implement more widespread limits on the maximum size of new housing would probably be quite difficult, and may face opposition from homebuilder industry groups, homeowner associations and sections of the public. It may then be more practical and feasible to reduce the frequency of very large homes by removing restrictions and policies that inhibit and disincentivize development of multifamily and small-lot single-family homes.

Demographic trends support the notion that less very large housing is needed. Almost all household growth in the US is of households of one or two people (U.S. Census Bureau, 2020b), which is reflected in the continued slow decline of household size illustrated in Chapter 3. Recent research shows substantial potential for reducing energy demand and emissions through a convergence of per capita floor area consumption to a level of 30 m²/cap globally (Grubler et al., 2018), or 40 m²/cap in the US (Hertwich et al., 2020). Taking the 3,000 ft² (279 m²) threshold above which no new homes are built in the Reduced Floor Area scenario of Chapters 5 and 6, and the limit of 40 m²/cap, a household would require seven occupants to justify such a large home. As essentially all of the household growth in the US is of one and two person households, we may well ask who are the very large (>3,000 ft²) homes being built for, and is such space necessary? Reducing floor area consumption to 30 or 40 m²/cap in the US may seem a distant prospect at the moment (current
national averages are 67 m²/cap in single-family, 43 m²/cap in manufactured housing, 41 m²/cap in multifamily, and 60 m²/cap across all types). On the other hand, establishing a consensus that very large homes are very rarely ‘necessary’ and never desirable from a climate change mitigation perspective seems like a less controversial proposition. Increasing public awareness of the strong connection between home size and residential GHG emission may dampen demand for very large new homes, particularly if peer influences are leveraged (Wolske et al., 2020), and if local regulations actually allow for greater supply of smaller typologies.

Increasing the total volume of new housing construction may also lower the average size of housing supply. Some explanations for the continued growth in size of new single-family housing over time center on the argument that purchasing new housing has increasingly become attainable only for high-income households, who tend to buy larger more expensive homes, and that lower or middle-income households can no longer afford to build or buy new homes (Carlyle, 2016). Increasing the affordability of newly built homes would likely go hand in hand with reducing their average size.

On this point, a restructuring of federal subsidies for home-ownership may make a lot of sense. The Home Mortgage Interest Deduction (HMID) is a federal tax deduction that subsidizes the cost of home-ownership. In a 2003 working paper, Glaeser and Shapiro investigated the effects of this deduction and noted that over approximately forty years, changing levels of the HMID had no effect on increasing home ownership, the apparent aim and raison d’être of the HMID (Glaeser & Shapiro, 2003). What the deduction does achieve however, is increased housing expenditures, particularly among wealthier households; around 75% of the deductions are claimed by households earning over $100,000 annually (A. F. Schwartz, 2015). This suggests that a primary outcome of the HMID is that wealthier households buy more expensive, larger homes (Glaeser, 2009). If this is the case, the HMID stands in direct opposition to reducing residential emissions through reducing the construction of very large homes. In Chapter 4 we recommend equalizing federal tax and finance regulations that currently encourage supply of single-family over multifamily homes. Restructuring
the HMID is a third way in which federal policy can be restructured to support climate mitigation, by removing incentives for building larger homes. Doing so would be an impressive feat of politics. Despite it’s unambiguously regressive nature, the HMID has proven to be very resilient against attempts at serious revision by both Democratic and Republican administrations, leading some analysts to dub it the ‘sacred cow’ of Federal tax policy (Dreier, 2006). Although President Trump’s 2017 Tax Bill did reduce the magnitude of the largest deductions (see note 8 of Appendix C.1), more substantial alterations would be required to scale back it’s regressive nature and remove the incentives for buying bigger, more expensive homes (Glaeser, 2009).

At the local level, there are encouraging examples of scaling back land-use restrictions, such as motions to remove or relax single-family zoning in cities including Minneapolis, Berkeley, Sacramento, Seattle, and Portland (Bliss, 2021). In addition to allowing buildings up to fourplexes in areas previously reserved for single-family homes, Portland’s ‘Residential Infill Plan’ restricts the size of new homes that replace existing homes to 3,500 ft$^2$ (Bailey Jr, 2020). A 2019 state-wide bill in Oregon also ended single-family-only zoning in most cities (House Bill 2001, 2019). As far as impacts on future residential energy and emissions are concerned, these are all positive developments. The scale of future impact is strongly dependent on how much new housing will be built in ‘de-zoned’ locations, and this in turn depends on local population projections. The differing housing growth futures in counties and states with contrasting population growth trajectories (Figure 5.6, Figure 6.5) helps to make this clear. Even if counties like Providence, RI changed zoning laws to be much more permissive of multifamily and smaller single-family, due to low projected population growth, new housing supply would still merely replaces older houses leaving the stock, and that will not happen very quickly. The potential for new, smaller residential building typologies to meaningfully change the characteristics of the overall stock is much greater in regions with strong projected population growth.
Empirical analyses of changes to local land-use restrictions are limited because most developments are still very recent. However, what empirical evidence does exist does support the claim that the potential effects of such local policy changes strongly depend on local growth conditions. Moderate relaxation of some zoning restrictions in Chicago (a city where population is not increasing) was found to correlate with short-term increases in property prices, but did not increase housing construction (Freemark, 2019). In contrast, in Houston (Harris County, TX), one of the fastest growing cities in the US, a change in local regulations to allow housing development on plots under 5,000 ft$^2$ led to a strong increase in smaller lots that were previously not permitted (Gray & Millsap, 2020). In other suburban areas surrounding cities in Texas, even relatively small minimum lot-sizes create binding restrictions that limit the supply of small-lot homes below market demand (Gray & Furth, 2019). The conclusion here is that while removing zoning or other local land-use restrictions will aid densification and permit supply of smaller, more energy efficient homes, the potential of such change is much greater in areas with growing population and housing stocks. Ensuring that smaller housing is allowed and encouraged in high-growth counties should therefore be the greatest priority where local land-use regulations are concerned. In regions of the US with low population growth, or population decline, removing supply restrictions will have a smaller impact. Many of the regions with low projected growth also have very old housing stocks. Providence is a good example (Fig 5.6), but a similar housing age profile is observed in most states in the Northeast and Midwest (Fig 6.5), and very few of these areas are projected to grow substantially in the coming decades. In such areas, renovations focusing on envelope energy efficiency, replacing fossil fuel with electric space and water heating equipment, and ensuring swift decarbonization of electricity supply will be key to reducing residential GHG emissions.

7.3 Summary of contributions

One important outcome of the research in this dissertation is that the most influential housing characteristic determining future residential energy and emissions is residential floor space per
person. This is well recognized in recent literature (Cohen, 2020; Ellsworth-Krebs, 2019; Hertwich et al., 2020; Ivanova & Büchs, 2020). Two innovations of this dissertation that go beyond existing literature relate to the explicit illustration of the challenges that historical growth in floor area of new housing pose for limiting future growth in floor space per person, and demonstration of the extent to which specific housing supply strategies (more multifamily, fewer mansions) can attenuate growth of floorspace per person. Modeling growth in floor space per person as the output of a housing stock model, as opposed to the more common approach of specifying floor space per person as an exogenous input (Grubler et al., 2018; Hertwich et al., 2020; Roca-Puigròs et al., 2020), facilitates these innovations.

The dissertation assesses efficiency (reduced MJ/m²) and sufficiency (reduced m²/cap) related approaches to residential decarbonization, and concludes that scaling up both approaches are required to bring US residential emissions in line with the less ambitious national commitments made under the Paris 2015 agreement, or the more ambitious target of limiting climate change to within 1.5 °C warming. Achieving such targets will require reducing floor area per person, faster electrification of all residential energy end-uses (which is the focus of future work), in addition to much more rapid decarbonization of the electricity supply system. Incorporating emissions from both new construction and energy consumption permit a first comprehensive comparison and contribution to the ‘retrofit vs rebuild’ debate for the US residential sector. Due increased embodied emissions from additional new construction, and greater floor area in new vs old homes, intensifying a ‘rebuild’ approach to reducing residential emissions would not be effective, and would in fact increase overall emissions. On the other hand, intensifying the ‘retrofit’ approach by increasing the retrofit rate and depth would measurably reduce emissions.

The localized housing stock model based on county housing characteristics and population projections demonstrate that different decarbonization pathways will be better suited to different regions, depending on projected population and housing stock growth, and initial housing stock
conditions. Regions with strong growth will have high leverage to influence evolving housing stock characteristics and energy efficiency by allowing and encouraging supply of less energy- and GHG-intensive (i.e. smaller single-family and more multifamily) housing to be built. Areas with low expected growth, which in the US tends to coincide with older housing stocks in colder regions in the Northeast and Midwest, have less potential for emission reduction through efficient and sufficiency-oriented stock growth, and will rely more heavily on renovations to existing housing in order to decarbonize. This represents a higher geographic resolution reiteration of global findings by Güneralp et al. (2017), who report that energy efficiency would be the main solution for curbing growth in urban energy demand in low-growth developed regions such as North America and Europe, while urban form and density have much greater potential to reduce energy use in growing cities in the developing world. The same principle applies here, but on a smaller scale.

Sufficiency is a relatively new addition to the suite of strategies being considered to combat climate change, but it’s potential cannot be overlooked. Compared to technological alternatives that require mass deployment of negative emission technologies yet to be demonstrated at scale, it appears much more achievable. Only with meaningful reductions in future floor area per person and energy demand per floor area will improvements external to the residential sector, such as decarbonization of energy supply and material production, be sufficient to set the US residential sector on an emissions trajectory to mitigate extreme climate change.
References


8. https://doi.org/10.1038/s41893-019-0462-4


EIA. (2014). *Newly released heat content data allow for state-to-state natural gas comparisons*.


EIA. (2018h). *What is the heat content of U.S. coal?*


through 2050. *Proceedings of the National Academy of Sciences, 114*(34), 201606035. https://doi.org/10.1073/pnas.1606035114


and Examples (Issue December). https://neep.org/sites/default/files/resources/Building
Energy Codes for a Carbon Constrained Era - A Toolkit of Strategies and Examples.pdf


Höhne, N., den Elzen, M., Rogelj, J., Metz, B., Fransen, T., Kuramochi, T., Olhoff, A., Alcamo, J., 
Winkler, H., Fu, S., Schaeffer, M., Schaeffer, R., Peters, G. P., Maxwell, S., & Dubash, N. K. 
(2020). Emissions: world has four times the work or one-third of the time. Nature, 579(7797), 
25–28. https://doi.org/10.1038/d41586-020-00571-x


https://doi.org/10.3390/en12193745


https://doi.org/10.1111/j.1467-9787.2006.00480.x

https://doi.org/10.1061/(asce)ae.1943-5568.0000401


Min, J., Hausfather, Z., & Lin, Q. F. (2010). A high-resolution statistical model of residential


144


USCB. (2019). *Housing Vacancies and Homeownership: Table 7a Annual Estimates of the Housing Inventory.* https://www.census.gov/housing/hvs/data/histtabs.html


Viggers, H., Keall, M., Wickens, K., & Howden-Chapman, P. (2017). Increased house size can


A Appendix to Chapter 2

Summary

This supplementary information document contains some methods descriptions and results that were not included in the main manuscript. Section A.1 contains details on the extensions we made to the USSEIO model from (Y. Yang et al., 2017) – incorporating the addition of household emission sectors to the model, and modifications to satellite tables to make them more comprehensive and temporally relevant to the corresponding IO tables. Section A.2 contains a summary description of the methods used to derive the capital flow matrix. Section A.3 contains a description of the hypothetical extraction method used to determine environmental impacts of classes of capital assets, and some results of carbon footprint multiplier by asset class. Section A.4 contains a discussion of the calculation of capital consumption through depreciation and how that can affect results. Section A.5 contains additional results – aggregate sector footprints for 2007, a contribution analysis total footprints and capital footprints in 2012, tables of absolute and proportional contributions of capital to footprints, a sensitivity analysis for carbon, energy and material footprints with different capital vintages, and contribution analyses of footprints by types of GHG, energy, and material. Section A.6 contains a description of the accompanying data file, and the location of scripts and source data which can be accessed to reproduce this work.
A.1 Extensions to original USEEIO model impact assessment

A number of key modifications were made to the USEEIO model of (Y. Yang et al., 2017) for the model used in this work. Foremost was the endogenization of capital through the creation of capital flow matrices for 2007 and 2012, prepared and described in detail in (T. R. Miller et al., 2019) and discussed in SI Section 2. Further modifications to modeling the environmental impacts are described in detail in the following subsections.

A.1.1 Adding household emissions sectors

Following the sectors of the BEA Make and Use tables, the original USEEIO model does not include final demand sectors that directly corresponded to certain activities by private householders which release substantial greenhouse. This is because these activities are not associated with an economic transaction at the point of emission generation. Household activities which do not have a separate sector cannot have an emission intensity factor in the S matrix. To resolve this issue, the following three commodities were added to the model to allow these emissions and their supply chains to be included:

- Residential natural gas (RNG)
- Residential petroleum fuels (RPF)
- Personal transport fuels (PTF)

The RNG commodity was created by moving all personal consumption expenditures (PCE) of natural gas distribution to expenditures on the newly created RNG commodity. In the Z matrix \((Z = A\bar{x})\) of interindustry commodity flows, the transaction value PCE of RNG was reassigned as an interindustry flow from Natural gas distribution to RNG. PCE of RPF and PTF were similarly shifted from PCE on petroleum refineries to the newly created sectors. Because in this case we created two new sectors, PCE of RPF and PTF were allocated based on energy consumption statistics for home fuels and personal transport fuels in Tables A-15 and A-20 of the ‘Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2016’ (EPA, 2018), and fuel prices in 2007 and
2012 (EIA, 2018e, 2018g, 2018f). The relevant calculation can be found in the ‘TransportationFuelUse’ tab of the GHG satellite data files. Residential petroleum fuels are comprised of distillate fuel oil, liquified petroleum gas (LPG) and kerosene. Expenditures for PTF constitutes the majority of household consumption of petroleum products, accounting for 91% in 2007 and 94% in 2012.

A.1.2 Modifications to Satellite tables

A number of modifications were made to the USEEIO v1.1 Satellite tables (Ingwersen et al., 2017) to make them consistent with our final commodity resolution and temporal focus (2007 and 2012), and in the case of materials to broaden the scope of what was considered. These modifications are described in the following sections. For 2007 satellite tables production intensities (impact per dollar industrial output) were created based on 2007 output valued both in 2007 and 2012 USD, so that 2007 multipliers could later be compared with 2012 multipliers in the same valuation (c.f. Table 2.4). Creating 2007 industry output in 2012 USD was done using sector specific chain type price indices published by BEA as part of the GDP by industry accounts (BEA, 2018a).

Modifications to GHG satellite table

The GHG Satellite table prepares sectoral intensities of GHG emissions per industrial output of industry sectors for 2007 and 2012. We used the most recent GHG inventory data (EPA, 2018), and we make note that the 2018 inventory contains some revised values for 2007 and 2012 which can be rather different to past GHG inventories, especially for CH₄ emissions from natural gas systems for example. Following the addition of the three household emission sectors described above, we create GHG intensities for these sectors, by allocating the relevant household emissions from the GHG inventory. Some choices were made in (Ingwersen et al., 2017; Y. Yang et al., 2017) to allocate and match industrial emissions from the GHG inventory by following BEA classifications (EIA, 2000) of detailed sectors within to the aggregate ‘Industrial’ and ‘Commercial’, and ‘Transport’ sector groups. A risk to this approach is that EPA and BEA have
different definitions of these aggregate sector groups. We closely follow the approach of (Ingwersen et al., 2017; Y. Yang et al., 2017), except that we place government emissions under ‘Transport’ rather than ‘Commercial’, which results in a much more similar intensity of CO₂ emissions per economic input of petroleum between sectors.

Modification to mineral resource use impact category

The original mineral resource use satellite table was compiled using 2014 mineral resource production data from the USGS Mineral Commodity Surveys (MCS). For this study, the satellite tables were modified to reflect mineral production in 2007 using the 2012 MCS (USGS, 2012), and mineral production in 2012 using the 2017 MCS (USGS, 2017). A significant expansion was made to quantification of material resource extraction, so as to cover not only mineral resources but also fossil fuels and biomass. We created four distinct material resource use impact categories: metals, fossil fuels, other minerals, and biomass. The sum of all of these impacts is presented in our impact analysis as total material footprint. Impacts per material category can be seen in Figure A.8 (E,F).

The choice of the material use categories is based on conventions used in the economy-wide material flow accounting literature (Fischer-Kowalski et al., 2011).

We classified the material resources originally described by (Ingwersen et al., 2017) as either a metal, or a non-metallic mineral, or fossil fuel (in the case of peat). Data for industrial roundwood and fuel wood production from (Howard & Jones, 2016) were added to biomass materials by adding appropriate rows, columns and values to the stressor and characterization matrices in the satellite excel files. The metrics of ‘Roundwood equivalents of production’ from Table 10, and ‘Fuelwood production and consumption’ from Table 8b provided the appropriate data for 2007 and 2012. We recognize that the biomass materials category is still far from complete – consisting now of just industrial roundwood, and fuelwood. The addition of food and fuel crops in particular would be a significant development to this material use category. Fossil fuel material extractions are calculated by using the reciprocal of the energy content of fossil fuels per unit mass in the characterization
matrix excel file, assuming energy contents of 22.99 MJ/kg for coal (EIA, 2018h), 53.2 MJ/kg for natural gas (EIA, 2018d), 50 MJ/kg for natural gas liquids which consist mostly of ethane and propane (EIA, 2014), and 43.8 MJ/kg for crude oil (EIA, 2019b).

Further extensions could still be made to refine the material impacts. A good example is in the aggregation of material use for non-metallic minerals. The extraction of minerals other than metals, stone, sand and gravel are currently allocated to a single BEA sector other nonmetallic mineral mining and quarrying. These material extractions are subsequently allocated to downstream consumption activities through the outputs of this economic sector to intermediate production. However, the materials in question here are diverse, as are the consuming sectors. The most prominent materials in terms of mass are salts, phosphate ore, gypsum, and clays. The main sectors which consume the outputs of other nonmetallic mineral mining and quarrying are ready mix concrete manufacturing, fertilizer manufacturing, grain farming and asphalt paving mixture and block manufacturing. Presumably all of these sectors require different types of non-metallic minerals, but the current aggregation allocates the average use of all of these materials to all of these consuming sectors. One method of resolving this issue would be to find out the inputs/purchases of raw minerals by large consuming sectors, and then allocate the extraction to those sectors rather than allocating all extractions to the 'Other nonmetallic mineral mining and quarrying' sector.

Modification to energy satellite table

The data source for energy satellite tables is EIA’s Monthly Energy Review (EIA, 2018c). The original energy satellite table was updated to reflect energy extractions and industry output in 2012 and 2007. Some aggregation issues exist for Oil and gas extraction, as discussed briefly in the main manuscript. The first issue relates to oil and gas imports. The domestic technology assumption would indicate that imports to this sector have the same technical and environmental coefficient as domestic production. However, in the US, natural gas is the dominant domestic component of oil and gas extraction, while imports of oil and gas extraction are overwhelming oil. We accommodate
this by including the economic and physical values of oil and gas imports when calculating fuel-specific energy coefficients of oil and gas extraction. In economic terms, inputs of oil and gas extraction to intermediate consumption in the US was about 50:50 domestic:imported in both 2007 and 2012 (EIA 2018).

A second issue arises from the fact that natural gas tends to be much cheaper than oil per unit energy, in other words its energy intensity (MJ/$) can be much higher. Due to the widening of the price differential per unit energy for oil and gas between 2007 and 2012, we see some unusual results in 2012 energy and material footprints for. In this model, each dollar of oil and gas extraction consumed by every sector in 2012 required 56MJ of crude oil, 5MJ of natural gas liquids, and 43MJ of natural gas (dry) production, regardless of what the consuming sector was. Due to the aggregation, sales of oil and gas extraction to petroleum refineries are assumed to have a higher proportion of (more energy intensive) natural gas than they actually do, while sales of oil and gas extraction to natural gas distribution are assumed to have a higher proportion of (less energy intensive) oil than they actually do. This results in material and energy footprints involving natural gas being underestimated, and footprints involving oil and petroleum products being overestimated. We confirmed this by comparing EF results against energy consumption statistics in tables A-15 and A-20 of the 2018 US Greenhouse Gas Inventory (EPA 2018). To resolve this issue, it would be necessary to disaggregate oil and gas extraction into two sectors for oil and gas, which was outside of the scope of this study. We recommend that this be done for future EEIO studies where sectoral energy or material flows are the prime subject of enquiry.

A.2 Preparation of capital flow matrix

A full description of the preparation of the capital flow matrix and the capital input per unit output matrices can be found in (T. R. Miller et al., 2019). Here we provide excerpts and a summary for readers of this article.
“There are two main steps in the process to endogenize capital in the USEEIO for a given year. The first and most intensive step is the preparation of the CFC [(consumption of fixed capital)] use matrix, $U^K$. The second step simply converts the $U^K$ matrix into the $A^K$ direct inputs requirements matrix [see Equation S1]. $A^K$ is then added to the original $A$ matrix and used for environmental impact calculations”.

To illustrate the first main step to prepare $U^K$, Figure 3 from that article is reproduced below in Figure A.1. The BEA’s fixed asset accounts (FAA, $H$) provide annual tables of investment and depreciation (synonymous with consumption) of fixed assets (FA, $h$) by summary industry groups (SIG, $\sigma$). The objective is to create a matrix such that the “dimensions of $U^K$ align with the detailed $U$: 405 commodity [detailed industry group] DIGs $\chi$ by 405 industry DIGs $\iota$ in producers’ value”.

In Figure A.1, “in step (a) CFC tables are created for each of the 13 final demand investment $Y^K$ categories in the format of the detailed $U$ in producers’ value. Next in step (b), these 13 tables are combined to create the $U^{K*}$ matrix. Then in step (c), modifications to the highway & streets allocation are made to create the final $U^K$ matrix.”

In Figure A.1(a), “sub-steps i and ii focus on the rows of the $U^{K*}$ matrix by associating assets with detailed commodities and converting from purchasers’ to producers’ value. The next sub-step iii applies CFC data, and the last sub-step iv addresses the columns of $U^{K*}$ by spreading the CFC to detailed investors. While the specific BEA tables used for each of the investor classes vary, the basic approach described below is followed for each of the three classes across the 13 $Y^K$ categories.” The first two sub-steps involved the bulk of the effort. The last sub-step uses gross operating surplus ($G$) as a proxy to spread CFC.

In Figure A.1(b), “This step simply involves summing the 13 $U^{K*}_{\chi \times \iota}$ matrices created for each $Y^K$ category. The resulting matrix approximately allocates CFC in producers’ prices based on
investment. This could be the final matrix, but we chose to address a further issue of asset use versus investment, described in the next section."

In Figure A.1(c), we address that “State and Local governments are the predominant investors in, but not the predominant users of, the DIG ‘Transportation structures and highways and streets’ (TSHS, denoted by ψ).” "The final $\mathbf{U}^K$ matrix differs from the intermediate $\mathbf{U}^{K,\gamma}$ matrix in that public TSHS are partially allocated to industries driving vehicles and using the roads. Households also use public TSHS; here, the household share is allocated to State and Local governments”.

Summarizing the second main step, $\mathbf{U}^K$ was converted into the direct capital input requirements matrix $\mathbf{A}^K$ using the industry technology construct. This is shown in Equation (A1), where $\mathbf{x}$ is total industry output, $\mathbf{V}$ is the Make matrix, $\mathbf{q}$ is total commodity output, $\mathbf{B}$ is the normalized capital use and $\mathbf{D}$ is the normalized Make, or ‘market shares’ matrix.

$$\mathbf{A}^K = \mathbf{U}^K \hat{x}^{-1} \mathbf{V} \tilde{q}^{-1} = \mathbf{B}^K \mathbf{D} \quad (A1)$$
Figure A.1: Overall approach for construction of the $U^K$ matrix in three steps. (a) Construction of IO CFC table in producer's value for each of the 13 final demand investment categories. Rectangles indicate created tables, while rounded rectangles indicate BEA tables. (b) Combination of the 13 tables into the $U^K_*$ matrix (c) Conversion of $U^K_*$ to $U^K$ by reallocating Highways & Streets. (T. R. Miller et al., 2019).
A.3 Hypothetical Extraction of capital assets

To determine environmental impacts of classes of capital assets, the hypothetical method (Gallego & Lenzen, 2005) was used to aggregate asset groups of detailed sectors from the $A^K$ matrix. First the environmental impacts of consumption and capital consumption were formulated as follows, with the same variables definitions as in Table 2.1, and $I$ is a 816 x 816 identity matrix.

\[
\begin{bmatrix}
  d^c \\
  d^K
\end{bmatrix} =
\begin{bmatrix}
  CS & 0 \\
  0 & CS
\end{bmatrix}
\begin{bmatrix}
  I - [A \\
  A^K + A^K]
\end{bmatrix}^{-1}
\begin{bmatrix}
  y^c \\
  0
\end{bmatrix}
\]  

(A2)

First we note that this method of calculating $d^K$ is an equivalent but concise approach compared to Equation (9) of Chapter 2. To determine the contribution of any asset class $a$ to total impacts of capital consumption $d^K$, the rows of the relevant detailed sectors which are members of $a$ were converted to zeros in $A^K$ (while $A + A^K$ remained unchanged). For instance, all detailed sectors which were members of the asset class ‘Mining and Fossil Extraction’ were converted to zero. $d^K$ was then recalculated without these production sectors contributing to the impact of capital consumption. This was done for each class, at the same resolution as the summary sector results presented in Figure 2.1 and Table 2.2, and each assets contribution $c^a$ to the total impact of capital consumption calculated as follows, where $d^{K-a}$ is produced by calculating impacts of capital consumption with the coefficients in the rows corresponding to capital asset $a$ in $A^K$ converted to zero. In this way the asset-wise contribution analysis presented in Figure 2.3 was prepared.

\[
c^a = \frac{\sum d^a}{\sum d^K} = \frac{(d^K - d^{K-a})}{d^K}
\]  

(A3)

Figure 2.3 shows the contribution of asset types to capital CF in 2012. We show a comparable figure for 2007 in Figure A.2. Metal, Vehicles and Machinery (25%, 22%), and non-residential construction (18%, 22%) have the highest contributions to capital CF among asset groups in both years (2007, 2012). We calculated carbon multipliers of these assets groups for 2007 and 2012, shown in Table A.1. This was done by calculating the CF of the capital consumption of each asset.
group $c^a$, and dividing by the economic value of capital consumption by summed by asset producing sector $i = a$ and all asset consuming sectors $j$ (Equation A4). Although ‘Other durables’ has the highest intensity, it has far less consumption than other assets.

\[ y^a = \sum_i \sum_j (A^k x) \]  

(A4)

Figure A.2 Contribution of capital assets to the CF of capital consumption sectors, 2007

Table A.1 Carbon multipliers of capital assets consumed, 2007 and 2012

<table>
<thead>
<tr>
<th>Asset</th>
<th>2007 (kg CO$_2$/2007USD)</th>
<th>2012 (kg CO$_2$/2012USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mining, Fossil extraction</td>
<td>0.64</td>
<td>0.73</td>
</tr>
<tr>
<td>Residential construction</td>
<td>0.54</td>
<td>0.36</td>
</tr>
<tr>
<td>Non-residential construction</td>
<td>0.52</td>
<td>0.48</td>
</tr>
<tr>
<td>Metals, Vehicles, Machinery</td>
<td>0.49</td>
<td>0.36</td>
</tr>
<tr>
<td>Other durables</td>
<td>1.21</td>
<td>0.88</td>
</tr>
<tr>
<td>Trade, Transport</td>
<td>0.38</td>
<td>0.31</td>
</tr>
<tr>
<td>Information, Entertainment</td>
<td>0.18</td>
<td>0.15</td>
</tr>
<tr>
<td>Real Estate</td>
<td>0.73</td>
<td>0.59</td>
</tr>
<tr>
<td>Science, Prof Services</td>
<td>0.29</td>
<td>0.23</td>
</tr>
</tbody>
</table>
A.4 Influence of capital depreciation on capital footprints

We note in the main manuscript the importance of the approach to calculating capital depreciation to capital footprints. The measurement of capital depreciation and different methods for doing so are important for systems of national accounts and estimating multi-factor productivity changes (OECD, 2009; Reinsdorf & Cover, 2005). Geometric depreciation is the most commonly applied method, and there appears to be a consensus that “the average experience of a group of assets is better approximated by geometric depreciation than by other forms” (Hulten, 2008). In the BEA fixed asset accounts (BEA, 2018b), capital consumption is calculated using the geometric depreciation of capital assets (Lally, 2004). This approach allocates more use of an asset to the earlier years of its service life, and so the sectoral capital consumption in any given year will be most sensitive to the level of investment in the most recent years. Our years of analysis, 2007 and 2012, illustrate this sensitivity well in the housing sectors. In the decade leading up to 2007, particularly after 2001, investment in residential construction was unusually high. After peaking in 2005, investment in and construction of new residential buildings reduced remarkably and did not start to pick up again until 2012 (Figure A.3). With declining capital consumption and increasing personal consumption, capital inputs (column sums of $A^K$) to housing thus reduced from $0.26$ for every $1$ output in 2007 to $0.21$ in 2012. This contributed to larger housing capital footprints in 2007 compared with 2012 (Table 2.3, Tables A.2-A.3). Had straight-line rather than geometric depreciations been used to calculate capital consumption, 2012 housing capital footprints would probably have been similar to 2007, as the stock of housing was $3\%$ higher in 2012 than 2007 (USCB, 2019).
A.5 Additional results

A.5.1 2007 Aggregate results

In Figure A.4 we show CF, EF and MF from capital investment and consumption in 2007, similar to Figure 2.1. Notable differences include the overall higher level of investment footprints in 2007, especially in residential construction. An exception to this is the higher carbon and energy footprints from mining and fossil extraction in 2012, driven by higher levels of investment in other support activities for mining, a sector which became more energy and carbon intensive in 2012. For capital consumption, the most notable difference is the lower consumption of housing and real estate as discussed above.
Figure A.4 Carbon, energy and material footprints of investment and consumption of capital by aggregate sectors, 2007
A.5.2 Contribution of production sectors to total footprints and capital footprints

Figure A.5 shows contributions of direct emissions or energy/material extractions by the production sectors most relevant to total CF, EF, and MF in 2012. Direct emissions from the major fossil energy extraction, refinement, and consumptions sectors of electricity, personal transport fuels, oil and gas extraction, truck transportation, residential natural gas, petroleum refineries, and air transportation, and contribute extensively to CF across the economy, and make up 63% of total CF in 2012. Agricultural production sectors beef cattle, dairy cattle, and grain farming, Industrial production sectors such as Waste and remediation and Iron and steel production, and SL government other services are other important sources of direct GHG emissions. Sources of EF and MF are concentrated on fewer production sectors, mostly related to energy extraction and other mining. The three sectors oil and gas extraction, electricity and coal mining are where most of the primary energy extractions occur. Most of material extractions meanwhile can be traced back to activities of oil and gas extraction and stone mining and quarrying.

In Figure A.6 we show contributions of production sectors to footprints of capital consumption. This is similar to the asset-wise capital CF results in Figure 2.3, except that contributions here are from detailed production sectors, rather than aggregated asset groups. Electricity and truck transportation are consistent major contributors to capital CF throughout the economy, while building materials (iron, steel, cement) and fossil extraction activities are also important, depending on the consumption activity. Oil and gas extraction and Other support activities for mining are the main contributors to capital EF, while Stone mining and quarrying and Other support activities for mining are the sectors where most of the capital MF occur.
Figure A.5 Contribution of production sectors to footprints of consumption in 2012
Figure A.6 Contribution of production sectors to footprints of capital consumption in 2012
A.5.3 Absolute contributions of capital to energy and material footprints

Tables A.2 and A.3 show the sectors with largest absolute capital energy and material footprints in 2012, and the corresponding capital footprints for these sectors in 2007. Due to the increased energy intensity and increased importance of Other support activities for mining as a capital input to drilling oil and gas wells, the capital EF (and CF) of personal transport fuels is a lot higher in 2012. The EF and MF of housing decreases considerably in 2012, related to the lower capital inputs to housing sectors discussed above, which has the effect of lowering the environmental multipliers of housing consumption. Beyond housing and transport fuels, the largest footprints of capital consumption come from government consumption, hospitals and some service sectors some as telecommunication carriers and restaurants.

Table A.2 Sectors with highest absolute 2012 capital EF (PJ), and capital percentage contribution to total EF

<table>
<thead>
<tr>
<th>Sector</th>
<th>Capital EF 2007</th>
<th>Capital EF 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Personal transport fuels</td>
<td>2,346 (10%)</td>
<td>3,835 (14%)</td>
</tr>
<tr>
<td>Owner-occupied housing</td>
<td>3,354 (80%)</td>
<td>2,475 (77%)</td>
</tr>
<tr>
<td>SL govt other services</td>
<td>1,575 (16%)</td>
<td>1,789 (22%)</td>
</tr>
<tr>
<td>Federal govt (defense)</td>
<td>1,470 (30%)</td>
<td>1,569 (32%)</td>
</tr>
<tr>
<td>SL govt education</td>
<td>996 (15%)</td>
<td>1,060 (19%)</td>
</tr>
<tr>
<td>Hospitals</td>
<td>956 (24%)</td>
<td>1,048 (22%)</td>
</tr>
<tr>
<td>Electricity</td>
<td>1,064 (4%)</td>
<td>919 (5%)</td>
</tr>
<tr>
<td>Federal govt (nondefense)</td>
<td>657 (35%)</td>
<td>669 (35%)</td>
</tr>
<tr>
<td>Tenant-occupied housing</td>
<td>861 (89%)</td>
<td>631 (86%)</td>
</tr>
<tr>
<td>Air transportation</td>
<td>310 (12%)</td>
<td>403 (17%)</td>
</tr>
<tr>
<td>Limited-service restaurants</td>
<td>363 (13%)</td>
<td>358 (13%)</td>
</tr>
<tr>
<td>Wired telecomm. carriers</td>
<td>351 (55%)</td>
<td>310 (45%)</td>
</tr>
</tbody>
</table>
Table A.3 Sectors with highest absolute 2012 capital MF (MT), and capital percentage contribution to total MF

<table>
<thead>
<tr>
<th>Sector</th>
<th>Capital MF 2007</th>
<th>(% of total)</th>
<th>Capital MF 2012</th>
<th>(% of total)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Owner-occupied housing</td>
<td>433</td>
<td>82%</td>
<td>252</td>
<td>76%</td>
</tr>
<tr>
<td>Personal transport fuels</td>
<td>225</td>
<td>29%</td>
<td>224</td>
<td>30%</td>
</tr>
<tr>
<td>SL govt other services</td>
<td>201</td>
<td>42%</td>
<td>174</td>
<td>44%</td>
</tr>
<tr>
<td>Federal govt (defense)</td>
<td>100</td>
<td>49%</td>
<td>87</td>
<td>47%</td>
</tr>
<tr>
<td>SL govt education</td>
<td>112</td>
<td>41%</td>
<td>84</td>
<td>41%</td>
</tr>
<tr>
<td>Electricity</td>
<td>110</td>
<td>30%</td>
<td>77</td>
<td>28%</td>
</tr>
<tr>
<td>Hospitals</td>
<td>81</td>
<td>47%</td>
<td>71</td>
<td>43%</td>
</tr>
<tr>
<td>Tenant-occupied housing</td>
<td>114</td>
<td>92%</td>
<td>63</td>
<td>87%</td>
</tr>
<tr>
<td>Federal govt (nondefense)</td>
<td>42</td>
<td>45%</td>
<td>38</td>
<td>43%</td>
</tr>
<tr>
<td>Wired telecomm. carriers</td>
<td>30</td>
<td>75%</td>
<td>25</td>
<td>68%</td>
</tr>
<tr>
<td>Limited-service restaurants</td>
<td>30</td>
<td>33%</td>
<td>25</td>
<td>32%</td>
</tr>
<tr>
<td>Air transportation</td>
<td>28</td>
<td>34%</td>
<td>24</td>
<td>34%</td>
</tr>
</tbody>
</table>

A.5.4 Relative contributions of capital to all footprints

Tables A.4 and A.5 show the sectors with highest proportional input of capital to all footprints in 2012, their environmental multipliers, and their total footprints. While results of absolute capital footprints are instructive in identifying the consumption sectors most linked to overall impacts, analyzing the proportional contribution of capital is helpful in identifying consumption sectors whose environmental profile is most affected by the inclusion of capital. Some of these are the same as sectors identified by the largest absolute footprints, such as housing sectors, which have the highest proportional contribution of capital for all three footprints. Beyond that, we see large contributions of capital to the multipliers of entertainment, specialist machinery and instruments, and information/communication sectors. The types of assets involved in these cases are often be media products, produced by motion picture and video industries, book publishers, and sound recording industries. Or in the case of specialized machinery and instruments, the assets are usually
intellectual products produced by scientific research and development. In any case, despite these sectors having high contributions from capital, their (capital inclusive) environmental multipliers are still generally well below the economy average, and only a few of these sectors have large capital or overall footprints.

Table A.4 Sectors with highest proportional contribution of capital to EF, energy multipliers, and total EF, for 2012

<table>
<thead>
<tr>
<th>Sector</th>
<th>Capital % of EF</th>
<th>Energy multiplier (MJ/$)</th>
<th>Total EF (PJ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tenant-occupied housing</td>
<td>86%</td>
<td>1.7</td>
<td>731</td>
</tr>
<tr>
<td>Owner-occupied housing</td>
<td>77%</td>
<td>2.5</td>
<td>3197</td>
</tr>
<tr>
<td>Sound recording industries</td>
<td>69%</td>
<td>2.4</td>
<td>12</td>
</tr>
<tr>
<td>Independent artists, writers, and performers</td>
<td>68%</td>
<td>1.3</td>
<td>0</td>
</tr>
<tr>
<td>Search, detection, navigation instruments</td>
<td>66%</td>
<td>3.7</td>
<td>0</td>
</tr>
<tr>
<td>Electromedical, electrotherapeutic apparatus</td>
<td>66%</td>
<td>4.8</td>
<td>13</td>
</tr>
<tr>
<td>Watch, clock, measuring devices</td>
<td>61%</td>
<td>4.2</td>
<td>22</td>
</tr>
<tr>
<td>Broadcast and wireless comms. equipment</td>
<td>61%</td>
<td>3.9</td>
<td>30</td>
</tr>
<tr>
<td>Radio and television broadcasting</td>
<td>59%</td>
<td>3.8</td>
<td>25</td>
</tr>
<tr>
<td>Telephone apparatus</td>
<td>58%</td>
<td>3.5</td>
<td>7</td>
</tr>
<tr>
<td>Death care services</td>
<td>51%</td>
<td>1.4</td>
<td>27</td>
</tr>
<tr>
<td>Electronic computers</td>
<td>51%</td>
<td>2.2</td>
<td>39</td>
</tr>
<tr>
<td><strong>Economy Average</strong></td>
<td><strong>19%</strong></td>
<td><strong>9.7</strong></td>
<td><strong>-</strong></td>
</tr>
</tbody>
</table>
Table A.5: Sectors with highest proportional contribution of capital to MF, material multipliers, and total MF for 2012

<table>
<thead>
<tr>
<th>Sector</th>
<th>Capital % of MF</th>
<th>Material multiplier (kg/$)</th>
<th>Total MF (MT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tenant-occupied housing</td>
<td>87%</td>
<td>0.17</td>
<td>73.0</td>
</tr>
<tr>
<td>Independent artists, writers, and performers</td>
<td>84%</td>
<td>0.07</td>
<td>0.0</td>
</tr>
<tr>
<td>Radio and television broadcasting</td>
<td>80%</td>
<td>0.23</td>
<td>1.5</td>
</tr>
<tr>
<td>Sound recording industries</td>
<td>80%</td>
<td>0.10</td>
<td>0.5</td>
</tr>
<tr>
<td>Search, detection, navigation instruments</td>
<td>79%</td>
<td>0.15</td>
<td>0.0</td>
</tr>
<tr>
<td>Electromedical, electrotherapeutic apparatus</td>
<td>76%</td>
<td>0.20</td>
<td>0.5</td>
</tr>
<tr>
<td>Owner-occupied housing</td>
<td>76%</td>
<td>0.26</td>
<td>334.2</td>
</tr>
<tr>
<td>Broadcast and wireless comms. equipment</td>
<td>75%</td>
<td>0.15</td>
<td>1.1</td>
</tr>
<tr>
<td>Watch, clock, measuring devices</td>
<td>73%</td>
<td>0.17</td>
<td>0.9</td>
</tr>
<tr>
<td>Pipeline transportation</td>
<td>73%</td>
<td>0.64</td>
<td>1.3</td>
</tr>
<tr>
<td>Telephone apparatus</td>
<td>72%</td>
<td>0.13</td>
<td>0.3</td>
</tr>
<tr>
<td>Wired telecomm. carriers</td>
<td>68%</td>
<td>0.21</td>
<td>35.8</td>
</tr>
<tr>
<td><strong>Economy Average</strong></td>
<td><strong>40%</strong></td>
<td><strong>0.33</strong></td>
<td><strong>-</strong></td>
</tr>
</tbody>
</table>

A.5.5 Sensitivity analysis of capital vintage

Figure A.7 shows the effect of changing the vintage-based environmental intensity of capital from 2012 to 2007 for capital consumed in 2012. In this sensitivity, the economic inputs to production \((A, A^k)\) are still based on 2012 transactions, but the stressor matrix \(S\) is based on 2007 environmental coefficients, with the economic denominator converted to 2012 USD using chain type price indices (BEA, 2018a). For most sectoral CF and EF, we don’t see a great difference in footprints between capital vintages. Material footprints however show larger differences. Petroleum dominated MF are notably larger with 2007 environmental intensity, while mineral dominated material footprints tend to be just slightly larger.

The reason that material impacts of capital are higher with 2007 intensity while EF are not so different is due to different energy and material intensities as well as differences in the market shares matrix \(D\). In the 2012 \(D\) the oil and gas extraction industry produces a lot more of the drilling
oil and gas wells and other support activities for mining commodities, and therefore more primary fossil energy is allocated to these sectors in 2012, with less allocated to oil and gas extraction. These differences in energy intensity between sectors in the two years balance out in overall EF. For materials however, in 2012 both other support activities for mining and oil and gas extraction have lower material intensities, due to less minerals and fossil materials being required respectively. In 2007 D, stone mining and quarrying (the main source of mineral MF) produces more of other support activities for mining compared to 2012, contributing to its higher material intensity. As a result, MF are notably higher in 2007 for both Oil and Gas extraction and Other support activities for mining.
Figure A.7 2012 Carbon, Energy, and Material Footprints with capital impacts based on 2007/2012 satellite accounts
A.5.6 Contribution of physical stressors to footprint results

Figure A.8 shows the CF, EF, and MF of the consumption activities with highest footprints in 2007 and 2012, broken into contributions from the main GHGs, primary energy resources, and material categories. CF is dominated by CO\textsubscript{2} emissions, although some consumption activities such as state and local government other services, or animal products, have higher contributions from CH\textsubscript{4} and N\textsubscript{2}O. Coal, oil and natural gas dominate EF results. Some of the aggregation related errors discussed above are apparent in these figures. For instance, the EF of personal-vehicle fuel consumption is shown to have a very large contribution from natural gas, due to the high presence of natural gas in US oil and gas extraction. MF results are dominated by fossil fuels and non-metallic (‘other’) minerals.
A.6 Description of scripts and data files

The database, results, and scripts used in preparation of this publication are made freely available in a number of formats. This section describes where, and in what format, the various files associated with this work can be accessed. An excel Data File containing IO and environmental matrices, numeric versions of figures in the main manuscript, more comprehensive tables of results, and total footprints and multipliers for 2007 and 2012 with and without capital and in purchaser and producers prices is included as a supplementary file. All other input data files and scripts are available online at github with an archived repository hosted by Zenodo (Berrill & Miller, 2019) – enabling a full reproduction of our research and analysis.
B Appendix to Chapter 3

B.1 Description of End-Use decompositions for energy and GHG emissions

Equations B1-B4 show decomposition of primary energy \( \hat{E} \) used for each end-use. \( \hat{E}'' \) refers to weather adjusted primary energy calculated assuming 1990 primary energy factors for electricity generation, \( \hat{E}'' \) refers to weather adjusted primary energy, and \( \hat{E} \) refers to unadjusted primary energy. For other energy, for which there is no weather adjustment, \( \hat{E}'' \) refers to primary energy calculated assuming 1990 primary energy factors for electricity generation. The index \( X_E \) on the right-hand side of the equations is a ratio of energy efficiency of primary to final energy conversion between 1990 and other RECS survey years. Other terms are as defined in Table 2 of the main text.

**Decomposition of primary energy for space heating:**

\[
E_1 = \sum I \sum_j \sum_k \sum_l \frac{P_i P_{ijk} N_{ijkl} A_{ijkl} \hat{E}_{ijkl}'}{P_i P_{ijkl} N_{ijkl} A_{ijkl} \hat{E}_{ijkl}''} = P \times R \times T \times C \times F \times H \times S \times I_1 \times X_E \times W
\]

**Decomposition of primary energy for space cooling:**

\[
E_2 = \sum I \sum_j \sum_k \sum l \frac{P_i P_{ij} N_{ijk} A_{ijk} \hat{E}_{ijk}'}{P_i P_{ijkl} N_{ijkl} A_{ijkl} \hat{E}_{ijkl}''} = P \times R \times T \times C \times H \times S \times I_2 \times X_E \times W
\]

**Decomposition of primary energy for domestic hot water:**

\[
E_3 = \sum I \sum_j \sum_k \sum l \frac{P_i P_{ijk} N_{ijkl} A_{ijkl} \hat{E}_{ijkl}'}{P_i P_{ijkl} N_{ijkl} A_{ijkl} \hat{E}_{ijkl}''} = P \times R \times T \times C \times F \times I_3 \times X_E \times W
\]

**Decomposition of primary energy for all other uses:**

\[
E_4 = \sum I \sum_j \sum_k \sum l \frac{P_i P_{ij} N_{ijk} A_{ijk} \hat{E}_{ijk}'}{P_i P_{ijkl} N_{ijkl} A_{ijkl} \hat{E}_{ijkl}''} = P \times R \times T \times C \times H \times I_4 \times X_E
\]

Equations B5-B8 show decomposition of GHG emissions form each end-use. \( G'' \) refers to weather adjusted GHG calculated assuming 1990 GHG intensity factors for electricity generation, \( G' \) refers to unadjusted GHG calculated assuming 1990 GHG intensity factors for electricity generation, \( G'' \) refers to the weather adjusted GHG.
to weather adjusted GHG, and \( G \) refers to unadjusted GHG. For other energy, for which there is no weather adjustment, \( G_o \) refers to primary energy calculated assuming 1990 GHG intensity factors for electricity generation. The index \( X_G \) on the right-hand side of the equations is a ratio of GHG intensity between 1990 and other RECS survey years.

Decomposition of GHG emissions from space heating: \hspace{1cm} (B5)

\[
G^1 = \sum_i \sum_j \sum_k \sum_l P \frac{P_i}{p_i} \frac{P_{ij}}{p_{ij}} \frac{P_{ijk}}{p_{ijk}} N_{ijk} A_{ijl} G_{ijkl}^{G^1} G_{ijkl}^{G^1} G_{ijkl}^{G^1} G_{ijkl}^{G^1} = P \times R \times T \times C \times F \times H \times S \times i^1 \times X_G \times W
\]

Decomposition of GHG emissions from space cooling: \hspace{1cm} (B6)

\[
G^2 = \sum_i \sum_j \sum_k \sum l P \frac{P_i}{p_i} \frac{P_{ij}}{p_{ij}} \frac{P_{ijk}}{p_{ijk}} N_{ijk} A_{ijl} G_{ijkl}^{G^2} G_{ijkl}^{G^2} G_{ijkl}^{G^2} G_{ijkl}^{G^2} = P \times R \times T \times C \times H \times S \times i^2 \times X_G \times W
\]

Decomposition of GHG emissions from domestic hot water: \hspace{1cm} (B7)

\[
G^3 = \sum_i \sum_j \sum_k \sum l P \frac{P_i}{p_i} \frac{P_{ij}}{p_{ij}} \frac{P_{ijk}}{p_{ijk}} N_{ijk} A_{ijl} G_{ijkl}^{G^3} G_{ijkl}^{G^3} G_{ijkl}^{G^3} G_{ijkl}^{G^3} = P \times R \times T \times C \times F \times i^3 \times X_G \times W
\]

Decomposition of GHG emissions from all other uses: \hspace{1cm} (B8)

\[
G^4 = \sum_i \sum_j \sum k P \frac{P_i}{p_i} \frac{P_{ij}}{p_{ij}} \frac{P_{ijk}}{p_{ijk}} N_{ijk} G_{ijkl}^{G^4} G_{ijkl}^{G^4} G_{ijkl}^{G^4} G_{ijkl}^{G^4} = P \times R \times T \times C \times H \times i^4 \times X_G
\]

Equations B9-B31 describe the estimation of driver effects, i.e. attribution of changes in the outcome variables final energy, primary energy, and GHG, represented as \( Y \), to changes in the driver indices decomposed in equations 1-4 of Chapter 3, equations B1-B8, and summarized in Table 3.2. Drivers are identified by the subscripts to \( \Delta Y^m \), e.g. \( \Delta Y^m_{P} \) represents the changes in space heating outcome \( Y \) between periods t-1 and t attributed to changes in overall population \( P \). Except for equations B17-B20, which describe changes attributed to energy end-use intensity for final energy only, all equations refer to final energy, primary energy, and GHG outcomes.
\[ \Delta Y_{p}^{n=1:4} = \sum_{ijk} w_{ijk}^{n} \ln \left( \frac{p_{ij}^{t}}{p_{ij}^{t-1}} \right) \quad \text{(B9)} \]
\[ \Delta Y_{r}^{n=1:4} = \sum_{ijk} w_{ijk}^{n} \ln \left( \frac{p_{ij}^{t} / p_{ij}^{t}}{p_{ij}^{t-1}/p_{ij}^{t-1}} \right) \quad \text{(B10)} \]
\[ \Delta Y_{f}^{n=1:4} = \sum_{ijkl} w_{ijkl}^{n} \ln \left( \frac{p_{ijkl}^{t} / p_{ijkl}^{t}}{p_{ijkl}^{t-1}/p_{ijkl}^{t-1}} \right) \quad \text{(B11)} \]
\[ \Delta Y_{c}^{n=1:4} = \sum_{ijk} w_{ijk}^{n} \ln \left( \frac{p_{ij}^{t}/p_{ij}^{t}}{p_{ij}^{t}/p_{ij}^{t}} \right) \quad \text{(B12)} \]
\[ \Delta Y_{f}^{n=1:3} = \sum_{ijkl} w_{ijkl}^{n} \ln \left( \frac{p_{ijkl}^{t} / p_{ijkl}^{t}}{p_{ijkl}^{t-1}/p_{ijkl}^{t-1}} \right) \quad \text{(B13)} \]
\[ \Delta Y_{c}^{n=1:2,4} = \sum_{ijk} w_{ijk}^{n} \ln \left( \frac{N_{ijkl}^{t}/p_{ij}^{t}}{N_{ijkl}^{t-1}/p_{ij}^{t-1}} \right) \quad \text{(B14)} \]
\[ \Delta Y_{s}^{1} = \sum_{ijkl} w_{ijkl}^{1} \ln \left( \frac{A_{ijkl}^{t}}{N_{ijkl}^{t-1}} \right) \quad \text{(B15)} \]
\[ \Delta Y_{s}^{2} = \sum_{ijkl} w_{ijkl}^{2} \ln \left( \frac{A_{ijkl}^{t}}{N_{ijkl}^{t-1}} \right) \quad \text{(B16)} \]
\[ \Delta Y_{l}^{1} = \sum_{ijkl} w_{ijkl}^{1} \ln \left( \frac{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}}{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}} \right) \quad \text{(B17)} \]
\[ \Delta Y_{l}^{2} = \sum_{ijkl} w_{ijkl}^{2} \ln \left( \frac{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}}{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}} \right) \quad \text{(B18)} \]
\[ \Delta Y_{l}^{3} = \sum_{ijkl} w_{ijkl}^{3} \ln \left( \frac{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}}{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}} \right) \quad \text{(B19)} \]
\[ \Delta Y_{l}^{4} = \sum_{ijkl} w_{ijkl}^{4} \ln \left( \frac{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}}{\gamma_{ijkl}^{t} / \gamma_{ijkl}^{t-1}} \right) \quad \text{(B20)} \]
\[ \Delta Y_{w}^{n=1:3} = \sum_{ijkl} w_{ijkl}^{n} \ln \left( \frac{\gamma_{ijkl}^{n,t} / \gamma_{ijkl}^{n,t-1}}{\gamma_{ijkl}^{n,t} / \gamma_{ijkl}^{n,t-1}} \right) \quad \text{(B21)} \]
\[ \Delta Y_{w}^{n=2,4} = \sum_{ijkl} w_{ijkl}^{n} \ln \left( \frac{\gamma_{ijkl}^{n,t} / \gamma_{ijkl}^{n,t-1}}{\gamma_{ijkl}^{n,t} / \gamma_{ijkl}^{n,t-1}} \right) \quad \text{(B22)} \]
\[ w_{ijkl}^{n,1:3} = \frac{\gamma_{ijkl}^{n,t} - \gamma_{ijkl}^{n,t-1}}{\ln (\gamma_{ijkl}^{n,t}) - \ln (\gamma_{ijkl}^{n,t-1})} \quad \text{(B23)} \]
\[ w_{ijkl}^{n,2,4} = \frac{\gamma_{ijkl}^{n,t} - \gamma_{ijkl}^{n,t-1}}{\ln (\gamma_{ijkl}^{n,t}) - \ln (\gamma_{ijkl}^{n,t-1})} \quad \text{(B24)} \]

Equations B25-B27 show the attribution of changes in the outcome to changes in \( X_E \) and \( X_G \), representing changes in primary energy requirements for electricity generation with respect to 1990, and changes in GHG intensity of electricity generation with respect to 1990, for the respective outcomes of primary energy and GHG.
\[ \Delta Y^{n=1,3}_X = \sum_{ijkl} w^{n}_{ijkl} \ln \left( \frac{y^{r,n,t}_{ijkl}}{y^{r,n,t-1}_{ijkl}} \right) \] (B25) \[ \Delta Y^{n=2}_X = \sum_{ijk} w^{n}_{ijk} \ln \left( \frac{y^{r,n,t}_{ijk}}{y^{r,n,t-1}_{ijk}} \right) \] (B26)

\[ \Delta Y^{n=4}_X = \sum_{ijkl} w^{n}_{ijkl} \ln \left( \frac{y^{4,t}_{ijkl}}{A^{4,t}_{ijkl}} \right) \] (B27)

Equations B28-B31 show the attribution of changes in primary energy and GHG outcomes to changes in primary energy and GHG intensities of each energy end-use. These differ from Equations B17-B21 in that outcomes are adjusted based on assumptions of 1990 electricity generation efficiency and GHG intensity. Changes in primary energy and GHG as described in B28-B31 therefore are attributed to changes in the primary and GHG intensity (as defined separately per each end use) before considering changes/improvements in electricity supply. We refer to these contributions to the primary energy and GHG changes as due to ‘end-use intensity’ changes. Similar to final energy, intensities are defined by outcome variable per heating floor area for space heating, per house with air-conditioning for space cooling, per person for domestic hot water, and per house for other end-uses.

\[ \Delta Y^1_t = \sum_{ijkl} w^1_{ijkl} \ln \left( \frac{y^{r,n,t}_{ijkl}}{A^{4,t}_{ijkl}} \right) \] (B28) \[ \Delta Y^2_t = \sum_{ijkl} w^2_{ijkl} \ln \left( \frac{y^{r,n,t}_{ijkl}}{A^{4,t-1}_{ijkl}} \right) \] (B29)

\[ \Delta Y^3_t = \sum_{ijkl} w^3_{ijkl} \ln \left( \frac{y^{r,n,t}_{ijkl}}{A^{4,t-1}_{ijkl}} \right) \] (B30) \[ \Delta Y^4_t = \sum_{ijkl} w^4_{ijkl} \ln \left( \frac{y^{r,n,t}_{ijkl}}{A^{n,t-1}_{ijkl}} \right) \] (B31)

Decompositions of changes in energy consumption is done between every RECS year, excluding 1997 which was omitted for data quality reasons. We decompose changes in end-use energy and GHG between 1990 and 1993, 1993 and 2001, 2001 and 2005, etc. Then to calculate changes over
longer periods, e.g. between 1990-2001, we add together the contributions from different drivers in each sub period, e.g. the contribution of population growth to changes in space heating between 1990 and 2001 is equal to the $\Delta E_P^i$ between 1990 and 1993, and $\Delta E_P^i$ between 1993 and 2001. Note that this gives a different result compared to if we simply decomposed changes between 1990 and 2001. Adding together the contributions from subperiods gives a more accurate representation of the contribution of each driver over the whole period, because this approach assumes a constant growth rate of end-use energy consumption and driving factors between smaller periods of time, which is likely more accurate than assuming a constant growth rate of energy and driving factors over the entire period. Weather adjusted energy consumption is calculated by altering recorded energy consumption for space heating and cooling and water heating by year-division specific ratios of HDD or CDD to the 1971-2000 30-year average values.

B.2 Note on update to RECS end-uses in 2015

The end-use estimation in RECS data was updated in the 2015 survey, and the improved estimation led to lower estimates of electricity use for other end-uses, and higher estimates of electricity for space and water heating (EIA, 2018b). Therefore, the 1990 values for other end-use energy and GHG are likely underestimated, the upward drivers of other energy and GHG underestimated, and decreases due to GHG intensity overestimated. On the other hand, 1990 values for space and water heating may be underestimated, and thus the growth in these end-uses 1990-2015 are probably slightly overestimated. This magnitude of these discrepancies is on the order of 250 PJ/yr final energy, or 50 Mton CO$_2$/yr, so it is possible that GHG from space and water heating have actually decreased between 1990-2015 and that GHG from other end-uses actually increased. This can help explain the increase and decrease in final energy intensities for domestic hot water and other end-uses respectively between 2009 and 2015 (Fig B.19, B.20), and the respective increase and decrease in end-use intensity for domestic hot water and other end-uses between 2001 and 2015 (Fig 3.3c, 3.3d).
B.3 Note on activity definition and effect of household size

Xu and Ang (2014a) note that IDAs of residential energy consumption tend to choose either population or number of households (equivalently number of occupied houses) as the activity indicator, and implications that this has on decompositions of residential energy demand (Xu and Ang 2014a, Table 2). Since that study was published, numerous further studies of residential energy use or GHG emission using IDA (in some cases combined with structural decomposition analysis) have been published (Balezentis, 2020; Huang et al., 2019; Shigetomi et al., 2018; Zang et al., 2017). Common to Xu and Ang (2014) and all of the more recent papers are reductions in household size over the study period. In two of these papers (Balezentis, 2020; Xu & Ang, 2014), population is the main activity variable, and the household size effect is found to increase the value of the outcome variable. In another three papers (Huang et al., 2019; Shigetomi et al., 2018; Zang et al., 2017), housing is the main activity variable, and the household size effect is found to decrease the value of the outcome variable. This can be understood with the help of the following simple example. Using data based solely on energy consumption $E$, number of households $H$, and population $P$, the two following IDAs could be defined:

$$E = P \times \frac{H}{P} \times \frac{E}{H} \quad \text{(B32)}$$

$$E = H \times \frac{P}{H} \times \frac{E}{P} \quad \text{(B33)}$$

A reduction in household size will result in an increase of the $H/P$ term in Eq. B32 where Population is the activity indicator, and the IDA will indicate that the increase of $H/P$ drives an increase in $E$. With the exact same data, in Eq. B33, a reduction in household size will result in a reduction of $P/H$ where Households are the activity indicator, and the IDA will indicate that the reduction of $P/H$ drives a reduction in $E$. The resolution to this apparent conundrum lies in what is the most reasonable disaggregation of $P$ and $H$ into two ‘independent’ terms. The act of allocating changes in an outcome variable to changes in each term in a decomposition equation implies independence
between each term; if one term changes, that change is assumed to be unrelated to changes in other terms. This has been recognised as a shortcoming of IPAT and other decomposition-based analyses (O’Neill & Chen, 2002). A good practice to mitigate effects of such interdependence is to define decomposition equations using terms that are less likely to be interdependent. In this specific example, we are interested in which of two options for decomposing changes in population and households is less influenced by interdependence. Household size, or it’s inverse, can be used to convert the decompositions in Eq. B32 and B33 into the equivalent Equations B34 and B35 respectively.

\[
E = P \times \frac{H}{P} \times \frac{E}{H} = H \times \frac{E}{H} \quad (B34)
\]

\[
E = H \times \frac{P}{H} \times \frac{E}{P} = P \times \frac{E}{P} \quad (B35)
\]

Figure B.1 demonstrate the underlying relational assumptions for each case. For both cases we add a latent variable which can influence the first two RHS terms in Eq. 32 and Eq. 33, to intuitively and qualitatively test for independence. In Fig B.1 (a) with population as the activity indicator, we recognize that some latent variables can cause changes in both aggregate population and household size, such as changes in fertility and mortality rates, and net immigration. The latent variables should not affect the result in the bottom, in this case number of households, directly, but can only influence through the intermediate factors of population and household size.

In Fig B.1 (b) we attempt to make a similar figure for the case when number of households is the activity indicator. Here we don’t find a convincing argument for the latent variables to influence the number of households directly, which could help the argument for independence between household size and number of households. However, we argue that the direction of the causal link between households and population in this version is backwards; growth in households does not drive growth in population, but growth in population can and does drive growth in number of households. Following this line of reasoning, the number of households does not exist
independently from household size. Household size and total population interact to define the total number of households. We mark out the arrows that we disagree with in Fig B.1 (b) and add in alternative arrows in dotted blue lines which provide what we feel are direct causal links. Population and household size, despite having some common determinants, can change independently. Population can grow while household size remains the same, or population could stay static while household size changed. The same is not true for number of households and household size. An increase in the number of households while keeping the same household size implies population growth; reductions in household size with a steady number of households reflects population decline. Population growth is the exogenous variable here, and combined with household size they determine the number of households. Changes in the number of households are not exogenous and do not determine changes in population.

Figure B.1 (a-b) Alternative definitions of activity in residential IDA models, and implications for effect of household size
### B.4 Supplementary Tables

#### Table B.1 Average household appliance ownership and size/usage characteristics in urban single-family detached homes by cohort, 2015

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>TVs</td>
<td>2.44</td>
<td>2.42</td>
<td>2.61</td>
<td>2.57</td>
<td>2.65</td>
<td>2.99</td>
<td>2.92</td>
<td>2.84</td>
</tr>
<tr>
<td>% ‘large’ TVs(^a)</td>
<td>52%</td>
<td>58%</td>
<td>63%</td>
<td>64%</td>
<td>69%</td>
<td>71%</td>
<td>74.4%</td>
<td>73%</td>
</tr>
<tr>
<td>Lights on 4hr/day</td>
<td>7.13</td>
<td>7.05</td>
<td>7.81</td>
<td>8.27</td>
<td>8.29</td>
<td>9.69</td>
<td>10.77</td>
<td>10.66</td>
</tr>
<tr>
<td>% 60+ lights(^b)</td>
<td>4.4%</td>
<td>9%</td>
<td>11%</td>
<td>8%</td>
<td>15%</td>
<td>24.4%</td>
<td>24.4%</td>
<td>21%</td>
</tr>
<tr>
<td>% own Clothes Dryer</td>
<td>90%</td>
<td>93%</td>
<td>96%</td>
<td>94.4%</td>
<td>94.4%</td>
<td>98%</td>
<td>98%</td>
<td>98%</td>
</tr>
<tr>
<td>Fridges</td>
<td>1.32</td>
<td>1.39</td>
<td>1.49</td>
<td>1.53</td>
<td>1.57</td>
<td>1.65</td>
<td>1.60</td>
<td>1.46</td>
</tr>
<tr>
<td>% ‘large’ Fridges(^c)</td>
<td>43%</td>
<td>46%</td>
<td>44.4%</td>
<td>48%</td>
<td>59%</td>
<td>63%</td>
<td>64.4%</td>
<td>62%</td>
</tr>
<tr>
<td>Personal electronics(^d)</td>
<td>3.64</td>
<td>3.38</td>
<td>3.81</td>
<td>3.89</td>
<td>4.13</td>
<td>4.66</td>
<td>5.22</td>
<td>5.56</td>
</tr>
<tr>
<td>Ceiling fans</td>
<td>1.94</td>
<td>2.30</td>
<td>2.44</td>
<td>2.74</td>
<td>3.34</td>
<td>3.47</td>
<td>3.49</td>
<td>3.14</td>
</tr>
</tbody>
</table>

\(^a\) Percent of homes whose primary TV is 40 inches or more; \(^b\) Percent of homes who have 60 or more lights installed; \(^c\) Percent of homes whose primary refrigerator is larger than 22.5 ft\(^3\); \(^d\) Average number of laptops, tablets, and smartphones per household

#### Table B.2 Average final energy demand (MJ) within ‘other’ end-uses in urban single-family detached homes by cohort, 2015

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothes Drying</td>
<td>2,331</td>
<td>2,321</td>
<td>2,424</td>
<td>2,555</td>
<td>2,459</td>
<td>3,084</td>
<td>2,881</td>
<td>2,830</td>
</tr>
<tr>
<td>Lighting</td>
<td>3,846</td>
<td>3,684</td>
<td>4,224</td>
<td>4,530</td>
<td>4,975</td>
<td>5,794</td>
<td>6,165</td>
<td>5,221</td>
</tr>
<tr>
<td>Refrigeration</td>
<td>2,495</td>
<td>2,679</td>
<td>2,984</td>
<td>3,204</td>
<td>3,415</td>
<td>3,761</td>
<td>3,695</td>
<td>2,865</td>
</tr>
<tr>
<td>TV and related</td>
<td>2,680</td>
<td>2,811</td>
<td>2,933</td>
<td>2,942</td>
<td>3,048</td>
<td>3,500</td>
<td>3,447</td>
<td>3,185</td>
</tr>
<tr>
<td>Ceiling fan</td>
<td>576</td>
<td>681</td>
<td>728</td>
<td>883</td>
<td>1,257</td>
<td>1,370</td>
<td>1,389</td>
<td>1,167</td>
</tr>
<tr>
<td>Elec n.e.c.</td>
<td>5,202</td>
<td>4,463</td>
<td>5,273</td>
<td>4,313</td>
<td>6,209</td>
<td>6,777</td>
<td>7,463</td>
<td>5,626</td>
</tr>
</tbody>
</table>

Electricity n.e.c. = electricity consumption not elsewhere classified
B.6 Supplementary Figures

Figure B.2 Weather-adjusted a) Residential final energy, b) primary energy, and c) GHG emissions by end-use, RECS survey years 1990-2015

Figure B.3 shows the hierarchical structure of the multilevel IDA model. In this example, for space heating, the data subset would be population living in South Atlantic (R5), in single-family detached homes (T2) built in the 1970s (C4) with electricity (H4) as the main heat fuel. Changes in household size, heated floor area, space heating energy intensity, weather, and electricity intensity/GHG intensity would between survey years are calculated for every such combination of the Region, Type, Cohort, Fuel dimensions, then aggregated based on the portion of space heating energy consumption by each population subset.
Figure B.3 Hierarchical structure of IDA model, example for space heating
Figure B.4 (a-d) Decomposition of changes in final energy for each end-use, 1990-2015
Figure B.5 (a-d) Decomposition of changes in primary energy for each end-use, 1990-2015

Figure B.6 (a-c) Disaggregation of final energy, primary energy, and GHG emissions for Other energy end-uses, 2015
B.7 Change in drivers over study period

Figures B.7-B.22 describe changes in values of the drivers that we identify and incorporate in our models of residential final and primary energy, and GHG emissions. All data are based on RECS (EIA, 2019d) unless otherwise indicated.

Figure B.7 Regional changes in household population distribution, 1990-2015

Figure B.8 House type changes in household population distribution, 1990-2015
Figure B.9 Regional changes in occupied homes per person, 1990-2015

Figure B.10 Changes in U.S. population distribution by housing age cohort, 1990-2015
Figure B.11 Changes in main fuel used for space heating at national level, 1990-2015

Figure B.12 Changes in main fuel used for domestic water heating at national level, 1990-2015
Figure B.13 Regional changes in population using a) gas b) electricity c) oil as main space heating fuel, 1990-2015
Figure B.14 Regional changes in portion of population using a) gas b) electricity as main water heating fuel, 1990-2015
Figure B.15 Regional changes in average heated floor area per home a) by type, b) by Division, 1990-2015
Figure B.16 Regional changes in percentage of homes with space cooling equipment, 1990-2015

Figure B.17 Regional changes in final energy for space heating per heated floor area, 1990-2015
Figure B.18 Regional changes in final energy for space cooling per housing with cooling equipment, 1990-2015

Figure B.19 Regional changes in final energy for domestic hot water per person, 1990-2015
Figure B.20 Regional changes in final energy for other end-use per house, 1990-2015

Figure B.21 Regional changes in GHG intensity of electricity, 1990-2015. Data from SEDS (EIA, 2019c)
Figure B.22 Regional changes in primary energy requirements of electricity, 1990-2015. Data from SEDS (EIA, 2019e)

Figure B.23 Average total floor area in new single-family (SF) and multifamily (MF) homes (U.S. Census Bureau, 2020a)

Figures B.24 and B.25 compare GHG emissions per kWh of useful heat delivered by standard fossil heating systems and electric heating systems. Efficiency estimates of heating conversion devices are based on unit efficiencies of most commonly sold heating units in recent years (EIA, 2017). In Figure B.24 we compare the regional GHG intensities of electricity (equivalent to the GHG
intensity per useful energy of electric resistance heating with a final to useful energy conversion efficiency of 100%) with GHG intensities of oil and gas furnaces/boilers with annual fuel use efficiencies of 80%. In Figure B.25 we estimate the GHG intensity per useful heat of electric heat pumps by dividing the regional GHG intensities of electricity by 2.4, reflecting estimated final to useful efficiencies of electric heat pumps with a heating seasonal performance factor of 8.2 (EIA, 2017). We use the same intensities for oil and gas-based heating systems to compare with the electric heat pumps. By these estimates, in most regions except Pacific and New England since 2017, switching from gas to electric resistance heating will result in an increase in GHG for meeting the same heating load, with the increases most pronounced in the West-North Central division. Switching from gas to electric heat pumps however would by 2017 lead to decreases in GHG emissions for the same heating load in everywhere except for the Mountain and West-North Central divisions. The GHG benefits of switching from gas to electric heating are thus not guaranteed in the short term, and depend on the regional grid intensity and electric technology choice, but reductions are far more likely when switching to electric heat pumps.

Figure B.24 Regional changes in GHG emissions per kWh of useful heat from resistance electric heating vs fossil-based heating, 1990-2015. By 2018, only New England and Pacific Census Divisions have GHG intensities of electricity which enable immediate reductions in GHG emissions when switching from gas to electric resistance heating.
Figure B.25 Regional changes in GHG emissions per kWh of useful heat from heat pump electric heating vs fossil-based heating, 1990-2015. In 2018, immediate GHG savings can be achieved when switching from oil to electric heat pumps in all Census Divisions, and when switching from gas to heat pumps in all Census Divisions except West-North Central and Mountain.
C Appendix to Chapter 4

C.1 Supporting notes

Note 1

After FIRREA, $1 million in starting capital could support a $25 million Federal Housing Administration or Veterans Affairs mortgage, a $12.5 million mortgage for a 1-4 family home, or a $6.25 million multifamily mortgage (A. F. Schwartz, 2015).

Note 2

In the main text we make note of several papers that show important effects of local regulations on housing outcomes, including effects on housing type mix. Ideally, a housing starts model would incorporate policy regulations at both local and federal levels. Existing local regulation data however do not support a time-series analysis incorporating the net effects of local housing or land use policies at the national level. The most comprehensive tabulation of land-use regulations at the local level is the Wharton Residential Land Use Regulatory Index. Until recently, this described the stringency of local land use regulations for about 2,500 local jurisdictions in 2006 (Gyourko et al., 2008). Recently an updated index has been published for jurisdictions in 2018 (Gyourko et al., 2019), facilitating documentation of changes between 2006 and 2018 in jurisdictions that answered both surveys. Many well cited publications have made use of the 2006 data, including Saiz (2010), and Hsieh and Moretti (2019), and the more recently published data will likely by greatly utilized too. A separate survey by Pendall et al. reported local land use regulations in 728 jurisdictions for two points in time (1994 and 2003) (Pendall et al., 2018).

While these datasets represent a very useful resource in comparing overall regulation between locations, and between two points in time, none of them are suitable for estimating the net stringency of local regulations at a national level over a substantial period of time at annual or sub-
annual time-steps. There must be interactions between regulations at the federal and local levels which together influence the share of new housing that is built as single-family rather than multifamily. However, due to the lack of data on local regulations throughout the country or at regular timesteps over long time periods, we specified our model of housing starts considering federal policies only. Lending some support for our decision to omit of local regulations, neither the surveys by Pendall (1994 and 2003), nor the surveys by Gyourko and colleagues (2006 and 2018) indicate that the overall intensity of local regulation relating to single-family and multifamily homes changed much over our time frame.

We also note in the main text that transport policies and infrastructure investments have been linked with depopulation of city centers and suburbanization of metropolitan areas (Baum-Snow, 2007). The transport policies which supported large investments in transport infrastructure such as federal highways may have had some influence on relative demand for single- and multifamily housing, for instance by facilitating growth of population in suburban areas where single-family housing is more prominent. The most relevant policies, the Federal Highways Acts in 1921 and the 1950s (1952, 1956), paved the way for growth in federal highway networks. These policies preceded the timeline of our housing starts model (1971-2018), but we investigated potential effects of increased use of highways in urban areas by incorporating data of total urban highway mileage (U.S. Bureau of Transportation Statistics, 2019; U.S. Department of Transportation, 1985, 2019a) and number of vehicles per person (U.S. Department of Transportation, 2019b, 2020) as covariates in our housing starts model. When doing so, we found negative coefficients for both variables (suggesting, counterintuitively, that longer urban road networks or increases in vehicles per person are associated with a smaller share of single family in new construction). In the case of vehicles per person the effect was insignificant. As neither the housing policy coefficients or the predictive power of the model changed much after the inclusion of these transport related metrics, we decided to omit them from the housing starts model.
In our housing starts model we assume that it took one year after PHM was announced for new housing starts to be affected by the moratorium. This is based on the likelihood that public housing starts through the end of 1973 were funded by money committed before the moratorium was announced. This timeline is consistent with data on total public housing construction, which peaks around 1975 (Vale & Freemark, 2012). Varying the quarter where PHM takes effect produces qualitatively similar results, with more substantial changes to the model outcomes occurring if PHM takes effect earlier than Q1 1974.

Note 3
When translating the outcomes of the housing starts model into a no-policy counterfactual housing stock in 2015, we assume that changes in the type mix of housing do not induce changes in the demolition flows or turnover of housing stock. Data from the American Housing Survey inform Census Bureau estimates of low loss rates for houses and apartments over the age ranges that would affect this study (U.S. Census Bureau, 2020c). Using the same rates as those used by the Census Bureau, we calculate that 99.5% of the total units constructed between 1973-2014 would still be part of the stock in 2015. The American Housing Survey ‘Components of Inventory Change 2015-2017’ however report loss rates for multi-unit buildings that are approximately double those for single-family buildings (Eggers & Moumen, 2020) (unlike the data used by the Census Bureau for housing unit estimates, these loss rates include sources of loss other than demolition, such as units being used for storage or commercial purposes, or interiors being exposed to the elements). Doubling the stock average loss rates used by the Census Bureau, we calculate that 99.0% of the total units constructed between 1973-2014 would still be part of the stock in 2015. Therefore, the potential influence of type-dependent loss rates on building stock turnover and on our estimated changes to the housing stock appears very small (<1%) and we don’t consider those differences in our counterfactual housing stock estimates. For longer range and projection-based studies, it may be necessary to consider different rates of demolition and turnover for different types of houses.
We note in the main text that completion of housing starts is lower in multifamily homes than single-family homes. The respective completion rates of housing starts as reported by Census Bureau New Residential Construction surveys are 92.5% for multifamily and 96.5% for single-family (U.S. Census Bureau, n.d.). The adjustment factor of 4.1% that we use to adjust changes in housing stocks based on housing starts is the percentage difference in completion rates, i.e.

$$\frac{0.965 - 0.925}{0.965} = 0.041.$$ 

In our model of housing starts, we chose quarterly real GDP and the 30-year mortgage rate as macroeconomic indicators, and quarterly population change as a demographic indicator, which we hypothesize may influence the single-family share of new housing starts. We use population growth as it is the closest readily available demographic proxy to household growth, which will influence new demand for housing. We choose quarterly real GDP as a variable representing overall economic activity and a proxy for growth in overall national wealth, which may influence the type characteristics of new demand for housing.

The model estimates that higher GDP is associated with a lower share of single-family housing in new residential construction, which may be a surprising result, as it would appear to contradict observed correlations between GDP per capita and floor space per person (Eom et al., 2012; Moura et al., 2015). Some studies report correlations between increasing urbanization and growth in GDP per capita (M. Chen et al., 2014; Eom et al., 2012), and there is more multifamily housing in US urban areas than rural areas (EIA, 2018a). While urbanization and GDP correlations may be an contributor to the negative coefficient of GDP on single-family share of housing starts, the economic determinants of urban form is not the focus of this paper, and we do not argue for a causal relation between GDP and type share of new housing based on our housing starts model. The inclusion of GDP in our model is simply as a control for level of macroeconomic activity, and the negative association identified is likely just a correlation, rather than a causal relationship.
Investigating implications of economic growth for urbanization and composition of housing stocks is an interesting area for future research.

Note 4

We omitted from the energy end-use model the following households: those with farm energy use or home businesses, those that included the energy use of tenants not within the household, and those with other unusual energy uses. In order to remain consistent with the other analyses in this paper, only urban households were included in the models. A Hausman test was performed to check the consistency of the estimators between the fixed and mixed effects models, finding that the ‘random’ effects of type and cohort were not independent from other covariates, therefore we adopted a fixed effects approach to modelling the influence of type and cohort combinations. Table C.5 shows summary statistics for the four end-uses.

Note 5

In scenarios CF1-CF4 we calculate reductions in energy demand resulting from a modeled change in type composition of the housing stock. These scenarios reflect different assumptions regarding how selection and household preferences will influence which households are likely to be affected by an increase in multifamily housing, and to what extent changes in house type might be accompanied by reductions in floor area for the affected households. CF1 depicts a scenario where the households affected by the counterfactual (i.e. who move from single- to multifamily) are low- and mid-income, representing a situation where there is substantial selection of housing type by income. CF2 represents energy savings for the average income household, with income controlled for as a covariate in $X$ (Chapter 4 equation 2). In both CF1 and CF2 we represent a strong preference among households who move from single- to multifamily for more floor area, by assuming that the floor area in the counterfactual multifamily homes is equal to the average floor area in single-family homes. In CF2 we also assumed that household income remains unchanged among the households.
that were affected. This was not necessary in CF1 as energy reductions are already calculated based on assumptions of which income groups were affected. In scenarios CF3 and CF4 we build on CF2, relaxing the assumption of no change in floor area, to show the effects of floor area reductions of 30% and 50%. The following paragraphs and equations describe the equations used to represent these assumptions for each scenario.

The general approach for calculating energy end-use consumption in the housing stock for scenarios CF1 and CF2 is to start with the base energy consumption in the stock disaggregated by housing type \( t \) and cohort \( c \), and add to that the sum of housing stock changes multiplied by average energy consumption per house affected by the housing stock counterfactual (equation C1). The sum of changes in the housing stock \( \Delta HousingStock_{t,c} \) is zero for the sum of all house types, positive for multifamily homes, and negative for single-family homes, representing a growth in the number of multifamily households calculated by our housing policy counterfactual.

\[
Energy_{t,c}^{CF=CF1,CF2} = Energy_{t,c}^0 + \sum_{t,c}(\Delta HousingStock_{t,c} \times EnergyPerAffectedHouse_{t,c}^{CF})
\]

\[\text{(C1)}\]

\( Energy_0 \) refers to the energy end-use consumption of the housing stock by type and cohort in the base case, as shown aggregated for all end-uses in the first column of Figure 4.2(b). The average end-use energy per affected house is based on the type-cohort effects (\( \varphi' \) for CF1, \( \varphi \) for all other scenarios) on energy end-uses, adjusted so that energy consumption in the reference level (Multifamily high 2000+) equals average consumption in the affected reference household. To achieve this, we add an offset representing average consumption in the affected reference household to each coefficient, preserving the relative difference between house type and cohorts (equation C2).

\[
EnergyPerAffectedHouse_{t,c}^{CF} = \varphi^{CF} + AvgEnergy_{ref}^{CF}
\]

\[\text{(C2)}\]
In CF1, we describe a scenario where the households affected by the counterfactual housing policy are 65% low-income and 35% mid-income. The type-cohort fixed effects $\phi_{\text{CF1}}$ for this combination of low- and mid-income (LMI) households is the 65:35 weighted sum of fixed effects for low and mid income households, minus the 65:35 weighted sum fixed effect for the reference Multifamily high 2000+ house type (equation C3).

$$\phi_{\text{CF1}} = (0.65\phi'_{\text{L1}} + 0.35\phi'_{\text{M1}}) - (0.65\phi'_{\text{L1,ref}} + 0.35\phi'_{\text{M1,ref}})$$  \hspace{1cm} (C3)

The fixed effects by type and cohort for each income group $\phi'$ is estimated in a modification of Chapter 4 equation 2 in the main text where income is incorporated by including the three income groups in fixed effects, rather than controlling for income as a covariate in the energy end-use model. The subtracted second term of equation C3 is required to have a value of zero for the reference level.

In CF2, we describe a scenario where the average single-family household is affected by the counterfactual policy. In this scenario, income is controlled for as a covariate in $X$ in the end-use model, so the fixed effects parameter $\phi$ applies to all households. Therefore, $\phi_{\text{CF2}}$ is equal to the fixed effects parameter $\phi$ estimated by the basic end-use models summarized in equation 2 of the Chapter 4.

The term $\text{AvgEnergy}_{\text{ref CF}}$ in equation C2 refers to the average consumption in the affected Multifamily high 2000+ household in scenarios CF1 and CF2. $\text{AvgEnergy}_{\text{ref CF1}}$ represents energy consumption in the average LMI household which lived in a single-family house in the base case, but in multifamily in the policy counterfactual. To estimate average energy consumption in this type-cohort combination, we add to the base case average energy consumption in Multifamily high 2000+ ($\text{AvgEnergy}_{\text{ref CF}}$) terms based on the floor area coefficient $\beta'_{\text{FA}}$ for each end-use multiplied by the difference in average floor area between average multifamily houses and average low- and mid-income single-family houses, respectively. $\Delta FA_{\text{SFLM}}$ is the difference in average floor area.
between multifamily houses (MF) and average low-income single-family (SFLI) houses, while $\Delta FA_{SFIM,MF}$ is the difference in average floor area between multifamily houses (MF) and average mid-income single-family (SFLI) houses. Floor area differences are based on houses built in 1970s or later, as those are the households that would be affected by the policy counterfactual. Again, the weighted low-income and mid-income effects are based on the 65:35 low- and mid-income split of households modeled in CF1 (equation C4).

$$AvgEnergy_{ref}^{CF1} = AvgEnergy_{ref}^0 + (0.65 \times \beta^{FA} \times \Delta FA_{SFLI,MF}) + (0.35 \times \beta^{FA} \times \Delta FA_{SFMI,MF})$$

(C4)

AvgEnergy$_{ref}^{CF2}$ represents energy consumption in the average household which lived in a single-family house in the base case, but in multifamily in the policy counterfactual. In CF2, the average energy consumption in the reference level (Multifamily high 2000+) household is based on the base case average energy consumption in that type-cohort combination ($AvgEnergy_{ref}^0$), adjusted for differences in floor area and income between the average single- and multifamily households.

$$AvgEnergy_{ref}^{CF2} = AvgEnergy_{ref}^0 + \beta^{FA} \times \Delta FA_{SF,MF} + \beta^{Inc} \times \Delta Inc_{SF,MF}$$

(C5)

$\Delta FA_{SF,MF}$ refers to the average difference in floor area between single- and multifamily homes built in 1970s or later, and $\Delta Inc_{SF,MF}$ refers to the average difference in household income between single- and multifamily households in 2015, living in houses built 1970s or later. In this way, average energy consumption in the average Multifamily high 2000+ home is adjusted upwards based on the assumption that households moving to multifamily maintain the same level of floor area demand and household income.

For scenarios CF3 and CF4, the energy reductions from CF2 are taken as a baseline, and further reductions are then calculated assuming that the multifamily homes occupied by the households affected by the counterfactual are 30% and 50% smaller than the (single-family) homes that they actually occupy. This would bring their floor area closer to what is common in multifamily homes,
but the floor area in these households would in most cases still be considerably larger than in the average multifamily homes in 2015 (Figure C.12). We summarize the calculation of energy consumption in the entire housing stock in CF3 and CF4 in equation C.6.

$$\text{Energy}_{t,c}^{CF=CF3,CF4} = \text{Energy}_{t,c}^{CF2} - \gamma^{CF} \cdot \overline{FA_{SF}} \cdot \beta_{FA} \cdot \sum_{t,c} (\Delta\text{HousingStock}_{t=MF,c})$$ (C6)

The energy consumption of the stock in CF2 is reduced by a floor area reduction in the multifamily homes affected by the housing stock counterfactual. The size of the floor area reduction $\gamma^{CF} \cdot \overline{FA_{SF}}$ is determined by a percentage reduction ($\gamma^{CF}$) of average single-family floor area ($\overline{FA_{SF}}$) in homes built 1970s or later.

It is worth noting that based on this approach to calculating energy consumption by house type and cohort in each scenario, average energy consumption by type for the households affected by the counterfactual is higher than actual averages for multifamily (due to the larger average floor area and income in multifamily homes in the counterfactual), and lower than current averages for single-family (suggesting that single-family households who move to multifamily in the counterfactual have lower energy consumption than the average single-family household).

**Note 6**

Data used for the housing starts model are freely available online from Freddie Mac (2020), the US Census Bureau (2020) and the US Bureau of Economic Analysis (2020b, 2020a, 2020c). Data detailing the existing housing stock used to support the residential energy end-use model, are freely available online from the US Energy Information Administration (2018a). All code was written in the R software environment, and can be accessed at https://github.com/peterberr/us_housing_energy/tree/master/policy_type_effects.
AHS surveys indicate that among home-owning households, single-family households are more likely to make energy efficiency improvements than multifamily (US Census Bureau, 2020a) (Fig. C.9). Information on what kind of energy efficiency improvements are made are not indicated, but a report from the Joint Center for Housing Studies shows that among home-owner households in 2017, around 1.8% upgraded insulation, while about 5.0% of households replaced their HVAC equipment, and 4.6% of households replaced their water heater (JCHS, 2019). Percentages are estimated by the authors, by dividing the total counts of households making upgrades in 2017 from JCHS by the American Community Survey count of total owner-occupied homes in 2017 (U.S. Census Bureau, 2019). Based on AHS 2015 and 2017 surveys, we developed linear models of likelihood to make an energy efficiency home improvement in owner-occupied single-family homes by three income groups (low income = <$40,000/year, mid income = $40-100,000/year, high income = >$100,000/year), controlling for age of house. We show the results of this model in Table C.1. This is not a strong model for predicting or explaining variation in home energy efficiency improvements (judging by R²), but it does indicate that the likelihood of making efficiency improvements in mid- and low-income households is 3 and 7-8 percentage points lower, respectively, than in high income households.

<table>
<thead>
<tr>
<th></th>
<th>Portion investing in energy eff. 2015</th>
<th>Portion investing in energy eff. 2017</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.18*** (0.01)</td>
<td>0.15*** (0.01)</td>
</tr>
<tr>
<td>Home Age</td>
<td>0.00*** (0.00)</td>
<td>0.00*** (0.00)</td>
</tr>
<tr>
<td>Income [Low]</td>
<td>-0.08*** (0.01)</td>
<td>-0.07*** (0.01)</td>
</tr>
<tr>
<td>Income [Mid]</td>
<td>-0.03*** (0.01)</td>
<td>-0.03*** (0.01)</td>
</tr>
<tr>
<td>Observations</td>
<td>31,308</td>
<td>30,382</td>
</tr>
<tr>
<td>R²</td>
<td>0.012</td>
<td>0.010</td>
</tr>
</tbody>
</table>

*p <0.05, **p <0.01, ***p <0.001  Data: American Housing Survey
Assuming that the higher rate of energy efficiency upgrades in single-family homes applied to the whole housing stock (not just owner-occupied homes) over the period of our housing stock counterfactual (1973-2015), it would follow that an increase in the share of multifamily homes will reduce the overall rate of energy efficiency upgrades in the housing stock. As the RECS data and our model are based on the actual housing stock in 2015, the differences we observe between multifamily and single-family already incorporate any differences in energy efficiency improvements by house type made over previous years and decades.

The apparent higher rates of energy efficiency investment in single-family homes, and in higher income homes, are not apparent when examining energy consumption data in RECS. Type-cohort effects on end-use energy consumption for each income group (Figure C.6) show higher energy consumption in higher income groups, especially in single-family detached homes, after controlling for floor area, climate, and household size. Therefore, even if there are higher rates of energy efficiency improvements in higher income single-family homes, those homes still have the highest energy consumption. In addition, RECS data suggest that multifamily homes are actually more likely (than single-family) to have space and water heaters that are less than 10 years old (Figure C.12). The implications of the apparent conflicting tendencies for high energy efficiency improvements and higher energy consumption in single-family detached homes for this study are that, without further research into determinants of energy efficiency adoption and effects of energy efficiency adoption on energy demand by building and tenure type, and by household characteristics, it is difficult to conclude how energy efficiency adoption might change if more households lived in multifamily housing, or to what extent those potential changes might affect aggregate residential energy demand.

*Note 8*

In the summary and discussion of the main text, we give some examples of concrete policy steps to encourage more construction of multifamily housing, including equalizing access to finance for
single-family and multifamily investors. This could be achieved for example by reducing the gap in required down payments for single- and multifamily mortgages backed by federal government-sponsored enterprises Fannie Mae and Freddie Mac, and encouraging smaller savings and loan banks to re-enter multifamily mortgage markets. Savings and loan banks have played increasingly smaller roles in the multifamily mortgage markets since the late 1980s. In their place, secondary mortgage markets and government-sponsored enterprises have accounted for much larger shares of multifamily mortgages, but these finance sources have been less likely to originate mortgages for lower-income and mid-sized buildings (5-49 units) (A. F. Schwartz, 2015).

We also note that the federal government could equalize tax treatments for rental and owned housing. Federal government advisory panels and commissions for Presidents G.W. Bush and Barack Obama recommended in 1995 and 2010 to replace the mortgage interest deduction with a mortgage interest-based, but more limited tax credit, equal to 15% of mortgage paid with the maximum mortgage limited to the average regional price of housing in 1995, and equal to 12% of mortgage interest paid limited to primary residences with mortgages up to $550,000 in 2012. In neither case were these recommendations acted upon (A. F. Schwartz, 2015).

President Trump’s 2017 Tax Bill made some changes to tax deductions which are relevant to this discussion. This bill reduced the limit on housing related debt on which interest deductions could be applied from $1,000,000 to $750,000 (this change applied only to housing investments made after December 15, 2017). It also capped mortgage deductions from state and local taxes at $10,000, while increasing the standard deduction (which is available to non-itemizing homeowners and non-homeowners alike). These changes are likely to have reduced incentives for home-ownership in high home-value and high property tax areas.
C.2 Supporting Figures

Figure C.1 (a) shows residential final energy consumption per-capita, for eight countries and the OECD-Europe region. Energy consumption tends per-capita tends to be higher in countries with colder climates, such as Canada and Russia. Final energy and population data come from the IEA World Energy Balances (International Energy Agency, 2019). Figure C.1 (b) shows residential final energy per capita-degree-day. In this figure the energy consumption per capita data was further divided by the sum of average (1964-2013) population weighted heating degree days and cooling degree days, to a base of 18.3°C (65°F), from Atalla and Lanza (2018). After Australia, the US has the second highest energy requirements per population and climate out of the nine countries analyzed.
Figure C.1 a, b Comparisons of residential energy intensities between US and other countries in recent years. Energy and population data from IEA (2019), degree-data data from Atalla & Lanza (2018)

Figure C.2(a) shows urban housing stock in 2015 by housing type and cohort. Figure C.2 (b) shows the counterfactual 2015 urban housing stock estimated by applying estimates of housing starts in the absence of PHM, TRA 86, and FIRREA.
Figure C.2 (a) Actual and (b) counterfactual urban housing stocks in 2015 by age cohort and type. Original data from RECS 2015 (EIA, 2018a), counterfactual calculated by authors based on housing starts model. Manufactured housing is unaffected by the counterfactual, and is omitted from the figure.

Figure C.3 shows historical and modelled single-family share of quarterly housing starts from 1971-2018. The black line trend is based on historical housing starts data (United States Census Bureau, 2020), the red line trend is the fitted values of the linear model of housing starts share, and the blue line trend is the modelled single-family share under the policy counterfactual where effects of PHM, TRA 86, and FIRREA are omitted.
Figure C.3 Share of single-family housing in quarterly total housing starts. Historical data are shown against modelled data before (red line) and after (blue) line removing the effects of the policies PHM, TRA86, FIRREA.

Figure C.4 shows a comparison of GHG impacts of scenarios CF1 – CF4 in absolute (a) and percentage (b) terms, and is complementary to Figure 5 in the main text.

Figure C.4 Comparison of residential GHG reduction strategies in each scenario for single-family homes a) in absolute terms and b) in percentage terms
Figure C.5 shows trends of average floor area in new single-family and multifamily homes from 1975-2019 (data for multifamily homes begins in 1999).

![Average Total Floor Area in Newly Built Homes, 1975-2019](image)

*Figure C.5 Average total floor area in new single-family (SF) and multifamily (MF) homes. Data from U.S. Census Bureau (2020a)*

Figure C.6 (a-c) show type-cohort effects on energy end-use consumption for three income groups (low, mid, high). These differences are calculated as fixed effect coefficients $\phi'$ by type, cohort and income group, after controlling for climate (HDD), heated floor area, and household size (Table C.8). We see that similar patterns hold across the three income groups – energy demand tends to be higher in older cohorts (although this trend is less conclusive for MF high), and energy demand tends to be higher in single-family than multifamily homes. Figure C.6 (d) replicates Fig. 4.3 for reference.
Figure C.6 (a-c) Effects of house type and cohort on urban residential energy end-uses in 2015 for three income groups. Effects are coefficient offsets by type-cohort to the reference of High-income multifamily high-density homes built 2000+, and are estimated by the linear models summarized in Table C.8. Heavier markers are used for effects which are significant at \( p<0.05 \). Fig (d) shows type-cohort effects for the average household after controlling for income, and is a replica of Figure 3 in the main text.
Figures C.7 (a) and (b) show distribution of households into house types by household size and income. Half of low-income (<$40,000 household income in 2015) households with 1-2 people live in multifamily homes; this share declines sharply to around 30% and 25% for mid- and high-income households.

![Urban Housing Type Mix by Income and Household Size, 2015](image)

Figure C.7 (a) Absolute and (b) relative distribution of urban households into multifamily (MF) and single-family (SF) housing types by three income groups and three household size groups. LowInc: annual housing income <$40,000; MidInc: annual housing income = $40,000-99,000; HiInc: annual housing income > $100,000.

Figure C.8 (a), based on RECS 2015 data, shows that over half of space heating equipment is older than 10 years old in urban single-family homes, while only 42% is older than 10 years multifamily homes. The difference is more pronounced for water heating (Fig. C.8 (b)), 37% of single-family
homes of have space heating equipment that is at least 10 years old, while 28% of multifamily homes have space heating equipment that is at least 10 years old.

![Graph](image)

Figure C.8 Age distribution of (a) space and (b) water heating equipment in urban multifamily (MF) and single-family (SF) homes in 2015. Households with no space and water heating equipment are removed from this comparison.

Figure C.9 shows home data on home improvements among single-family and multifamily homeowners for the years 2011-2019, showing a consistently higher tendency for efficiency improvements in single-family homes (US Census Bureau, 2020a). These data are collected only for homeowners.

![Graph](image)

Figure C.9 Percentage of owner-occupied homes with at least one energy efficiency home improvement in past two years. Source: American Housing Survey Table 15
Figure C.10 shows the share of (a) space and (b) water heating fuels used in single-family (SF) and multifamily (MF) homes. The most prominent difference is a higher use of electricity in multifamily, and natural gas in single-family homes. Electric heat pumps (HP) heaters are more common in single-family, but still represent a small share.

Figure C.10 (a,b) Differences in main space and water heating fuel by urban house type, RECS 2015. MF = multifamily, SF = single-family; HP = heat pump. Households with no space and water heating equipment are removed from this comparison. RECS 2015 does not indicate whether electric water heaters are heat pumps.

Figure C.11 (a) shows growth of access to space cooling equipment in Census Divisions from 1990-2015, from RECS data as analysed by Berrill et al. (2021b). Figure C.11 (b) compares access to space cooling by Division and house type in 2015, with Divisions ordered from left to right in order of increasing average cooling degree days (CDD) between 1990-2018 (EIA, 2019c).

Figure C.12 compares average total floor area in single-family and multifamily homes for three income groups, and the average of all households. For each income group, we demonstrate the effect of a 30% and 50% reduction in floor area as modelled in scenarios CF3 and CF4. Percentage reductions in floor area are measured as a percentage of average single-family homes built from 1970 onwards (i.e. the average among cohorts which would be affected by the policy counterfactual housing stock). For all income groups except low income, the 50% reduction in floor area would still result in a floor area higher than the average multifamily floor area in that income group.
Average total floor area in single-family (SF) and multifamily (MF) homes in 2015 by three income groups and average among all income groups. The effect of a floor area reduction of 30% and 50% of average SF floor area is shown for each income group.

C.3 Supporting Tables

Table C.2 shows the full results of the linear models of energy consumption end-uses, as shown in Table 4.2. Here we also include the numerical values of the intercept, and the type-cohort fixed effects relative to the reference of multifamily-high density homes built 2000+. The type-cohort fixed effects are depicted visually in Figure 4.3. Table C.3 shows appliance ownership statistics by housing cohorts for urban single-family detached households, based on RECS 2015 microdata (EIA, 2018a). There are clear trends for ownership of more appliances, and larger appliances in newer-built homes, with the exception of houses built in the 2010s which tend to have less appliances than homes built in the 1990s and 2000s. Table C.4 shows final energy consumption statistics by housing cohort for disaggregated ‘other’ energy end-uses in urban single-family detached houses in 2015. Similar to the higher ownership, size, and usage statistics presented in Table C.3, there is a strong trend for higher energy consumption in newer-built homes, although the cohort related increases appeared to peak in houses built in the 2000s. Comparing the oldest
cohort with houses built in the 2000s, increases are most pronounced for lighting, refrigeration, and electricity not elsewhere classified.

Table C.2 All coefficient estimates from regression models of energy end-uses in urban homes in 2015 (MJ)

<table>
<thead>
<tr>
<th>HH Income</th>
<th>Space Heating</th>
<th>Space Cooling</th>
<th>Water Heating</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>MF low &lt;1950</td>
<td>-3.2 (3.237)</td>
<td>3.479*** (706)</td>
<td>1.679 (880)</td>
<td>-1.788 (1.953)</td>
</tr>
<tr>
<td>MF low 1950-60s</td>
<td>3.563 (2.918)</td>
<td>2.186*** (639)</td>
<td>255 (793)</td>
<td>-1.615 (1.768)</td>
</tr>
<tr>
<td>MF low 1970s</td>
<td>3.280 (2.770)</td>
<td>1.761** (606)</td>
<td>253 (753)</td>
<td>-1.799 (1.680)</td>
</tr>
<tr>
<td>MF low 1980s</td>
<td>2.781 (2.771)</td>
<td>855 (606)</td>
<td>-146 (753)</td>
<td>-874 (1.681)</td>
</tr>
<tr>
<td>MF low 1990s</td>
<td>-2.256 (3.249)</td>
<td>839 (710)</td>
<td>-839 (883)</td>
<td>-1.124 (1.970)</td>
</tr>
<tr>
<td>MF low &lt;1950</td>
<td>1.5428*** (3.504)</td>
<td>4.318*** (765)</td>
<td>3.201*** (952)</td>
<td>4.532* (2.115)</td>
</tr>
<tr>
<td>MF low 1950-60s</td>
<td>8.305* (3.949)</td>
<td>3.335*** (864)</td>
<td>1.446 (1.073)</td>
<td>-762 (2.395)</td>
</tr>
<tr>
<td>MF low 1970s</td>
<td>7.199 (4.128)</td>
<td>2.800*** (902)</td>
<td>-664 (1.122)</td>
<td>-730 (2.503)</td>
</tr>
<tr>
<td>MF low 1980s</td>
<td>3.889 (4.300)</td>
<td>1.658 (939)</td>
<td>1.190 (1.169)</td>
<td>2.506 (2.699)</td>
</tr>
<tr>
<td>MF low 1990s</td>
<td>2.158 (5.177)</td>
<td>670 (1.131)</td>
<td>549 (1.407)</td>
<td>-121 (3.141)</td>
</tr>
<tr>
<td>MF low 2000+</td>
<td>7.283 (4.716)</td>
<td>576 (1.030)</td>
<td>-1.474 (1.282)</td>
<td>5.362 (2.861)</td>
</tr>
<tr>
<td>SF Det &lt;1950</td>
<td>27.869*** (4.140)</td>
<td>4.996*** (903)</td>
<td>-18 (1.126)</td>
<td>498 (2.512)</td>
</tr>
<tr>
<td>SF Det 1950-60s</td>
<td>19.607*** (3.657)</td>
<td>3.986*** (800)</td>
<td>1.759 (994)</td>
<td>433 (2.220)</td>
</tr>
<tr>
<td>SF Det 1970s</td>
<td>18.181*** (3.477)</td>
<td>3.979*** (760)</td>
<td>1.112 (946)</td>
<td>2.510 (2.111)</td>
</tr>
<tr>
<td>SF Det 1980s</td>
<td>8.491* (3.236)</td>
<td>2.043* (707)</td>
<td>-86 (880)</td>
<td>2.437 (1.964)</td>
</tr>
<tr>
<td>SF Det 1990s</td>
<td>13.568*** (3.685)</td>
<td>2.634** (805)</td>
<td>708 (1.002)</td>
<td>1.752 (2.235)</td>
</tr>
<tr>
<td>SF Det 2000+</td>
<td>6.300 (3.298)</td>
<td>1.896** (720)</td>
<td>-451 (898)</td>
<td>694 (2.003)</td>
</tr>
<tr>
<td>SF Det &lt;1950</td>
<td>39.336*** (2.350)</td>
<td>6.109*** (511)</td>
<td>1.578* (644)</td>
<td>3.439*** (1.436)</td>
</tr>
<tr>
<td>SF Det 1950-60s</td>
<td>29.721*** (2.254)</td>
<td>5.987*** (489)</td>
<td>1.781** (615)</td>
<td>4.723** (1.373)</td>
</tr>
<tr>
<td>SF Det 1970s</td>
<td>22.838*** (2.397)</td>
<td>5.292*** (521)</td>
<td>1.038 (653)</td>
<td>5.622*** (1.459)</td>
</tr>
<tr>
<td>SF Det 1980s</td>
<td>18.818*** (2.450)</td>
<td>4.396*** (530)</td>
<td>1.577* (669)</td>
<td>6.981*** (1.492)</td>
</tr>
<tr>
<td>SF Det 1990s</td>
<td>21.130*** (2.491)</td>
<td>4.921*** (539)</td>
<td>3.589*** (681)</td>
<td>8.381*** (1.519)</td>
</tr>
<tr>
<td>SF Det 2000+</td>
<td>12.592*** (2.399)</td>
<td>4.050*** (519)</td>
<td>1.861** (656)</td>
<td>8.350*** (1.459)</td>
</tr>
</tbody>
</table>

| Observations | 4,493 | 4,493 | 4,393 | 4,393 |
| R²           | 0.549 | 0.570 | 0.496 | 0.284 |

*p < 0.05, **p < 0.01, ***p < 0.001

MH = manufactured home, MF = multifamily, SF = single-family. Type-Cohort fixed effects are relative to the reference level “MF hi 2000+”
Table C.3 Average household appliance ownership and size/usage characteristics in urban single-family detached homes by cohort, 2015

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>TVs</td>
<td>2.44</td>
<td>2.42</td>
<td>2.61</td>
<td>2.57</td>
<td>2.65</td>
<td>2.99</td>
<td>2.92</td>
<td>2.84</td>
</tr>
<tr>
<td>% ‘large’ TVs&lt;sup&gt;a&lt;/sup&gt;</td>
<td>52%</td>
<td>58%</td>
<td>63%</td>
<td>64%</td>
<td>69%</td>
<td>71%</td>
<td>74.4%</td>
<td>73%</td>
</tr>
<tr>
<td>Lights on 4hr/day</td>
<td>7.13</td>
<td>7.05</td>
<td>7.81</td>
<td>8.27</td>
<td>8.29</td>
<td>9.69</td>
<td>10.77</td>
<td>10.66</td>
</tr>
<tr>
<td>% 60+ lights&lt;sup&gt;b&lt;/sup&gt;</td>
<td>4.4%</td>
<td>9%</td>
<td>11%</td>
<td>8%</td>
<td>15%</td>
<td>24.4%</td>
<td>24.4%</td>
<td>21%</td>
</tr>
<tr>
<td>% own Clothes Dryer</td>
<td>90%</td>
<td>93%</td>
<td>96%</td>
<td>94.4%</td>
<td>94.4%</td>
<td>98%</td>
<td>98%</td>
<td>98%</td>
</tr>
<tr>
<td>Fridge&lt;sup&gt;c&lt;/sup&gt;</td>
<td>1.32</td>
<td>1.39</td>
<td>1.49</td>
<td>1.53</td>
<td>1.57</td>
<td>1.65</td>
<td>1.60</td>
<td>1.46</td>
</tr>
<tr>
<td>% ‘large’ Fridges&lt;sup&gt;c&lt;/sup&gt;</td>
<td>43%</td>
<td>46%</td>
<td>44.4%</td>
<td>48%</td>
<td>59%</td>
<td>63%</td>
<td>64.4%</td>
<td>62%</td>
</tr>
<tr>
<td>Personal electronics&lt;sup&gt;d&lt;/sup&gt;</td>
<td>3.64</td>
<td>3.38</td>
<td>3.81</td>
<td>3.89</td>
<td>4.13</td>
<td>4.66</td>
<td>5.22</td>
<td>5.56</td>
</tr>
<tr>
<td>Ceiling fans</td>
<td>1.94</td>
<td>2.30</td>
<td>2.44</td>
<td>2.74</td>
<td>3.34</td>
<td>3.47</td>
<td>3.49</td>
<td>3.14</td>
</tr>
</tbody>
</table>

<sup>a</sup>Percent of homes whose primary TV is 40 inches or more; <sup>b</sup>Percent of homes who have 60 or more lights installed; <sup>c</sup>Percent of homes whose primary refrigerator is larger than 22.5 ft<sup>3</sup>; <sup>d</sup>Average number of laptops, tablets, and smartphones per household

Table C.4 Average final energy demand (MJ) within ‘other’ end-uses in urban single-family detached homes by cohort, 2015

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Clothes Drying</td>
<td>2,331</td>
<td>2,321</td>
<td>2,424</td>
<td>2,555</td>
<td>2,459</td>
<td>3,084</td>
<td>2,881</td>
<td>2,830</td>
</tr>
<tr>
<td>Lighting</td>
<td>3,846</td>
<td>3,684</td>
<td>4,224</td>
<td>4,530</td>
<td>4,975</td>
<td>5,794</td>
<td>6,165</td>
<td>5,221</td>
</tr>
<tr>
<td>Refrigeration</td>
<td>2,495</td>
<td>2,679</td>
<td>2,984</td>
<td>3,204</td>
<td>3,415</td>
<td>3,761</td>
<td>3,695</td>
<td>2,865</td>
</tr>
<tr>
<td>TV and related</td>
<td>2,680</td>
<td>2,811</td>
<td>2,933</td>
<td>2,942</td>
<td>3,048</td>
<td>3,500</td>
<td>3,447</td>
<td>3,185</td>
</tr>
<tr>
<td>Ceiling fan</td>
<td>576</td>
<td>681</td>
<td>728</td>
<td>883</td>
<td>1,257</td>
<td>1,370</td>
<td>1,389</td>
<td>1,167</td>
</tr>
<tr>
<td>Elec n.e.c.</td>
<td>5,202</td>
<td>4,463</td>
<td>5,273</td>
<td>4,313</td>
<td>6,209</td>
<td>6,777</td>
<td>7,463</td>
<td>5,626</td>
</tr>
</tbody>
</table>

Electricity n.e.c. = electricity consumption not elsewhere classified

Table C.5 shows summary statistics of energy consumption end-uses in urban households in 2015.

Space heating is the dominant end-use, accounting for 44% of energy consumption in the mean household. In all cases, especially space heating and cooling, the median is notably lower than the mean, suggesting right-skewed distributions of household energy consumption.

Table C.5 Summary statistics of residential energy end-uses in urban homes, 2015 (GJ/year)

<table>
<thead>
<tr>
<th></th>
<th>Space Heating</th>
<th>Space Cooling</th>
<th>Water Heating</th>
<th>Other</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>35.86</td>
<td>6.80</td>
<td>15.70</td>
<td>23.88</td>
<td>82.24</td>
</tr>
<tr>
<td>Median</td>
<td>22.82</td>
<td>3.90</td>
<td>13.73</td>
<td>19.92</td>
<td>71.63</td>
</tr>
<tr>
<td>Std Dev</td>
<td>32.28</td>
<td>8.35</td>
<td>9.65</td>
<td>17.93</td>
<td>51.95</td>
</tr>
</tbody>
</table>

Table C.6 shows average energy demand in urban houses in 2015 by house type and cohort. Single-family houses tend to require more energy, and there is a general downward trend of energy
consumption in newer houses, excepting an increase in energy consumption in houses built in the 1990s and 2000s. Table C.7 shows the average carbon intensity of energy end-uses for urban houses of different types in 2015, calculated based on the average energy carrier mix for each end-use and housing type, and with Census Division average electricity grid mixes (EIA, 2019e) and associated carbon intensities. Differences in intensities shown in this table reflect differences in fuel mixes used for end-uses, and differences in geographical distribution of house types combined with variations in GHG intensity of electricity by Division (e.g. multifamily high use more resistance electricity heating, causing their GHG intensity for heating to be higher, while single-family detached tend to be located in Divisions with higher carbon intensity of electricity, causing their GHG intensity for space cooling to be higher).

Table C.6 Average energy demand in urban houses in 2015, by house type and age cohort (GJ/year)

<table>
<thead>
<tr>
<th>Type/Cohort</th>
<th>&lt;1950</th>
<th>1950s</th>
<th>1960s</th>
<th>1970s</th>
<th>1980s</th>
<th>1990s</th>
<th>2000s</th>
<th>2010s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manuf. Housing</td>
<td>94.8</td>
<td>68.5</td>
<td>53.2</td>
<td>65.4</td>
<td>53.4</td>
<td>53.2</td>
<td>66.6</td>
<td>56.0</td>
</tr>
<tr>
<td>Single-fam Det</td>
<td>117.1</td>
<td>101.9</td>
<td>103.6</td>
<td>98.1</td>
<td>96.2</td>
<td>110.1</td>
<td>103.8</td>
<td>88.5</td>
</tr>
<tr>
<td>Single-fam Att</td>
<td>101.8</td>
<td>84.2</td>
<td>67.9</td>
<td>72.6</td>
<td>60.4</td>
<td>72.0</td>
<td>60.8</td>
<td>72.3</td>
</tr>
<tr>
<td>Multi-fam Low</td>
<td>78.1</td>
<td>62.2</td>
<td>39.7</td>
<td>46.9</td>
<td>42.5</td>
<td>43.5</td>
<td>49.2</td>
<td>25.6</td>
</tr>
<tr>
<td>Multi-fam High</td>
<td>44.7</td>
<td>36.3</td>
<td>35.5</td>
<td>37.0</td>
<td>32.7</td>
<td>32.2</td>
<td>35.6</td>
<td>37.1</td>
</tr>
</tbody>
</table>

Table C.7 Average GHG intensity of energy end-uses in urban houses in 2015 by house type (kg CO$_2$-eq/MJ)

<table>
<thead>
<tr>
<th>End-Use/Type</th>
<th>Manuf. Housing</th>
<th>Single-fam Det.</th>
<th>Single-fam Att.</th>
<th>Multi-fam Low</th>
<th>Multi-fam High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Space Heat</td>
<td>0.069</td>
<td>0.062</td>
<td>0.060</td>
<td>0.065</td>
<td>0.080</td>
</tr>
<tr>
<td>Space Cool</td>
<td>0.127</td>
<td>0.137</td>
<td>0.123</td>
<td>0.125</td>
<td>0.125</td>
</tr>
<tr>
<td>Hot Water</td>
<td>0.093</td>
<td>0.069</td>
<td>0.070</td>
<td>0.070</td>
<td>0.083</td>
</tr>
<tr>
<td>Other</td>
<td>0.112</td>
<td>0.120</td>
<td>0.109</td>
<td>0.102</td>
<td>0.115</td>
</tr>
</tbody>
</table>

Table C.8 shows coefficient estimates $\beta'$ from a variant of the linear model of energy end-uses summarised in equation 2 of Chapter 4, with income modelled as a factor variable of three income groups interacted with type and cohort fixed effects.
Table C.8 Coefficient estimates from linear regression models of energy end-uses in urban homes in 2015 (MJ), with income modelled as a fixed effect interacting with house type and cohort, rather than a continuous covariate

<table>
<thead>
<tr>
<th></th>
<th>Space Heating</th>
<th>Space Cooling</th>
<th>Water Heating</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH Size</td>
<td>-500</td>
<td>154*</td>
<td>4,262***</td>
<td>1,953***</td>
</tr>
<tr>
<td>HDD</td>
<td>7.69***</td>
<td>0.89***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CDD</td>
<td>4.24**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Heated Area</td>
<td>10.07***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cooled Area</td>
<td>2.09***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Area</td>
<td>0.20</td>
<td>(0.11)</td>
<td>3.56***</td>
<td>(0.24)</td>
</tr>
</tbody>
</table>

Type-Cohort-Income FE | Y | Y | Y | Y
Observations          | 4,393 | 4,393 | 4,393 | 4,393
R²                    | 0.553 | 0.575 | 0.503 | 0.291

*p <0.05, **p <0.01, ***p <0.001

Dependent variables are annual energy consumption for the four energy end-uses. Coefficients reflect the modelled effects of each variable on each energy end-use, measured in MJ. Household size is measured in number of householders, HDD and CDD in °F-day, and floor area in square-foot. HH = household, HDD = heating degree day. CDD = cooling degree day. FE = fixed effects. Type-Cohort-Income FE are displayed in Supp. Fig. 14 (b-d).

Table C.9 shows differences in total, heated, and cooled floor area by three income groups in 2015, demonstrating the large differences in average house size by type that exist for all income levels.

Total and heated floor area for high-income multifamily homes are approximately half of total and heated floor area in low-income single-family homes.

Table C.9 Difference in total, heated, and cooled floor area in urban homes in 2015, distinguished by household income group and house type

<table>
<thead>
<tr>
<th></th>
<th>Total Floor Area (m²)</th>
<th>Heated Floor Area (m²)</th>
<th>Cooled Floor Area (m²)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Low-Inc</td>
<td>Mid-Inc</td>
<td>Hi-Inc</td>
</tr>
<tr>
<td>SF</td>
<td>189.8</td>
<td>224.1</td>
<td>304.7</td>
</tr>
<tr>
<td>MF</td>
<td>83.3</td>
<td>91.5</td>
<td>99.6</td>
</tr>
</tbody>
</table>
D  Appendix to Chapter 5

D.1 Development of stock model from AHS surveys

Metrics obtained from AHS sample case history and general survey data for use in our model include:

- Annualized housing loss rates for combinations of housing type, age range, vacancy status, and US Census region
- Vacancy rates by housing type, Census region, and age cohort
- Annualized total and occupied housing stock growth
- Percent of addition and losses from new construction and demolition, respectively

D.1.1 Population and household size

We use the SSP2 scenario projection of county populations by Hauer, which is the mid-range SSP projection, but is higher than the two scenarios most recently produced by the US Census Bureau (Fig. D.1). We scale the SSP2 projection to the mid-range Census Bureau projection, and scale again to the actual population recorded on July 1, 2020.

![US Population Projection Scenarios](image)

*Figure D.1 US total population projection for three Shared Socioeconomic Pathways (Hauer, 2019) and USCB 2017 projections (US Census Bureau, 2017a)*
Future changes in household size are estimated by household and population projections from McCue (2018) (Fig. D.2). We apply the same relative reduction to all house types. In the high multifamily scenarios, we project no change in household size by type, as reductions in average household size will already be accounted for by increases in population in multifamily housing, which has smaller household size that single-family housing.

![Relative reduction in average HHS, 2020-2060](image)

Figure D.2 Relative reduction in household size 2020-2060, based on an extension of data adapted from McCue (2018).

Figure D.3 shows population projections for the four counties use for our demonstration of county level model outputs. As is seen, Harris, TX demonstrates strong population growth, Providence, RI shows low population growth, San Juan, NM shows strong population decline, and Marquette, MI shows moderate population decline.
Figure D.3 Population projections by house type for the counties of Harris TX, Providence, RI, San Juan, NM, and Marquette, MI.

D.1.2 Loss rates by region, type, and age range

Loss rates (incorporating removal of housing from the stock for any reason, including demolition, use for non-residential purposes, falling into a state of disrepair which is unfit for habitation, and mobile homes moving to different sites) are shown in Table D.1 for housing by type, age range, and vacancy status. Generally, loss rates increase with age, and are much higher for vacant units than occupied units. Loss rates are also notably higher for manufactured housing than for single- or multifamily. Generally, for both growing and declining housing stocks, losses from stock are calculated as shown in Chapter 5 Eq. 2 using the given rates as applicable. In growing housing stocks, vacancies are kept at reasonable levels which approach the natural rate as shown in Chapter 5 Eq. 4. Because there is no representation of loss in the calculation of addition to stock for
declining housing stocks (Ch. 5 Eq. 1), it is possible for the model to produce infeasible vacancy rates (i.e. less than zero). It is also possible for the vacancy rate to continually increase far above natural rates. In these cases, we introduce clauses in the model to reduce loss rates if vacancies get too far below the natural rate, and to reduce addition rates of vacancies get too high above the natural rate.

Table D.1 Housing stock loss rates for single-family (SF), multifamily (MF), and manufactured homes (MH) by Census region, age range, and vacancy status (Occ = Occupied, Vac = Vacant). Calculated from AHS data (US Census Bureau, 2017c)

<table>
<thead>
<tr>
<th>Region</th>
<th>Type</th>
<th>0-19, Occ</th>
<th>0-19, Vac</th>
<th>20-59, Occ</th>
<th>20-59, Vac</th>
<th>60+, Occ</th>
<th>60+, Vac</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>SF</td>
<td>0.18%</td>
<td>0.20%</td>
<td>0.39%</td>
<td>1.00%</td>
<td>1.42%</td>
<td>2.63%</td>
</tr>
<tr>
<td>MF</td>
<td>0.43%</td>
<td>0.61%</td>
<td>0.84%</td>
<td>1.38%</td>
<td>3.76%</td>
<td>4.27%</td>
<td></td>
</tr>
<tr>
<td>Midwest</td>
<td>SF</td>
<td>0.11%</td>
<td>0.19%</td>
<td>0.44%</td>
<td>0.78%</td>
<td>1.81%</td>
<td>4.74%</td>
</tr>
<tr>
<td>MF</td>
<td>0.26%</td>
<td>0.53%</td>
<td>1.44%</td>
<td>0.56%</td>
<td>3.09%</td>
<td>5.13%</td>
<td></td>
</tr>
<tr>
<td>South</td>
<td>SF</td>
<td>0.28%</td>
<td>0.42%</td>
<td>0.97%</td>
<td>1.31%</td>
<td>3.72%</td>
<td>6.63%</td>
</tr>
<tr>
<td>MF</td>
<td>0.35%</td>
<td>0.88%</td>
<td>1.93%</td>
<td>0.89%</td>
<td>3.06%</td>
<td>5.96%</td>
<td></td>
</tr>
<tr>
<td>West</td>
<td>SF</td>
<td>0.17%</td>
<td>0.27%</td>
<td>0.55%</td>
<td>1.14%</td>
<td>2.55%</td>
<td>4.13%</td>
</tr>
<tr>
<td>MF</td>
<td>0.27%</td>
<td>0.63%</td>
<td>1.19%</td>
<td>1.06%</td>
<td>2.53%</td>
<td>3.24%</td>
<td></td>
</tr>
<tr>
<td>US</td>
<td>MH</td>
<td>2.59%</td>
<td>2.19%</td>
<td>2.97%</td>
<td>6.16%</td>
<td>6.33%</td>
<td>11.21%</td>
</tr>
</tbody>
</table>

D.1.3 Comparison of construction/addition, and demolition/losses.
We estimate the portion of additions to stock coming from sources other than new construction based on historical data varying by region and house type, summarized in Table D.2. Similarly, we estimate the portion of losses to stock coming from sources other than demolition based on historical data shown in Table D.3. For the model implementation, we estimate national average percentages for each house type, slightly higher than the data presented here, based on the assumption that in any given year, some housing which previously left the stock but was not demolished would be demolished.
Table D.2 Percentage of additions to stock that comes from sources other than new construction, by types and region

<table>
<thead>
<tr>
<th>Region / Type</th>
<th>SF</th>
<th>MF</th>
<th>MH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>17.0</td>
<td>20.8</td>
<td>18.0</td>
</tr>
<tr>
<td>Midwest</td>
<td>14.6</td>
<td>20.8</td>
<td>20.7</td>
</tr>
<tr>
<td>South</td>
<td>13.8</td>
<td>19.1</td>
<td>20.9</td>
</tr>
<tr>
<td>West</td>
<td>10.5</td>
<td>13.0</td>
<td>24.0</td>
</tr>
</tbody>
</table>

Table D.3 Percentage of losses that comes from demolition, by types and region

<table>
<thead>
<tr>
<th>Region / Type</th>
<th>SF</th>
<th>MF</th>
<th>MH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast</td>
<td>23%</td>
<td>12%</td>
<td>41%</td>
</tr>
<tr>
<td>Midwest</td>
<td>37%</td>
<td>21%</td>
<td>44%</td>
</tr>
<tr>
<td>South</td>
<td>33%</td>
<td>23%</td>
<td>51%</td>
</tr>
<tr>
<td>West</td>
<td>27%</td>
<td>18%</td>
<td>36%</td>
</tr>
</tbody>
</table>

D.1.4  Additions to stock under negative OSG
Figure D.4 Stock addition rates vs occupied stock growth rates for single-family houses in the US and three Census regions. Even in times of negative occupied stock growth, it is usual to have a positive addition rate. Each observation corresponds to stock additions and stock growth between successive AHS surveys.

Table D.4 Linear Models of Stock Addition Rate (AR) for three house types

<table>
<thead>
<tr>
<th></th>
<th>AR – SF</th>
<th>AR – MF</th>
<th>AR – MH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.008*</td>
<td>0.011***</td>
<td>0.032***</td>
</tr>
<tr>
<td>OSG – SF</td>
<td>0.806**</td>
<td>0.918***</td>
<td>1.184***</td>
</tr>
<tr>
<td>OSG – MF</td>
<td></td>
<td>0.653</td>
<td></td>
</tr>
<tr>
<td>OSG – MH</td>
<td></td>
<td></td>
<td>0.653</td>
</tr>
<tr>
<td>Observations</td>
<td>15</td>
<td>15</td>
<td>15</td>
</tr>
<tr>
<td>R²</td>
<td>0.516</td>
<td>0.653</td>
<td>0.653</td>
</tr>
</tbody>
</table>

*p <0.05, **p <0.01, ***p <0.001

D.1.5 Estimation of stock growth factor based on changes in vacancy rates

Next three figures, linear models are calculated only for cases of positive occupied and total stock growth, and for GF values lower than 2.5. In the prediction models, GF values are limited to a lower bound of and an upper bound of 1.3 for single-family and multi-family homes, and 1.35 for manufactured homes. This also prevents vacancy ratios and factors from returning to the natural rate too quickly.
Figure D.5 Growth Factor vs Change in Vacancy Factor, Single-Family

Figure D.6 Growth Factor vs Change in Vacancy Factor, Multifamily
**Figure D.7 Growth Factor vs Change in Vacancy Factor, Manufactured Housing**

**Table D.5 Linear Models of Stock Growth Factor (GF) for three house types**

<table>
<thead>
<tr>
<th></th>
<th>GF: SF</th>
<th>GF: MF</th>
<th>GF: MH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>1.05*** (0.02)</td>
<td>1.09*** (0.06)</td>
<td>0.99*** (0.05)</td>
</tr>
<tr>
<td>dVF: SF</td>
<td>38.89*** (2.60)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>dVF: MF</td>
<td></td>
<td>25.50** (4.22)</td>
<td></td>
</tr>
<tr>
<td>dVF: MH</td>
<td></td>
<td></td>
<td>16.44*** (2.42)</td>
</tr>
<tr>
<td>Observations</td>
<td>13</td>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>R²</td>
<td>0.953</td>
<td>0.839</td>
<td>0.885</td>
</tr>
</tbody>
</table>

*p <0.05, **p <0.01, ***p <0.001

D.1.6 Historical vacancy rates by house type

To estimate initial vacancy rates by type and cohort by county, we use the sums of total stock by type and by cohort (separately) from ACS Table DP04, and use the estimates of stock by type and cohort (nested) from B25127 to estimate nested total housing stock by type and cohort, and then combine the total stock and occupied stock estimates to calculate vacancy rates per house type and cohort for each county. RAS matrix balancing is used to produced balanced estimates of total housing stocks by type and cohort (Lenzen et al., 2009), using on the type-cohort distribution of occupied housing as a starting point. Note that the vacancy ratio calculated here is higher than the vacancy rates for rental and homeowner vacancy rates published by the Census Bureau, due to different definitions. The vacancy ratio that we calculate is the total number of units that were vacant at time of survey but fit for residential use (this excludes units that are damaged, or exposed
to the elements, or housing units that are in use for non-residential purposes, such as commercial use or for storage) divide by the total number of housing units fit for residential use. Our calculation includes vacant units that are held off market for temporary use or other reasons. The rental and homeowner vacancy rates published by the Census Bureau only refers to units that are vacant for rent or vacant for sale (US Census Bureau, 2017b).

Further steps are taken to divide the total stock by each type into age cohorts and vacancy status, based on the propensity for different age groups to be occupied or vacant. For single family, we reduce the vacancy rate in the 11-30 age range by 0.5% and increase the vacancy rate in the 61+ age range by 0.5%. For multifamily, we increase the vacancy rate in the 0-10 age range by 0.5% and reduce the vacancy rate in the 31-60 age range by 0.5%. For manufactured homes, we reduce the vacancy rate in the 0-10 age range by 1.7% and increase the vacancy rate in the 31-60 age range by 1.7%. This represents filtering among households into the buildings that are more/less likely to be occupied based on what age group they fit into. In some cases this adjustment can produce an estimate of vacant units within a cohort that is higher that the total number of units in that cohort. In such cases, we reduce the magnitude of the adjustment, and if the discrepancy still remains, we remove this adjustment altogether.

**D.1.7 Floorspace estimates**

Estimates of average floorspace per house type and cohort by county produced by generating a large (200,000) representative sample of the US housing stock from the ResStock housing characteristics database (NREL, 2020), which uses AHS 2017 data to define floor area bins for US Core-Based Statistical Areas (CBSA) and non-CBSA Census Division areas. We then calculate average floor area for type-cohort-county combinations with at least five sample points, and use averages of higher regional aggregations (State, Division, etc.) to estimate county averages for combinations with less than five sample points. Distributions of new construction by house type
into floor area bins are shown aggregated to the national level for three of the housing stock scenarios in Figure D.12.

D.1.8 Additional Figures
In Figure D.8 we show national average vacancy rates and factors by house type calculated from AHS surveys 1985-2019. Average rates by Census region and house type were used to inform estimates of the natural vacancy rate used in Eq. 4 of Chapter 5.

![Vacancy Ratio and Factor Graph](image)

*Figure D.8 Historical trends and averages of vacancy rates and vacancy factors for three house types*

In Figure D.9 we show rates of stock additions and losses for the four demonstration counties. Figure D.10 shows fluctuations in vacancy rates by house type for selected counties in the Baseline scenario. Figure D.11 shows mean floor area by type in all scenarios compared to the Reduced Floor Area scenario 5. Figure D.12 shows differences in floor area distributions by house type in scenarios 1 (also represents scenario 2), 3 (also represents scenario 4), and 5.
Figure D.9 Stock addition and loss rates for four counties in the Baseline scenario. Different y-axis used for Harris County, TX.
Figure D.10 Vacancy Rate for selected counties with diverging population trajectories, baseline scenario

Figure D.11 Mean Floor area by type, cohort, and scenario
Figure D.12 Floor area distributions by house type for new construction in scenarios 1, 3, and 5
E Appendix to Chapter 6

E.1 Energy retrofits to pre-2020 building stock

The characteristics of the houses that exist in 2020 will evolve in two main ways, being renovated, and being removed from the occupied stock. Once existing houses are no longer part of the occupied stock, we do not model their energy consumption anymore. There is good reason to believe that energy consumption in vacant housing is non-zero, but without a reliable approach to estimate, or reduce energy consumption in vacant housing, we do not incorporate energy consumption in vacant units in this analysis.

In this section we describe how renovations to existing buildings is implemented in our model. A great many housing characteristics can be altered through a home renovation, and many home renovations do not target energy efficiency improvements but are concerned with other targets. For this analysis we consider only energy related renovations to upgrades of space heating, space cooling, and water heating equipment, and insulation upgrades for crawlspace, unfinished basements, external walls, and unfinished (unheated) attics, as we can obtain statistics on the rate of adoption for these types of retrofits, and we consider these to be the main types of retrofits with potential for energy reduction (E. Wilson et al., 2017). Two pieces of information are considered for each renovation, the rate of renovation in the housing stock (equivalently the probability of a given housing making a specific type of renovation), and the characteristics of a given system post-renovation, given information about it’s pre-renovation status. To represent these information, we use data from American Housing Surveys (AHS) covering the period 1995-2019, for which period surveys included questions on home improvements, including whether homes replaced or added central AC, space heating equipment, water heaters, or insulation. These questions were only asked of owner-occupied households. We do not know if the same renovation rates or characteristics apply to tenant-occupied households, but without specific data for tenant households, we assume
that the rates and characteristics identified for owner-occupied homes apply to all homes. We define two renovation scenarios, standard and advanced. The standard renovation scenario is based on a continuation of recent trends, and a moderately optimistic implementation of the depth or stringency of renovations, in other words how efficient are the equipment adopted during renovations. In the advanced renovation scenario, we multiply the probability of undergoing renovations by a factor of 1.5, and we give stronger preference to higher efficiency replacement equipment, and a higher shift towards electric space and water heating systems, and heat pumps in particular.

We outline in detail the approach for describing renovation rate for space heating equipment, and then give summary statistics for renovation rates of other types. In general the same approach applies to estimating renovation rates for all systems considered.

E.1.1 Renovation rates

We estimate renovations rates separately for combinations of four Census Regions (Northeast = NE, Midwest = MW, South = S, West = W) and three house types (single-family = SF, multifamily = MF, manufactured home = MH). In Figure E.1 we show trends of replacement rates of space heating equipment over the period 1995-2019 by Census Region (a) and by house type (b). Indicated on the figures are implied lifetime of the equipment, or period between replacements, as the inverse of the replacement rate. Over this period, replacement rates averaged around 2.7%, implying a lifetime of 36.7 years. Rates appear higher post-2005, and are notably higher in SF than
MF or MH housing. Replacement rates are also higher in the (colder) NE and MW Census Regions.

![Figure E.1 Replacement Rate for Space Heating Equipment, 1995-2019 broken out by (a) Census Region and (b) House Type.](image)

To calculate the probability of replacement for each house type and region combination, I calculate the average replacement rate for each housing type over the previous five surveys (2011-2019), and then multiply that rate by the ratio of the US average and each Regions average over the same period. For instance, the mean replacement rate for all SF homes 2011-2019 was 3.1%, and rate (for all housing types) in NE were on average 1.16 times higher than the national average over the same period, so I calculate the heating equipment replacement rate for SF homes in NE as 1.16*3.1% = 3.6%, which corresponds to an average equipment lifetime of ~28 years. This approach was preferred to estimating the rates by combinations of region and type in the AHS data, due to small sample sizes when isolating homes of a certain type in a certain region which had a heating system renovation. We show renovation rates calculated for each type-renovation system combination in each Census Division in Table E.1.
Table E.1 Annual renovation rates (probabilities) by Census Region (rows) for house type and equipment combinations

<table>
<thead>
<tr>
<th></th>
<th>SF heat</th>
<th>MF heat</th>
<th>MH heat</th>
<th>SF AC</th>
<th>MF AC</th>
<th>MH AC</th>
<th>SF H₂O</th>
<th>MF H₂O</th>
<th>MH H₂O</th>
<th>SF ins</th>
<th>MF ins</th>
<th>MH ins</th>
</tr>
</thead>
<tbody>
<tr>
<td>NE</td>
<td>0.036</td>
<td>0.026</td>
<td>0.027</td>
<td>0.02</td>
<td>0.017</td>
<td>0.019</td>
<td>0.047</td>
<td>0.034</td>
<td>0.042</td>
<td>0.027</td>
<td>0.012</td>
<td>0.024</td>
</tr>
<tr>
<td>MW</td>
<td>0.036</td>
<td>0.027</td>
<td>0.027</td>
<td>0.026</td>
<td>0.022</td>
<td>0.024</td>
<td>0.051</td>
<td>0.037</td>
<td>0.046</td>
<td>0.023</td>
<td>0.01</td>
<td>0.021</td>
</tr>
<tr>
<td>S</td>
<td>0.028</td>
<td>0.02</td>
<td>0.021</td>
<td>0.039</td>
<td>0.033</td>
<td>0.037</td>
<td>0.044</td>
<td>0.032</td>
<td>0.039</td>
<td>0.018</td>
<td>0.008</td>
<td>0.016</td>
</tr>
<tr>
<td>W</td>
<td>0.026</td>
<td>0.019</td>
<td>0.019</td>
<td>0.023</td>
<td>0.02</td>
<td>0.022</td>
<td>0.047</td>
<td>0.034</td>
<td>0.043</td>
<td>0.019</td>
<td>0.009</td>
<td>0.017</td>
</tr>
</tbody>
</table>

E.1.2 Renovation characteristics – space heating

For space heating renovations, we implement the possibility that a household changes main heating fuel, as well as the likelihood that the efficiency of the system in use increases. We assume that there is no changes in heating distribution systems, i.e. if a house has a gas-fired forced air furnace with ducted distribution, then that household could upgrade to a more efficient gas furnace, or a furnace heated by another fuel source, or a ducted air-source heat pump, but it could not upgrade to a non-ducted heating system, such as a gas boiler or a mini-split (un-ducted) heat pump.

From AHS data we estimate the probability of fuel switching by extracting the households who replaced/added space heating equipment in a given survey year (say 1997), and comparing the main heating fuel of that same household in the given survey year, and the previous survey year (1997 and 1995). For this step, we grouped the heating fuels as Electricity, Electricity Heat Pump, Gas (including propane), Fuel Oil, and Other/None, except for 2015-2019, when propane is distinguished as a separate heating fuel. Because this calculation requires knowledge of the main heating fuel during the previous survey, we cannot estimate switching rates for years 1995 or 2015 (when a new sample was drawn). In this way we calculate the probability of a heating equipment replacement being accompanied by a change in main heating fuel, and which fuel it is likely to be replaced by. We distinguished fuel switching by Census Region, as incumbent heating fuel and fuel switching trends can vary substantially by geography. In Figure E.2 we show the probability of
having a heating fuel after a heating system renovation, conditional on the initial heating fuel. There is evidence for sizable replacement of electricity and oil by natural gas, and smaller levels of switching to electricity from gas and oil.
Figure E.2 Likelihood of heating fuel change to specific fuels, during replacements of (a) electric, (b) gas, and (c) oil heating equipment, 1997-2019. Gas includes LPG/propane.

Using these trends of fuel switching during heating equipment replacement, we estimate probabilities of a fuel switch to fuel $y$ when replacing heating equipment which uses fuel $x$, based on average switching rates over the five most recent surveys (2009, 2011, 2013, 2017, 2019). We then split out the rate of switching to gas and propane by disaggregating the rate of switching to gas, based on the gas:propane splits in 2017 and 2019.

We show fuel switching rates for each fuel combination in each Census Region in Table 1. Here the columns represent the previous heating fuel, and the rows depict the new heating fuel.
Based on Table E.2, we can see that fuel switching to gas from electricity is quite common, particularly in NE. Switching from fossil fuels to electricity, and to heat pumps, is a trend that is seen mostly in S and W regions. Although data are shown for the portion of households switching from Fuel Oil in each region, only in NE is there a significant number of houses using oil in the first place. The switching rates demonstrate that almost one quarter of NE homes replacing an oil heating system switch to a new fuel, which is most likely to be gas, followed by propane and electricity. Rates shown for switching from other/none to electricity, oil, and gas are approximations based on actual rates in 2017 and 2019, but in renovation scenarios we do not model changing of heating fuel from/to other/none, these will remain unchanged. In the advanced renovation scenario, we increase the rate at which fossil fuels switch to electricity, and in particularly to electricity heat pumps.
To reflect improvements in efficiency level associated with a renovation, we generally take an approach in the regular renovation scenario that upon undergoing a renovation, a system moves up one or two efficiency levels with 50:50 probability, and in the advanced scenario, with 25:75 probability, so there is a higher diffusion of more efficient equipment in the advanced renovation scenario. When systems are at the second to highest efficiency level, a renovation is modelled as a replacement to the system of the highest efficiency level. If the incumbent system was already the highest possible efficiency, no change is made. Figures E.3-E.5 shows the projection of pre-2020 housing units grouped by space heating fuel and technology/efficiency combinations for housing with electricity, gas, and oil as main heating fuels, for two (baseline, high turnover) stock scenarios and two renovation scenarios. These figures include fuel switching (so a 2020 housing unit with electric heating could switch to be counted as a unit with gas heating in 2025), and stock decay/demolition. The much slower decay of units with electric heating reflects the fuel switching that takes place from combustion fuels to electricity. Note the increase in air source heat pump (ASHP) and mini-split heat pump (MSHP) heating systems.
Figure E.3 Scenario-based evolution of heating efficiency in pre-2020 housing units with electric heating
Figure E.4 Scenario-based evolution of heating efficiency in pre-2020 housing units with gas heating
E.1.3 Renovation characteristics – space cooling

Rates for space cooling renovations shown in Table E.2 refer to replacement/addition of central AC systems in owner-occupied homes, but we use these rates to reflect renovation of room or central space cooling in all homes. Replacement rates are by far the highest in the South, and lowest in the Northeast. Similar to space heating, we calculate the average replacement rate for each housing type over the previous five surveys (2011-2019), and then multiply that rate by the ratio of the US average and each Region’s average over the same period. For space cooling we also represent the dynamic of increased cooling adoption; switching from no AC to room/central AC, and from
room AC to central AC. These rates are calculated separately from renovation rates, and are based on data for all tenancy types and AC systems, not just central AC in owner-occupied homes. Most of the switching is from none to central AC, and room to central AC, although there is also some switching from room to none. We assume that houses that have central AC remain on central AC, neglecting the small switches from central to room/none seen in the data. Figure E.6 shows the projection of pre-2020 housing units grouped by air-conditioning technology/efficiency combinations for two (baseline, high turnover) stock scenarios and two renovation scenarios. Note the decline in the number of units that have no space cooling equipment.

Figure E.6 Scenario-based evolution of air-conditioning systems in pre-2020 housing units
E.1.4 Water Heating Systems

Renovation rates for water heating systems vary less by region, and are more frequent than for space heating and cooling. National average replacement rates 1995-2019 are about 4.2%, implying an average product lifetime of about 23.7 years. Similar to space heating, fuel switching also occurs when water heating equipment is replaced, albeit at lower rates. Figure E.7 shows the projection of pre-2020 housing units grouped by water heating fuel and technology/efficiency combinations for two (baseline, high turnover) stock scenarios and two renovation scenarios. The increase in heat pump and tankless water heaters is notable.

Figure E.7 Scenario-based evolution of water heating systems in pre-2020 housing units
E.1.5 Insulation

Insulation tends to be added/replaced at lower rates than heating and cooling equipment, judging by the data shown in Table E.2. Rates are particularly low in MF housing, suggesting that replacing or adding insulation may be more difficult, and much less likely, in MF buildings. In single family homes, the likelihood of replacing insulation is about 2% in a given year. Due to climatic differences, insulation upgrades are more common in NE and MW. Figure E.8 shows the projection of pre-2020 housing units grouped by wall and insulation systems for two housing stock and two renovation scenarios.

Figure E.8 Scenario-based evolution of insulation systems in pre-2020 housing units
E.2 Housing characteristics of new construction post-2020

Characteristics of envelope systems and energy consuming appliances are determined in accordance with IECC building energy codes, currently planned updates to federal regulations on appliances, and assumptions of the characteristics and stringency of future codes and standards. We assume that IECC building codes apply to all types of buildings, although in reality different energy codes apply to high-rise (above four-story) multifamily (ASHRAE 90.1) and manufactured housing. Adoption of energy codes is determined by state, and then average adoption rates are assumed by climate regions and ResStock custom regions, based on which states have plurality of the population in each climate region and ResStock region. The need for aggregating states to different regions is due to many of the code-dependent characteristics being defined in the ResStock database by ResStock custom region.

In Table E.3-E.4 I show assumptions on how building energy code adoption will develop over the four future vintages, by ResStock custom region (Location Region) and IECC climate zone (CZ). These are based on current code adoptions by state, matching of states to custom regions and judging which code is most prevalent in each custom region, and matching of custom regions to climate zones and judging which climate zone is most prevalent in each custom region (see Fig. E.9-E.11). These tables will be used to define future housing characteristics that are influenced by building codes (as indicated in Table E.3), such as Ducts, Insulation, and Windows.
Table E.3 Assumption of representative climate zone and projection of representative IECC code adoption by Custom Regions (Location Region) and selected state groups

<table>
<thead>
<tr>
<th>Location Region</th>
<th>Main IECC-CZ</th>
<th>IECC Code Level by Vintage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2020s</td>
</tr>
<tr>
<td>LR2</td>
<td>6A</td>
<td>2009</td>
</tr>
<tr>
<td>LR3</td>
<td>5A</td>
<td>2015</td>
</tr>
<tr>
<td>LR4</td>
<td>5A</td>
<td>2012</td>
</tr>
<tr>
<td>LR5</td>
<td>5B*</td>
<td>2009</td>
</tr>
<tr>
<td>LR6</td>
<td>4C**</td>
<td>2018</td>
</tr>
<tr>
<td>LR7 (excl NY)</td>
<td>5A***</td>
<td>2009</td>
</tr>
<tr>
<td>LR8 (excl NE-DE-MD)</td>
<td>4A*</td>
<td>2009</td>
</tr>
<tr>
<td>LR9 (excl TX, FL)</td>
<td>3A</td>
<td>2009</td>
</tr>
<tr>
<td>LR10</td>
<td>2A****</td>
<td>2009</td>
</tr>
<tr>
<td>LR11/CA</td>
<td>3C</td>
<td>2018</td>
</tr>
<tr>
<td>TX-FL</td>
<td>2A</td>
<td>2018</td>
</tr>
<tr>
<td>NY</td>
<td>4A+</td>
<td>2018</td>
</tr>
<tr>
<td>NE-DE-MD</td>
<td>4A</td>
<td>2018</td>
</tr>
</tbody>
</table>

* Area-wise 6B appears to be the deominant CZ here, but as Denver region, Boise, and Salt Lake City are all in 5B, most likely that the 5B is the most common CZ by population.

** Again, as Portland and Seattle are in 4C, it must be the most common CZ by population in LR6.

***Difficult to say whether 4A or 5A are dominant here, but as PA has the bigger population, I go with 5A.

****This is maybe the most contentious, as there are many CZ here, but I go with 2A which is where Phoenix is, although Las Vegas /Albuquerque have different CZ +NY is tricky as there are 4/5/6A present there, but most population is in 4A.

Table E.4 Assumption of representative IECC code adoption by Climate Zone

<table>
<thead>
<tr>
<th>IECC-CZ</th>
<th>IECC Code Level by Vintage</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2020s</td>
</tr>
<tr>
<td>6A</td>
<td>2009</td>
</tr>
<tr>
<td>5A*</td>
<td>2012</td>
</tr>
<tr>
<td>5B</td>
<td>2009</td>
</tr>
<tr>
<td>4C</td>
<td>2018</td>
</tr>
<tr>
<td>4A**</td>
<td>2015</td>
</tr>
<tr>
<td>3A</td>
<td>2009</td>
</tr>
<tr>
<td>2A***</td>
<td>2015</td>
</tr>
<tr>
<td>3C</td>
<td>2018</td>
</tr>
</tbody>
</table>

*Combination of LR3, LR4, and LR7.

**Combination of LR8, NY, and NE-MD-DE

***Combination of LR10 and TX-FL
Figure E.9 ResStock Custom Regions, from Wilson et al. (2017)

Figure E.10 IECC Climate Zones
Figure E.11 Residential Code Adoption by State, as of September 2020 (EIA, 2020c)

E.3 Additional Figures

Figure E.12 shows the development of aggregated national average CO₂ intensity of electricity for the two electricity grid scenarios used in our analysis. These data are from the Standard Scenarios of electricity grid development produced by NREL (Cole et al., 2019). These scenarios are estimated until 2050. For both scenarios, we assumed a continued rate of decarbonization of electricity for the period 2050-2060. Although intensities are shown here at the national level, for our calculation of GHG emissions intensities at the level of 18 regional transmission organizations are used.
In Figure E.13 we show total residential emissions 2020-2060 broken into emissions from total construction (materials and construction activities), energy use by fuel, in the baseline stock scenario with advanced renovation, for Mid-Case and Low RE Cost electricity scenarios. This figure shows steady emissions from fossil fuel use, even in a scenario with increased renovation and a greater propensity for fuel switching towards electricity. Electricity is also much more common in newer housing, but some new housing is still assumed to be built with gas and propane heating systems. With faster decarbonization of electricity (Fig E.13b), emissions from electricity reduce, but emissions from construction and onsite fuel use do not, demonstrating the challenge of moving residential emissions towards zero.
In Figure E.14 we show differences in cumulative 2020-2060 emission in each housing stock, renovation, and electricity grid scenarios, indexed to emissions in the baseline stock scenario with regular renovation and mid-case electricity decarbonization.

In Figure E.15 we compare multifamily housing share and average energy consumption per person for counties in the states of Indiana and Florida in 2020. The point of this figure is to demonstrate visually the inverse correlation between multifamily share and energy demand. While not exact negatives, the two images per state demonstrate that in counties with high multifamily share, energy requirements per person tend to be lower, and vice versa. Counties with high multifamily tend to
have a larger urban core. In Indiana the highest multifamily share counties host the cities of Lafayette (Tippecanoe County), Bloomington (Monroe County) and Indianapolis (Marion County).

In Florida, the high multifamily counties correspond the Miami metropolitan area (Miami-Dade, Broward, and Collier Counties) and have lower than average energy consumption. In both states, the counties with highest multifamily share have average energy per capita requirements about 20% lower than the state average.

Figure E.15 Comparison of multifamily share of occupied housing units and residential energy per person in counties in Indiana (a-b) and Florida (c-d)