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Inform me when it matters: Cost salience, energy consumption, and efficiency investments☆

Puja Singhal[1]

Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany

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ABSTRACT

Using a large-scale natural experiment in staggered billing dates for energy use in Germany and a unique billing dataset for multi-apartment buildings, this paper shows that the month of billing is a significant determinant of heat energy consumption. A large set of residential buildings demand significantly more heat energy annually, when the bill is issued during off-winter months. The paper finds evidence for salience cycles of heating bills that last up to 4 months, likely because consumer attention to heat energy costs is short-lived and absent during months when heating is off. Importantly, this phenomena is pervasive enough to be detectable even in aggregated building-level consumption data. Results suggest that the mere knowledge of costs is not sufficient and that the response to billing information also hinges on its time-varying salience. These findings underscore the importance of understanding the dynamic and heterogeneous nature of cost salience in the design of effective billing for energy conservation.

1. Introduction

Behavioral economic theory challenges standard models that assume agents are fully attentive to information when making economic decisions (DellaVigna, 2009; Gabaix, 2019). For boundedly rational agents, the value of information may depend on when it is delivered to the decision maker. The theoretical prediction of consumer inattention has been widely tested. Numerous studies have shown that consumers react less to information when it is relatively less salient. Chetty et al. (2009) show using a field experiment that tax-inclusive prices at the grocery store induced a stronger behavioral response than sales tax added at the register. DellaVigna and Pollet (2009) find that investor response to earnings information is stronger when the announcements are received during business hours on a weekday, when attention is more likely.

Empirical work also demonstrates that automated bill payment technology reduces price salience when agents do not need to view costs or prices, whether it is during payment of road tolls (Finkelstein, 2009) or monthly electricity bills (Sexton, 2015). Consumers who are ill-informed or unaware do not perceive the full cost of consumption, leading to higher energy demand. In intermittent billing contexts, studies have shown that information on bills has a strong effect on consumption. Gilbert and Graff Zivin (2014) show that households alter electricity consumption significantly only in the first week after the monthly electricity bill arrives, when attention is likely highest. This pattern is also consistent with the bill-shock regulation effect discussed in Grubb (2015). While Wichman (2017) evaluates the response of water use due to an increase in the frequency of bills (bi-monthly to monthly) and finds that the information intervention was ineffectual for those consumers that were inattentive.

This study furthers our understanding of consumer decision making in the residential energy setting. One focus of the literature in this field is on the role that information barriers play in energy consumption. Information can alter decision making through two channels – an information effect and a salience effect – and to date most research has not been able to isolate the effect of each mechanism and tend to report the combined impact of information and salience. This paper seeks

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E-mail address: singhal@pik-potsdam.de.

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to isolate the latter in the context of residential heating in Germany by studying the response of heat energy demand to the time-varying salience of intermittent billing.

The unique delivery system of utility bills in Germany provides an interesting setting for the empirical test of persistent consumer inattention. Households receive energy bills once a year, as opposed to quarterly or monthly, with information on their metered annual usage, prices, and charges.[2] Crucially, the annual billing date varies across buildings. This discrepancy arises from differences in the closing date for billing, specifically the heat submeter reading appointment by the energy meter company providing the billing service does not take place in the same month for every building. As a result, households do not receive bills in the same month.

This paper takes advantage of staggered billing dates for heat energy use. It investigates the effect of (not) receiving energy bills when it matters the most for heat energy demand — during the heating season.[3] Some households receive their annual bill during the high consumption winter months and other receive their annual bill during the low consumption summer months. This paper tests whether buildings billed in peak demand winter months are more responsive to bills than those billed in low demand summer months — which identifies the role of salience in the consumer response to heating bills.[4] Using a large billing dataset, the paper finds that buildings billed in summer months consume 7.5 percent more energy than those billed during the heating season, from 2008 to 2018, a period of both increasing and decreasing, but relatively high fuel prices[5] (See Fig. 1).

To the best of my knowledge, this paper is the first to use the staggered nature of billing dates to understand the extent to which energy demand depends on the timing of bills. The results offer new insight on consumer inattention to energy bills — for a non-US population. First, households are attentive to energy bills for a time-horizon that is less than the full billing period of 12 months, and are effectively adjusting consumption in the first few months of the year-long billing period. Evidence suggests that higher consumption due to salience cycles is pervasive and applies to all building types, fuel sources, and socio-economic regions in Germany. Thus there remains significant potential to conserve energy via low-cost behavioral interventions such as appropriately-timed bills that improve the salience of energy cost information.

Unlike space heating, energy for water heating is consumed year-round and thus should not be as responsive to different billing month treatments. This paper tests the same mechanism on hot water use and find evidence to suggest that households billed during the off-heating season actually cut back on energy for water heating. This further suggests that households have limited annual budgets for expenditures on energy services and thus may be compensating for their inattention or inability to control annual energy consumed for space heating by adjusting hot water use.

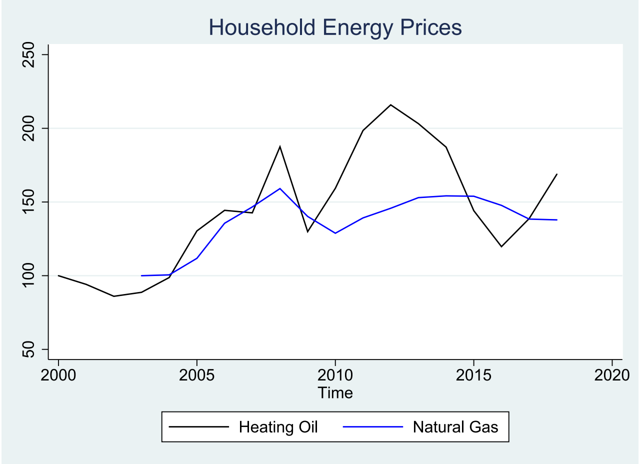

Fig. 1. Evolution of heating fuel prices in Germany. *Notes:* The heating oil series shows annual consumer prices for light heating oil (for consumption of 5000 l) in Euro cents per liter and natural gas series presents annual averages of biannual household prices in Euros per gigajoule. Due to data limitations, the natural gas price index is calculated using a combination of two different time series: (1) 2003 to 2007 price data applies to consumption class between 20 and 200 GJ and (2) 2008 to 2018 price data applies to consumption of 83.70 GJ. Both price series include all taxes and fees. For plotting, the raw data were indexed: heating oil (2000 = 100) and natural gas (2003 = 100). *Sources:* Mineralöl Wirtschaftsverband e.V. for leichtes Heizöl and Eurostat Datenbank for Preise Gas für Haushaltskunde.

Table 1
Heating needs during the year.
Data Source: German Weather Service (DWD).

Month	Mean temperature	Heating Degree Days (HDD)		
		Monthly	3-month sum	Annual sum
January	0.52	449.0	1184.1	2426.2
February	0.68	404.2	911.4	2424.5
March	4.33	330.9	590.1	2414.3
April	9.26	176.3	284.9	2412.0
May	13.23	82.9	118.5	2409.8
June	16.59	25.7	48.2	2414.3
July	18.60	9.9	79.1	2414.3
August	17.82	12.6	245.2	2414.5
September	14.09	56.6	529.0	2414.4
October	9.40	176.0	878.1	2413.6
November	5.12	296.4	1149.3	2404.6
December	1.92	405.6	1247.0	2405.8
Total	9.30	202.2	605.4	2414.0

Notes: The second column reports the daily mean temperature recorded during each month of the year. The third column reports the number of heating degree days during each month, calculated as the total sum of differences between the daily mean temperature and the heating limit of 15 degree Celsius on days with recorded mean temperatures less than 15 degrees. The fourth column reports the rolling sum of heating degree days recorded in the 3 month period starting in the month indicated, while the last column reports the 12-month sum of heating degree days. These values are calculated by the author using daily observations from 2003-01-01 to 2018-12-31 at 204 nearest weather stations to 8303 zipcodes in Germany. In the mapping used, average distance between zip code and nearest weather station is 18.3 km, with standard deviation of 10.4 km, minimum and maximum distance of 0.076 km and 59.86 km respectively.

This paper further examines whether differences in consumer inattention to energy costs had a long-term impact on technology choices and investments. It finds suggestive evidence that property owners reacted to higher annual heating expenditures by investing in long-term thermal insulation of buildings. This suggests that, despite the split-incentive problem between landlords and tenants, investments in heat energy-efficiency in multi-apartment buildings did take place in the past. These decisions to retrofit were driven by distortions in economic incentives, due to salience bias in building-level energy demand, rather

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[2] Each household makes monthly advance payments (in equal installments, called "Abschlag") towards the annual bill. At the end of the billing period, each household then receives an individualized-bill (due to the billing regulation in the Heat Cost Ordinance 1981) based on accurate metered consumption, a summary invoice with the actual consumption and costs, along with the final sum to be refunded or due as payment after factoring in the advance payments.

[3] The majority of the heating costs incurred by households in Germany are due to space heating, for which the demand is practically zero during the summer season. See Table 1 for information on the average temperature and heating degree days experienced each month of the year from 2003 to 2018.

[4] Note that residential energy consumption occurs before payment and thus present-bias may play a role in general (Werthschulte and Löschel, 2021). In the empirical design, however, all billing periods are 12 months long, thus households face identical intertemporal commitment and budgeting problems.

[5] We expect households that are unable to react timely (during winter season) to billing information to be less affected in response to price declines. But heating fuel prices were relatively high for most of the sample time period.

than energy-efficiency shortcomings of buildings billed during the summer. This interpretation may further suggest that investments in energy upgrades for existing buildings do respond to energy cost shocks. The gain in energy-savings were not large enough to counteract higher heat demand due to consumer inattention, however. These results highlight the importance of understanding consumer behavior in the design of low-energy buildings for a low-carbon future.

The paper is organized as follows. The next section discusses the related literature. Section 3 describes the unique billing data for multi-apartment buildings in Germany. Section 4 discusses the extent to which the billing period assignment offers a quasi-natural experiment setting. Section 5 presents the main results and discusses the mechanism in detail. Section 6 investigates whether salience bias in consumption had long-term effects on energy-efficiency investments by building owners. Section 7 concludes.

2. Related literature

In the field of energy and environmental economics, providing consumers real-time information on usage and prices has been shown to significantly reduce electricity and water demand (Gans et al., 2013; Carroll et al., 2014; Jessoe and Rapson, 2014; Pon, 2017; Tiefenbeck et al., 2018). Prest (2020) demonstrates using machine learning methods that consumer awareness is most predictive of heterogeneous demand response to time-of-use prices displayed on in-home monitors. Together these studies suggest that the effectiveness of information treatments may be largely driven by high baseline users, during peak consumption periods, when usage costs are most salient. Even in an environment with complete and easily accessible information, energy users may be unlikely to pay attention to everything that matters to their household budgets. More importantly, the effectiveness of the pricing mechanism to reduce energy use depends on the extent to which energy costs are salient to consumers. To date, the role of salience vis-à-vis information is seldom addressed in the literature (Gerarden et al., 2017; Giraudet, 2020).

Information provision to energy users during consumption or purchase events alter the beliefs about energy costs and make them salient simultaneously. For this reason, the salience effect of information and the response to the information itself tend to be intertwined. When measuring the effectiveness of information treatments, empirical results from the field may lead to contradictory results for the effect on energy-efficiency of purchases (Newell and Siikamäki, 2014; Houde, 2018; Andor et al., 2019; d'Adda et al., 2020). This may arise because some consumers are misinformed on the one hand, while for some consumers the operating costs of the energy-using durable is not a salient product attribute (Allcott, 2011). Field experiments that draw significant attention to a household's consumption profile, with real time feedback or intermittent information nudges like home energy reports (as in Allcott and Rogers 2014), are unable to credibly isolate the salience effect of energy costs from the pure information effect. One of the aims of this paper is to fill this gap.

Another important strand of literature investigates the implications of complex billing or pricing structures. Ito (2014) finds strong evidence that consumers are responding to average prices as opposed to marginal prices. which makes non-linear pricing for electricity unsuccessful. Similarly, in the residential water demand setting, studies have found that customers are poorly informed about marginal prices, have better knowledge of total costs and consumption (Brent and Ward, 2019) and likely respond to average prices (Wichman, 2014). This paper adds to the discourse on potential billing strategies to help the pricing mechanism in achieving its policy goal of energy conservation.

Previous studies have also focused heavily on electricity consumption, which involves accumulated costs for the household use of multiple energy-consuming appliances, which adds complexity to demand optimization. In contrast, change in heat consumption requires regulating room temperature, which is simpler, particularly when homes are equipped with programmable thermostats. This study is the first to test for consumer inattention to heating, which continues to be one of the most carbon-intensive energy services consumed by the residential sector (AGEB, 2018). Few papers have studied consumption behavior related to heating and thus are unable to comment on the importance of the billing system for heat energy. If households consistently pay attention to energy costs throughout the year, the timing of bills becomes irrelevant. This paper provides evidence to the contrary.

The energy sector experienced an unprecedented gas supply crunch in 2022 that led to dramatic shifts in household prices for heating in Germany. This energy crisis was an event in which cutting heat demand became crucial for households to keep energy costs in check and prevent a deficit in gas storage for the next winter. During periods of high prices and market volatility, inattention to energy costs could lead to significant overconsumption of energy. This paper suggests that appropriately-timed bills would help optimize energy demand during times of energy security risk and also in the design of low-energy buildings for a low-carbon future.

3. Data

3.1. Description

The paper uses large panel data on heating bills from centrally heated, residential, multi-apartment buildings in Germany.[6] These are bills starting from January 2008 to June 2018 with 12-month billing periods — each bill covers 365 or 366 days, but with varying billing start and end dates. The end of the billing period is always on the 30th or 31st day of a month. The sample covers multi-apartment buildings using all main fuel types, with 2 or more apartment units, with close to comprehensive regional coverage — 7830 postal codes in all sixteen states of Germany are represented. I observe a building on average 9 times and a maximum number of 11 times.

Each bill, at the building level, reports information on the annual metered units of energy consumed for space and water heating (if included) separately, along with yearly costs incurred for the fuel type used.[7] I also observe important characteristics of buildings that help determine the energy requirements of each building: living space (in square meters), building size (in number of apartments), location (zip code), and heating fuel type. Complementing this information, I also have data, for about 44% of the building sample, on energy performance certificates (EPC) reporting energy performance scores, the year building was constructed, and the year of construction or renovation year of key building components such as the heating system, roof, top floor or loft ceiling, outer wall, windows, and basement ceiling. For an even smaller subgroup of buildings (about 20%), I further observe whether these key building components met thermal-efficiency standards regulated under the 1995 Thermal Insulation Ordinance (Wärmeschutzverordnung or WSVO 1995) at the time of certification. These certificates were issued to the buildings from 2008 to 2019, largely in 2008, and I matched them to the primary data on consumption bills.

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[6] The data is confidential and was received as part of a partnership between the German Institute for Economic Research (DIW Berlin) and ista Deutschland GmbH (a leading energy metering company) to produce the Heat Monitor (Singhal and Stede, 2019). ista GmbH is an independent firm that takes care of installing meters, reading meters, meter maintenance and creating individual household heating bills on behalf of the property manager of each building — that is, each residential customer living in a building receive a heating bill via ista GmbH (See weblink: Heating Bill Services). Household-level bills were unavailable due to data protection rules.

[7] Note that each building is equipped with a heating system which is connected to a common central heating supply for all residents of the building. To allocate the total costs of central heating fairly, meters have been installed in each apartment to record consumption as accurately as possible.

I calculate the annual quantity of space heating energy consumed per square meter of heated living space. Majority (70%) of the buildings in the billing sample are billed for both space heating and water heating. First, building-specific consumption values are limited to the amounts of energy used for heating space. Then consumption units are multiplied by the heating value corresponding to the building's energy fuel type, giving us the absolute heating energy consumption in kilowatt-hours (kWh) for a building during the billing period. Finally, I divide total kilowatt-hours consumed by the amount of heated living space in the building. The units for heat energy consumption are therefore, kilowatt-hours per square meter of heated living space per year (kWh/m^{2}a). I measure the price of heat energy by dividing the annual fuel costs reported on each bill by the total kWh units of heat energy consumed by the building.

I supplement the billing dataset with weather station data from the German weather service (Deutscher Wetterdienst). I find the nearest available weather station to 8303 geocoded zip codes of Germany, provided that there is not more than one consecutive daily observation record missing for mean temperature for each weather station from 2003 to 2019. For the few missing values, I impute using the average of mean temperatures recorded for the previous and next day. This procedure amounts to using daily mean temperatures from 204 German weather stations to calculate heating degree days corresponding to each billing month and year. Heating degree days are calculated as the total sum of differences between the daily mean temperature and the heating threshold of 15 °C on days with recorded mean temperatures less than 15 °C. That means that for a month with 31 days, HDD would be calculated as $\text{HDD}_t = \sum_{d=1}^{31} \mathbb{1}[\text{temp}_d < 15] \times (15 - \text{temp}_d)$. This definition is standard in the environmental and energy economics literature.

The paper also uses two socio-economic variables at the zipcode level: the unemployment rate and the purchasing power[8] per household in 1000 EUR computed using grid level (1 × 1 km cells) data from RWI and microm (2020) aggregated to the zip code level and matched to the billing sample. This data were limited to years 2005 and 2009 to 2016.

3.2. Sample preparation

In this paper, I limit the study to buildings (407,284 buildings) using the three most common sources of heating in German households: (1) natural gas (high calorific), (2) district heating, and (3) heating oil. Then I remove buildings with more than 100 apartment units (404,781 buildings). This amounts to excluding very large apartment complexes and those buildings using low-calorific natural gas, LPG, pellets, electricity, wood, coal, brown coal, steam, and coke as the main heating fuel.

It is plausible that buildings that are newer and thus more energy-efficient (due to building codes or improvements in building construction over time, for instance) are more likely to be assigned certain billing dates. For this reason, I limit the sample to residential buildings with complementary data from energy performance certificates and information on the year of construction (156,653 buildings). This would allow me to control for the information provided on energy performance certificates (year of construction or renovations of building components). I also label the buildings by the class of building codes.[9]

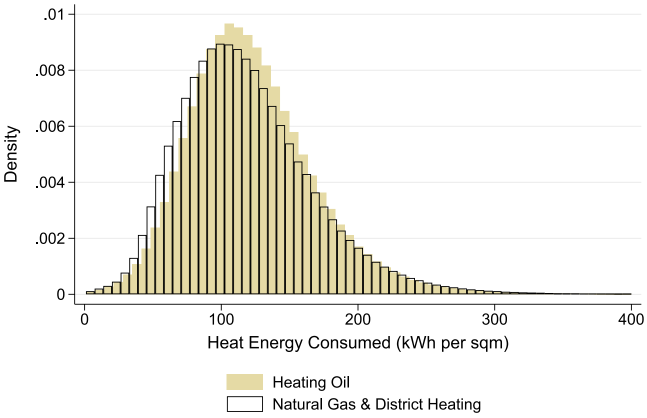

Fig. 2. Distribution of annual heat demand. *Notes:* The histogram presents the trimmed distribution of annual heat energy consumed for space heating, such that annual energy consumption is above 1 kWh/sqm and below 400 kWh/sqm of heated living space.

Note that the sample of buildings reporting energy performance scores is possibly more energy-efficient on average than the full sample, because the building owner's decision to produce the EPC is likely correlated with recent energy-related renovations that affect energy demand or entry on the housing market for rent or purchase.

The billing date assigned to a building is generally fixed over time. Only 5% of the buildings in the sample had switched from one billing month to another in the time period observed from 2008 to 2018. Buildings in the sample do not change billing dates unless undergoing refurbishments or heating technology. This is apparent in the data as the buildings drop out from the panel, before I observe a change in the billing date. Given the cross-sectional nature of the identification strategy, I drop such buildings from the estimation sample.

In the analysis that follows, I also trim the main dependent variable such that annual consumption is above 1 kWh/sqm and below 400 kWh/sqm of heated living space.[10] Moreover, I remove bills that report implausibly high energy prices, above 0.20 Euros per kWh, which amounts to removing observations in the top 1% of the price distribution. As a result, the sample for estimation comprises 152,025 buildings. The qualitative conclusions are not sensitive to removing the long upper tails of the distributions (see Table B.5).

3.3. Summary statistics

Table 2 shows the mean values for key variables used in the analysis. It is evident from the data that buildings with the calendar year billing tend to be larger and newer than buildings with non-calendar year billing, and likely as a consequence have lower energy performance scores (higher energy efficiency) on average. Table 3 reports the means of the variable by terciles of the unemployment rate distribution at the zip code level. As expected, postal codes that fall in the tercile with the highest average unemployment rates (Tercile 3) are also associated with lowest average purchasing power per household. These postal codes are more likely to have older, larger multi-apartment buildings, with smaller apartments, but less likely to use heating oil as the main fuel source.

The last rows report summary statistics on the full sample. Statistics on these variables are not available for the German population, even from German federal statistical offices and thus a comparison between the sample date and the population cannot be done.

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[8] A measure of disposable income — "The variable purchasing power reflects the household income. It comprises information on labour supply, capital wealth, rental and leasing income minus taxes and social security contributions, including social transfers such as unemployment benefits, child-allowances and pensions" Breidenbach and Eilers (2018).

[9] Energy efficiency regulation in Germany has largely taken the form of building codes, defining the building-aggregate maximum annual energy requirement per square meter of living space for newly constructed homes. The Heat Insulation Ordinance was first introduced in 1977, amended and made progressively more stringent in 1984 and 1995. It was replaced by the Energy Saving Ordinance in 2002. There were no minimum energy standards for buildings built before 1978. See Table B.4.

[10] See Fig. 2 for a plot of the trimmed distribution of the outcome variable.

Table 2
Descriptive statistics.
Sources: Author calculations using dataset from ista Deutschland GmbH and RWI and microm (2020).

Bill start	kWh/m^{2}a	Price per kWh	# of Apts	Apt size	Construction year	Score	Issue Year	PP per HH	# of Bills
January	113.6	6.85	12.8	74	1968	123	2013	42.6	879,588
February	124.5	6.69	6.1	76	1959	135	2012	42.8	11,394
March	123.3	6.63	6.7	90	1962	136	2012	42.5	13,167
April	120.4	6.66	6.6	78	1966	131	2012	43.6	24,568
May	126.5	6.81	8.9	76	1958	135	2012	42.9	32,080
June	124.6	6.89	5.9	79	1962	136	2012	44.7	86,941
July	120.1	6.90	9.0	77	1965	131	2012	44.1	53,813
August	121.4	6.93	6.1	80	1965	132	2012	45.2	13,571
September	121.4	6.77	6.1	79	1964	133	2012	44.3	15,632
October	116.4	6.98	10.0	75	1965	126	2012	42.8	37,646
November	123.3	6.51	6.7	78	1965	132	2013	43.7	18,092
December	124.1	6.52	6.7	76	1962	134	2012	43.0	14,216
All bills	116.0	6.84	11.4	75	1967	126	2013	43.0	1,200,708
	(43.9)	(1.99)	(12.8)	(67)	(35)	(41)	(5)	(8.1)	

Notes: The table reports average values calculated using bills from 2008-01 to 2018-06 for buildings using natural gas, heating oil, or district heating as the main heating source. The first column reports the annual heat energy consumption per square meter of living space. Price of heating fuel is given in Euro cents per kWh. Building size is given by the column indicating the number of apartments. Apartment size reports the average size of an apartment in a building, measured by the heated square meters of living space. Score is the minimum energy performance score reported on energy performance certificates for each building, while "Issue Year" is the year the last EPC was issued. PP per HH is the purchasing power per household at the zip code level. Standard deviations are shown for the full sample in parentheses.

Table 3
Descriptives by terciles of the unemployment rate distribution.

Terciles	T1	T2	T3	Full sample
Consumption kWh/m^{2}a	115.47	118.25	114.73	115.99
Unemployment %	2.26	4.22	9.01	6.11
Purchasing power per HH	50.22	46.01	37.86	42.97
Price per kWh (Euros)	0.066	0.066	0.072	0.069
No. of apartments	8.8	9.0	13.9	11.3
Apartment Size	80.3	78.5	71.3	75.4
Year of construction	1978	1973	1959	1967
Calendar year	0.66	0.69	0.77	0.72
May to July	0.19	0.17	0.12	0.15
Oil	0.42	0.31	0.16	0.26
Natural Gas	0.55	0.63	0.64	0.62
District Heating	0.03	0.06	0.20	0.12
Zip codes	2518	3037	2804	6834
No. of bills	208,345	319,901	485,187	1,013,433

Notes: The table reports average values of the main variables using the full sample of heating bills from 2009 to 2017, by terciles of the unemployment rate. Unemployment rate and purchasing power per household (in 1000 EUR) are computed at the zipcode level using data from RWI and microm (2020). The rest of the variables are building-level statistics. Price of heating fuel is given in Euros per kWh. Apartment Size reports the average heated living space in square meters of an apartment unit in a building. Calendar year reports the share of buildings that were treated with the January to December billing accounts. May to July reports the proportion of buildings with billing accounts starting in those months. Oil, Natural Gas, and District Heating are dummy variables for the main fuel types.

4. Billing months: a quasi-natural experiment

The paper uses variation in billing months to test for the presence of salience effects on annual heat energy consumption. There are two potential sources of endogeneity that need to be addressed in the analysis. First, the amount of heat energy consumed by a building depends on its energy efficiency. The assignment process of billing dates to buildings may depend on building attributes, such as building size and the year of construction — factors that are strongly associated with the overall energy efficiency of buildings.

Second, there is the possibility of selection by households into billing months. In this paper, I only consider centrally heated multi-apartment buildings with apartment units that are for the most part occupied by renters in Germany,[11] and thus building level attributes along with a building's billing date tends to be taken as given by residents and thus not part of the decision set of an individual household. Also, larger buildings have significantly more apartments units, which diminishes the opportunity for any given apartment owner to influence building-level features.[12]

In general, the beginning or the end of the billing month is not chosen (or even discussed) by residents or property managers, but depends instead on building-level attributes, mainly on the heating fuel source, which affects the process management infrastructure of the energy metering company providing the billing service.[13] The billing months are likely at the discretion of the metering/billing company to keep firm's operation costs to a minimum. Table 4 summarizes the share of buildings by fuel type and billing account types in year 2008. Natural gas (high calorific) is the most common fuel source for heating, and most of the bills are on calendar year billing, indicated by the "January" column. This is also the case for properties supplied by a district heating network. The column indicating "April to August" reports the share of buildings that were assigned to annual billing periods that start during or beginning of the summer months. This column shows that a significant share of the bills are settled during these off-winter months, especially for buildings using heating oil. For properties using heating oil, the billing month depends on the purchase of the fuel stock, which happens often during the summer months (about 40%). Moreover, about half of the buildings using heating oil are not on calendar year billing, with bills starting in January.[14]

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[11] 83% of apartment units in multi-apartment buildings are rented out in 2018 (Destatis, 2019).

[12] Estimated results hold after removing two-family homes and are homogeneous across building size classes. See the robustness section in Appendix A.

[13] This statement is based on an email exchange with the billing data provider, responsible for metering the building and preparing bills. The distinction comes from whether the heating fuel is supplied directly by a utility company or bought by the property manager of the building. Natural gas and district heating are supplied to the building directly through an energy supplier and thus the billing month is at the discretion of the utility company. On the other hand, non-wired supply of fuel types like oil, wood, and pellets are purchased by the owner of the building.

[14] Tables B.1 to B.3 show in further detail the distribution of billing months by building size of up to 10 apartments for properties fired with oil, natural gas, and district heating respectively. Note that calendar year billing (January

Table 4
Incidence of billing months by fuel type.

	First month of yearly bill			
	April to August	January	Remaining months	Sample share
Natural gas H	0.16	0.68	0.16	0.59
Oil	0.39	0.49	0.11	0.32
District heating	0.15	0.76	0.09	0.08
Natural gas L	0.00	0.21	0.79	0.00
Other	0.24	0.64	0.12	0.01
Total	23%	63%	14%	

Notes: The first column show the share of buildings in year 2008 with annual heating bills starting in April to August. The second column indicates the share of buildings with accounts starting in January (calendar year billing that ends in December). The third column reports the share of buildings with the remaining billing months. The last column reports the share of buildings by heating fuel type observed in 2008, sample of 256,295 buildings. “Other” fuel types consist of LPG, pellets, electricity, wood, coal, brown coal, steam, coke, and others.

Table 5
Differences in the price of fuel.

Bill start	*Dependent variable*: Euro Cents/kWh		
	(1)	(2)	(3)
May to July	0.00 (0.00)		
April to August		−0.01** (0.00)	
February			0.01 (0.01)
March			0.06*** (0.01)
April			0.06*** (0.01)
May			0.04*** (0.01)
June			0.03*** (0.00)
July			−0.05*** (0.01)
August			0.02 (0.01)
September			0.01 (0.01)
October			0.03*** (0.01)
November			0.02*** (0.01)
December			0.02*** (0.01)
Constant	6.84*** (0.00)	6.86*** (0.00)	6.85*** (0.00)
Observations	1,052,398	1,090,537	1,200,692
Adj R^2	0.551	0.549	0.547

Notes: Table reports coefficients from simple regressions of price of fuel incurred per unit of energy (kWh) consumed for heating on the starting month of the billing period, with fixed effects for the year, fuel type, building size, zip code, and robust standard errors. The omitted month is January which corresponds to calendar year billing, the control group. Constant reports the average price per kWh that was paid by buildings in the control group. Standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

I test for balance across billing months on one of the main determinants of heat energy consumption, price per unit of kWh by heating energy type. Table 5 reports t-tests of differences in mean fuel price using simple regressions with fixed effects for the billing year, fuel type, building size, and zip code. In the third column, I find statistically significant differences in the mean price of fuel for the majority of billing months, compared to prices faced by buildings with calendar year billing. However, the reported coefficients show that these differences are very small in magnitude. There does not seem to be any economically significant variation in prices across billing months. Given the large number of observations, it is perhaps not surprising that I am able to detect such small differences in average prices.

Households in multi-apartment buildings do not choose their billing dates, but they do choose where to live. If billing dates are determined by building type and location, then they may still be correlated with the demographic composition of its residents. This would arise, if for example (1) more energy-saving or poorer households live in larger and older buildings, and (2) more energy-consuming households choose to live in richer neighborhoods with more one-family or two-family homes and fewer multi-apartment buildings.

Because the data available for analysis lacks socio-economic information at the building level, I cannot completely rule out that any consumption differences between buildings on different billing months are at least partially driven by socio-economic factors such as income.[15] However, by controlling for all factors that determine building type (year of construction, size), quality (energy efficiency performance), and location (zip code), I argue that the remaining variation in billing months is conditionally exogenous — there is no systematic sorting of household types by when a building is billed for energy.

5. Empirical design

5.1. Model

To quantify salience bias in annual heat demand, I use the sample of buildings that likely receive their bills during the summer months as the treatment group and buildings that are billed for the calendar year (January to December) as the control group.

To adjust for the somewhat arbitrary choice of treatment and control billing months and the possibility that the salience of a billing date may vary from year to year depending on the intensity of the heating season, I use dummy variables for each winter season. In this manner I control for whether a building’s billing period begins during the winter heating months (October to March), separately for each yearly season.[16] But the months in which the heating season occurs may vary considerably across years, and thus a measure of heating degree days (HDD) is better-suited to capture this variation in the timing of the heating season. For example, the sum of heating degrees days recorded in the few months after the end of a billing period may be a more accurate definition of whether the receipt of a bill coincides with the heating season in any given year. This would flexibly adjust for the fact that the salience of costs may be lower (higher) if the beginning of the billing period is particularly warm (cold).

I use the following specification:

$$y_{it} = \alpha_0 + \beta \,\text{Summer Billing}_i + \delta \,\text{price}_{it} + \mathbf{z}_i' \boldsymbol{\pi} + \mathbf{w}_{zt}' \boldsymbol{\kappa} + \lambda_t + \epsilon_{it} \tag{1}$$

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to December) increases significantly with building size, while the share of bills that begin during off-winter months decreases. These tables document that the assignment of billing months to a building may be more than just a function of heating fuel type.

[15] The analysis in this paper is at the building level, but one could observe household-level billing dates along with household characteristics in survey data available in the German Residential Energy Consumption Survey from 2008–2011 (RWI-GRECS). It is thus possible to evaluate whether household-level variables are balanced across billing account types, albeit using a different database and sample population.

[16] For example, the indicator for “Winter 2009/2010” equals 1 when the billing period starts either in October to December of 2009 or January to March of 2010, otherwise zero.

Table 6
Effect of summer billing on heat energy consumption.

	Dependent variable: ln $(\mathrm{kWh/m^2a})$				
	(1)	(2)	(3)	(4)	(5)
April to August	0.044*** (0.003)	0.075*** (0.009)	0.075*** (0.009)	0.069*** (0.007)	0.049*** (0.011)
Cents per kWh	−0.040*** (0.001)	−0.040*** (0.001)	−0.040*** (0.001)	−0.032*** (0.001)	−0.048*** (0.000)
April to August					
× Tercile 2					0.002 (0.005)
× Tercile 3					0.030*** (0.005)
Winter Seasons	Yes				
HDD sums		Yes	Yes	Yes	Yes
Building code FE	Yes	Yes			
Construction Year FE			Yes	Yes	Yes
Minimum EPC score				Yes	
Issue Year FE				Yes	
N	1,088,000	1,088,000	1,088,000	1,087,990	914,506
Adj R^2	0.532	0.532	0.532	0.639	0.304

Notes: The table reports estimated versions of Eq. (1), for the full sample of buildings. Summer refers to the set of buildings with billing period that start in April, May, June, July, or August. The control group comprises buildings with calendar year billing accounts (starting in January). "Winter Seasons" in the first specification are dummy variables, controlling for whether a building's billing period begins during winter heating months (October to March), separately for each yearly season. For example, the indicator for Winter 2009/2010 equals 1 when the billing period starts either in October to December of 2009 or January to March of 2010, otherwise zero. Columns 2 to Columns 5 instead use HDD controls, which flexibly adjust for when the heating season actually occurred during a 12-month billing period. "Minimum EPC score" controls for the minimum energy performance score reported on any energy performance certificates issued between 2008 to 2019, while "Issue Year FE" control for the last year EPC was issued for the building. The specification in Column 5 reports on the interaction terms between the summer billing and terciles of the unemployment distribution. Columns 1 to 4 control for # of Apts X Zip Code FE, while the specification in Column 5 controlled for # of Apts X State FE. All regressions included the following: Year FE, Fuel Type by Year FE and control for the 12-month HDD sum. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

where y_{it} denotes natural log of annual energy units consumed (kWh) per sqm for space heating by building i during the billing period that started in year t. Summer Billing$_i$ indicates buildings with billing dates that start in the beginning of summer (April, May, June, July, and August). price$_{it}$ captures the fuel-specific cost per kWh unit of energy consumed. $\mathbf{z}_i$ captures a rich set of building-level controls: fuel type by year fixed effects, building size by zip code fixed effects, and fixed effects for the year in which the building was constructed, instead of the cruder control consisting of building standards regulation.[17] λ_t are fixed effects for the year in which billing starts. ϵ_{it} is the error term, clustered at the building level.

Eq. (1) improves upon the identification of time-varying salience by including the following HDD controls in $\mathbf{w}_{zt}$: (1) the sum of HDD in the first 3 months during each billing period t (3 month HDD sum), (2) the sum of HDD in the 4th to 6th months of each billing period t (4 to 6 month HDD sum), and (3) the sum of HDD in the 7th to 12th months of each billing period (7 to 12 month HDD sum). Note that the sum of these three HDD sum covariates totals the 12-month rolling sum of HDD in each annual billing period. The 12 month HDD is required as a control because, by design, heating bills from different billing dates do not cover the exact same 12 months.[18]

Since the building year is not a precise or complete measure to learn about the energy standards of a building, I also use the reported energy performance score to control for thermal energy performance, along with the year in which the latest energy performance certificate was issued. However, the energy performance score is partially an endogenous explanatory variable in this setting, because a high share of energy performance scores are measured using building-level consumption ("Verbrauchsausweis") that took place in the past years (which may include the potential effects of consumer inattention to energy costs due to untimely billing — the main thesis of this paper). Notwithstanding this important caveat, I find that the inclusion of energy performance scores of buildings do not undo the main results.

In a nutshell, I identify the salience effect of energy costs or bills on energy demand by analyzing differences in energy consumed per unit of living space between buildings with identical building attributes and location, but happened to have received different billing month accounts.

5.2. Results

Table 6 reports estimated versions of Eq. (1) discussed above. The first column estimates the model with dummies for the winter heating seasons. All specifications starting Column 2 use more precise HDD controls: first 3 month HDD sum, 4th to 6th month HDD sum, and 7th to 12th month HDD sum. Column 3 estimates the preferred equation, which introduces fixed effects for the year of building was constructed. Relative to calendar year billing, April to August billing months lead to 7.5 percent higher heat energy consumption annually by multi-apartment buildings. By way of comparison, an additional cent per kWh of heat energy is associated with a 4 percent fall in annual energy demand for space heating.

In order to limit any bias arising from differences in energy-efficiency of buildings on different billing months, I control for the scores reported on energy performance certificates in Column 4. As discussed earlier, the energy performance scores are frequently measured using building-level consumption in the past years and thus may not be a good measure of the energy standards of buildings and may even introduce bias in the coefficient estimates. Nevertheless, I report the estimation results using the minimum energy performance score reported in the sample, irrespective of the year when the EPC was issued. Column 4 of Table 6 shows that potential differences in these energy-performance metrics measured across billing dates does make a small change in the magnitude of the results, but the main conclusion stands. Finally, the last column tests for heterogeneous effects across socio-economic regions by investigates the interaction between summer billing and the terciles of the unemployment rate distribution. The results serve as suggestive evidence that buildings in zip codes that fall in Tercile 3 (i.e. zip codes with nationally high unemployment rates) may be more prone to salience bias in heat energy consumption, compared to buildings in Tercile 1 and Tercile 2. This raises potential distributional concerns associated with billing dates that warrant additional research.

In general, the estimate of salience bias during the summer billing months is robust to more conservative specifications. These findings strongly suggest that households livings in buildings billed during the summer months consume more energy relative to buildings billed in December. This is likely because heating bills received during the summer, when heating is off, are not salient, which would matter when energy users do not pay attention to the costs of consumption year-round.

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[17] $c = 0$ if Year Built < 1977, $c = 1$ if $1978 \leq$ Year Built < 1984, $c = 2$ if $1984 \leq$ Year Built < 1995, $c = 3$ if $1995 \leq$ Year Built < 2002, $c = 4$ if $2002 \leq$ Year Built < 2009, $c = 5$ if Year Built ≥ 2009. This would control for the stringency of minimum energy standards by year of construction shown in Tables B.4.

[18] In the last two columns of Table 1, I show that the 12-month rolling sum of heating degree days do not differ significantly across billing months. I further show that close to half the share of the total 12-month sum is experienced in the first three months when billing starts in November, December, and January. Moreover, the share of annual heating degree days experienced in the first 3 months post-billing is closest to zero for billing periods that start in May, June, and July.

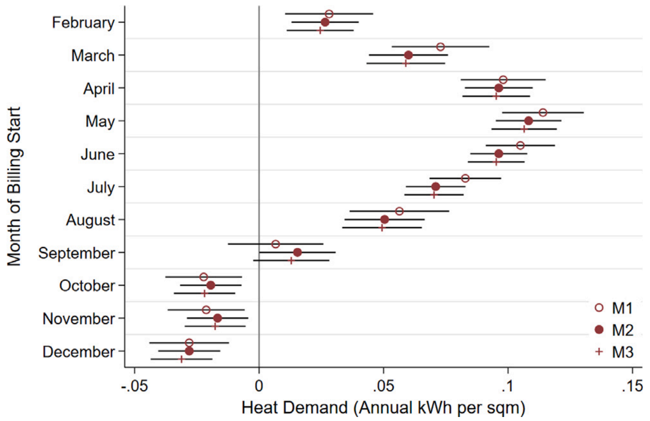

Fig. 3. Estimated effects for all billing months. *Notes:* The graph plots estimated versions of Eq. (1) using the sample of all three main heating fuel sources. The omitted month is January, which corresponds to calendar year billing. Model specification M1 is the preferred equation with fixed effects for the construction year, M2 adds a control for the minimum EPC score reported, along with fixed effects for the year in which the last EPC was issued to the building. The last model M3 further includes fixed effects for size classes l of living units in buildings, which control for differences in the average square meter space of a housing unit in buildings, where $l = 1$ if $\text{m}^2 < 40$, $l = 2$ if $40 \leq \text{m}^2 < 60$, $l = 3$ if $60 \leq \text{m}^2 < 80$, $l = 4$ if $80 \leq \text{m}^2 < 100$, $l = 5$ if $100 \leq \text{m}^2 < 120$, $l = 6$ if $120 \leq \text{m}^2 < 140$, $l = 7$ if $\text{m}^2 \geq 140$. All three regressions include the following controls: Year FE, Fuel Type x Year FE, # of Apts X Zip Code FE, Year of Construction FE, and the price of energy and HDD controls. 95% confidence intervals provided. These regression estimates are documented in the paper, Table 7.

5.3. All billing months

Given that attention diminishes with time, the temporal gap between the receipt of the energy bill and the heating season may be limiting the salience of billed energy costs. I ascertain that the results across all billing dates are indeed consistent with this insight, particularly affecting those households that are billed during peak summer months.

Instead of pooling buildings during any specific summer months to form the treatment group, I now include a dummy for each possible billing month observed in the data sample and re-estimate versions of the preferred model in Eq. (1). Table 7 shows that the estimated effects on heat demand for buildings assigned to April, May, June, and July, and August billing accounts are highly positive and statistically significant. Fig. 3 plots these estimates and shows that estimated effects on heat demand between billing months follow apparent “salience cycles”. This is largely consistent with the potential seasonal salience of heating bills and suggests that buildings billed during the spring and autumn months (March and September) may also consume more heat energy relative to calendar year accounts. Interestingly, the estimated coefficient on the December dummy suggests that buildings on calendar year billing demand 3 percent more heat energy annually compared to billing periods starting in December. The pattern of coefficients indicate that poor salience of annual energy bills is less of a concern during months that require heating, and may imply that consumer attention to billing settlements are highest during months that are followed closely by winter months that require heating, when households can react to cost signals effectively.

Overall, the results suggest that households may be least attentive to annual heating costs that are revealed during the summer. They may tend to react to costs in the few months post-billing and thus unable to respond to the energy costs billed during the summer because heating choices take place during the winter — by then, the heating bill may have become less relevant to the household budget or expenses.

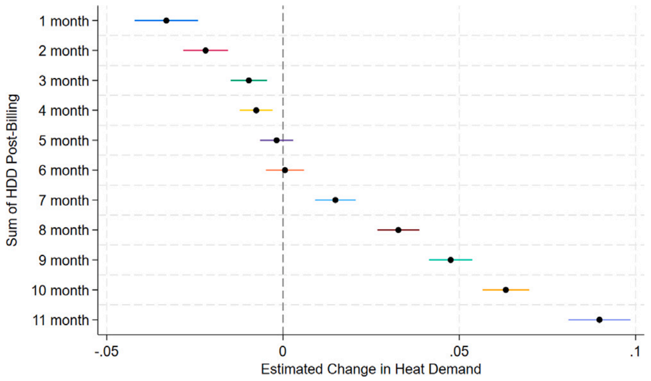

Fig. 4. Varying HDD sums post-billing. *Notes:* The graph plots estimates Eq. (2) using the full sample of all three main heating fuel sources. Each regression includes fixed effects for the building and billing year. The dependent variable is the absolute annual energy units consumed (kWh) for space heating, while the regressor of interest is the number of heating degree days 1 up to 11 months post billing date. In each regression. the HDD sum post-billing variable is scaled by 1000. The graph shows the effect on heat consumption in response to an increase of 1000 heating degree days in the first to 11 months post billing date. 95% confidence intervals are provided. An increase of 1000 heating degree days has the largest effect on heat consumption when experienced in the first month after billing. This rate is decreasing with each month post-billing, and eventually the effect reverses sign the further in time the heating season take place post billing date.

5.4. Attention span

To test for the underlying salience mechanism, I use staggered sums of heating degree days (1,2,3,4 months and so on) post-billing date as a continuous treatment variable, which varies both across buildings and yearly bills from 2008 to 2018. By altering the treatment variable of interest, I am able to incorporate fixed effects at the building level. The model can be expressed as follows:

$$y_{it} = \alpha_0 + \beta\,\text{j-month HDD sum}_{it} + \gamma\,\text{12-month HDD}_{it} + \zeta_i + \lambda_t + \epsilon_{it} \tag{2}$$

where y_{it} denotes absolute annual energy units consumed (kWh) for space heating by building i during the billing year t. j-month HDD sum_{it} is the treatment variable capturing the number of heating degree days 1 up to 11 months post billing date. This variable is scaled by 1000. 12-month HDD controls for the total heating degree days which is a baseline measure of how much heat energy a building required during the billing period. ζ_i are building fixed effects that account for all time-invariant differences between buildings and λ_t are fixed effects for billing year. ϵ_{it} is the error term, clustered at the building level.

I vary the timeframe for the treatment variable from 1 month to 11 months cumulative sums of HDD post billing, keeping the total number of heating degree days constant using 12 month HDD as a control. This allows me to test the salience mechanism directly, by exploring estimated effects on heat consumption had the cold season followed shortly after the billing date, without relying on the binary summer dummy variable. Fig. 4 shows the effect on heat consumption in response to an increase of 1000 heating degree days in the first to 11 months post billing date.

The coefficient for each HDD sum is precisely estimated. An increase of 1000 heating degree days experienced in the first month after billing takes place matters the most. Annual heat consumption is lower by 5 percentage points if billing is followed immediately by a winter heating month. The graph shows that the rate is highest in the first month and decreasing with each month post-billing, and eventually the effect reverses signs the further in time the heating season take place post billing date.

Perhaps more importantly, I have shown that the estimated differences in annual heat consumption of buildings is sensitive to the share

Table 7
All billing months.

	Dependent variable: ln (kWh/m^{2}a)		
	M1	M2	M3
February	0.024*** (0.009)	0.023*** (0.007)	0.022*** (0.007)
March	0.071*** (0.010)	0.058*** (0.008)	0.057*** (0.008)
April	0.096*** (0.009)	0.094*** (0.007)	0.094*** (0.007)
May	0.112*** (0.008)	0.106*** (0.007)	0.106*** (0.007)
June	0.102*** (0.007)	0.094*** (0.006)	0.094*** (0.006)
July	0.081*** (0.007)	0.070*** (0.006)	0.070*** (0.006)
August	0.058*** (0.010)	0.052*** (0.008)	0.053*** (0.008)
September	0.009 (0.010)	0.018** (0.008)	0.018** (0.008)
October	−0.018*** (0.008)	−0.015*** (0.006)	−0.014*** (0.006)
November	−0.018** (0.008)	−0.014** (0.006)	−0.013** (0.006)
December	−0.027*** (0.008)	−0.027*** (0.006)	−0.027*** (0.006)
Cents per kWh	−0.041*** (0.001)	−0.033*** (0.000)	−0.033*** (0.000)
Construction Year FE	Yes	Yes	Yes
Minimum EPC score		Yes	Yes
Issue Year FE		Yes	Yes
Living space class FE			Yes
N	1,198,171	1,198,161	1,197,107
Adj R^2	0.526	0.638	0.638

Notes: The table estimates versions of Eq. (1) using the sample of all three main heating fuel sources. The omitted month is January, which corresponds to calendar year billing. Model specification M1 is the preferred equation with fixed effects for the construction year, M2 adds a control for the minimum EPC score reported, along with fixed effects for the year in which the last EPC was issued to the building. The last model M3 further includes fixed effects for size classes l of living units in buildings, which control for differences in the average square meter space of a housing unit in buildings, where $l = 1$ if $m^2 < 40$, $l = 2$ if $40 \leq m^2 < 60$, $l = 3$ if $60 \leq m^2 < 80$, $l = 4$ if $80 \leq m^2 < 100$, $l = 5$ if $100 \leq m^2 < 120$, $l = 6$ if $120 \leq m^2 < 140$, $l = 7$ if $m^2 \geq 140$. All three regressions include the following controls: Year FE, Fuel Type × Year FE, # of Apts X Zip Code FE, Building Year FE, controls for the price of energy and HDD. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of the total sum of heating degree days that is recorded in the first few months of the billing period. Short-term variation in temperatures is unlikely to be correlated with socio-economic variables and energy-efficiency parameters of buildings. This evidence of an effect of heating degree days in the first few months of the billing period on total consumption gives me further confidence in interpreting residual differences in consumption across billing months as salience bias, as opposed to differences in demographic characteristics of building residents.

This section provides supporting evidence that (1) households are indeed more attentive to costs when heating needs increase, and (2) attention span takes place in the first four months post billing month, after which salience of costs has faded significantly. This further suggests that to maximize energy-savings, calendar year billing may still be sub-optimal as the benchmark. Given that the heating season lasts longer than four months, households that are informed of their heat energy expenses at least twice during the winter heating season may be comparatively better off.

6. Long-term investments

In this section, I address how building-level investments in energy-efficiency technology (thermal insulation or heating fuel efficiency in this context) may have been affected over the long-run by enduring differences in the salience of heating bills and thus energy cost expenditures. To my knowledge, the long run link between consumer inattention to consumption and energy efficiency investments for residential apartment buildings has not been explored in the literature (Gerarden et al., 2017).

Keeping all else equal, I expect that homes that incur higher annual costs for their energy needs to have higher economic incentives to invest in thermal efficiency for energy savings. In the previous sections, I show that multi-apartment buildings that are billed during the summer months are prone to higher consumption levels, which translates into higher annual costs of home heating. Given this backdrop, I empirically test whether these persistent shocks to energy expenditures led to statistically significant differences in investments by property owners in energy-efficiency technology.

I perform this test using data from energy performance certificates that were issued between 2014 and 2019 to buildings that use heating oil — because of the high share of buildings that are billed during the months April to August.[19] In order to limit potential bias arising from differences in energy-efficiency of buildings on different billing months, I also focus only on the subset of observed buildings that were built before 1978, and therefore were not required to comply with minimum thermal insulation standards during construction. This allows me to plausibly argue that any detectable differences in thermal insulation standards are due to investments in renovations post-construction and not due to federal building-level energy codes.

Table 8 provides summary statistics of the sample. Using energy performance certificates issued starting 2014, I observe data on (1) the year of construction or the year of renovation of each building component that is associated with heat energy efficiency, and (2) whether the building component meets efficiency standards regulated under WSVO 1995 (building-level thermal insulation standards).[20]

Panel A shows that the mean age of building is statistically identical (t-test of difference in means yielded p-value = 0.3077) across treatment and control groups. This is also true for the outer wall and the basement ceiling, but fails for all other thermal-insulation features of the building: heating system, roof, loft or top-floor ceiling, and windows.

Panel B shows even more interesting descriptive statistics. The first column under "Overall" indicates how many of the five building components (roof, loft ceiling, outer wall, windows, and basement ceiling) were certified to meet the thermal insulation standards under WSVO 1995. On average, buildings with summer billing accounts were associated with a higher share of key building components that met the 1995 thermal-insulation standards (a t-test of differences in the means yielded p-value of 0.000).

Now I test my hypotheses of differences in energy-efficiency investments in a more systematic manner — using a regression that controls for observable characteristics of buildings and zip code/location. I use the following linear probability model to estimate differences in heating-efficiency investments across billing months:

$$y_i = \alpha_0 + \beta \text{Summer Billing}_i + \mu_b + \gamma_{Size} + \theta_z + \lambda_t + \epsilon_i \tag{3}$$

where y_i in an indicator for whether each of the seven measures (overall, heater, roof, outer wall, loft, windows, and basement) of building i meets the thermal insulation standards set out in WSVO

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[19] I use the sample of buildings using heating oil because the share of non-calendar billing accounts is significantly higher irrespective of building size — which maximizes the sample of buildings in the treatment group

[20] Because the average age of buildings in the full sample is 1967 and over 80% of the buildings were built before 1995 ("Altbau"), achieving the 1995 standard is arguably a suitable benchmark for high energy performance of buildings. I am unable to consider stricter thermal insulation standards due to lack of data.

Table 8
Sample means — Buildings built Pre-1978.

	Panel A: Year of construction/renovation						
	Year built	Heater	Roof	Loft	Outer wall	Windows	Basement
Calendar year	1955.8	1996.1	1974.9	1968.3	1965.6	1977.0	1960.8
(SD)	(29.4)	(12.1)	(26.9)	(27.5)	(27.5)	(25.4)	(26.5)
N	14,164	12,451	5163	7473	8360	6303	9373
April to August	1956.2	1995.5	1979.8	1969.6	1966.2	1983.2	1960.5
(SD)	(30.8)	(12.4)	(27.0)	(27.9)	(28.9)	(29.3)	(27.5)
N	11,683	9814	3579	5574	6428	4466	7391
	Panel B: WSVO 1995 Indicator (=1 if meets standards)						
	Overall	Heater	Roof	Loft	Outer wall	Windows	Basement
Calendar year	1.299	0.611	0.326	0.343	0.196	0.360	0.074
(SD)	(1.506)	(0.488)	(0.469)	(0.475)	(0.397)	(0.480)	(0.262)
N	5741	12,451	5741	5741	5741	5741	5741
April to August	1.713	0.601	0.428	0.440	0.241	0.524	0.080
(SD)	(1.471)	(0.490)	(0.495)	(0.496)	(0.428)	(0.499)	(0.272)
N	3958	9814	3958	3958	3958	3958	3958

Notes: Calendar Year is the comparison group of buildings with the billing period that ends in December, while April to August represents the treatment group with billing periods that start during the off-winter heating or summer season. Standard deviations in parentheses. N reports the number of buildings in the sample. "Overall" indicates the number of building components (roof, loft ceiling, windows, outer wall, and basement ceiling) that meet thermal efficiency standards under WSVO 1995 building codes. This information was only available from energy performance certificates issued from 2014 to 2019.

Table 9
Differences in energy efficiency investments — Buildings built Pre-1978.

Bill start	*Dependent variable*: WSVO 1995 indicator (=1 if meets standards)						
	Overall	Heater	Roof	Loft	Outer wall	Windows	Basement
April to August	0.218*** (0.042)	−0.000 (0.012)	0.060*** (0.015)	0.054*** (0.015)	0.017 (0.012)	0.086*** (0.014)	0.001 (0.008)
Construction Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issue Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Apts FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Zip code FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8274	9465	8274	8274	8274	8274	8274
Adj R^2	0.192	0.072	0.135	0.126	0.103	0.174	0.079

Notes: The table shows estimates of Eq. (3). The omitted billing month is January (calendar year billing), the comparison group. April to August represents the treatment group of buildings with billing periods that start during the off-winter heating or summer season. "Overall" indicates the number of building components (roof, loft ceiling, windows, outer wall, and basement ceiling) that meet thermal efficiency standards under WSVO 1995 building codes. Data is limited to energy performance certificates issued 2014 to 2019. Standard errors in parentheses clustered at the zip code level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1995 regulation, at the time of certification. For the heating system, I use the indicator for whether the year of heating system installed is greater or equal to 1995. Summer Billing$_i$ indicates whether the billing date associated with building i starts in April, May, June, July, or August. The comparison group comprises buildings with the calendar year billing that starts in January. μ_b captures fixed effects for the year in which the building was newly constructed. γ_{size} and θ_z capture the building size and zip code fixed effects respectively. λ_t are fixed effects for the year in which the EPC was issued and ϵ_i the error term, clustered at the zip code level.

Table 9 demonstrates that building owners treated with summer billing invested to retrofit a higher share of the building envelope to meet the 1995 thermal insulation standards, captured by the variable "overall". The estimate of 0.218 translates to a 4.4 percentage point increase in the share of building components receiving an insulation upgrade. Based on the regression coefficient estimates for specific building components, the estimate for "overall" was likely powered by higher investments in insulating the roof, the loft or top floor ceiling, and windows. The windows component was particularly affected — with an increase of 9 percentage point in the share of buildings that received renovation at the 1995 insulation standard. I do not find any statistically significant differences in the shares for the exterior wall and basement ceiling, on the other hand.

Although the economic significance of these differences in renovation rates across billing dates may not be high, the results in this section do provide some evidence that long-term incentives for energy-efficiency do matter, and owners of multi-apartment buildings responded to differences in expected returns to investments in energy-efficiency — at least for buildings built before 1978, that are generally associated with low rates of renovation (Galvin and Sunikka-Blank, 2013).

These results suggest that salience of costs affect not only short-term consumption behavior of tenants/residents, but also feed into long-run investment decisions of multi-apartment building owners. In this context, however, the significantly more cost-effective solution may have been to draw the users' attention to true energy costs — by improving the salience of energy costs on annual bills.

With respect to salience bias in heat energy demand, the results in this section further imply that the short-run effect on heat consumption is likely even higher, all else equal. The results captured in this paper capture the effect of lingering inattention over the long-run, after learning and investment adjustments have taken place as result of the treatment. I confirmed this in Appendix A by considering a sample of buildings that are as similar as possible, controlling for all building components that are associated with heat- and energy-efficiency.

7. Conclusion

By exploiting the billing month assignment in a large scale natural experiment in Germany, I estimate that buildings that are billed during the summer months, and thus are treated with low salience of energy costs, are consuming at significantly higher heat energy levels annually. Empirical results in this paper are intuitively consistent. Effective attention to costs take place in the few months immediately after billing.

Consequently, buildings billed for heating during off-winter months are subject to salience bias, leading to their perceived cost of consumption to be lower — resulting in higher heat energy demand. Results demonstrate that buildings that are issued bills for space heating during the summer consume on average 7.5 percent more than those that are issued bills during the winter heating months.

This research highlights the importance of improving the salience of billing information on energy prices and consumption to encourage consumer attention and alter household behavior. Engaging energy users with bills during high-consumption events has significant potential to achieve energy savings in the building sector, both in the short- and long-runs. Determining the appropriate billing system and gaining a thorough understanding of the effect on consumer behavior can inform billing design in both developed and developing regions alike (Wong et al., 2022). It might be appropriate to directly survey consumers to ascertain their preferences regarding various billing frequencies or dates and then reconcile these consumer preferences with administrative constraints faced by meter reading companies.

Several caveats to the empirical design are in order. I do not observe directly the level of attention households pay to bills and how this differs by month of bill receipt. Moreover, I do not know the exact date the metering/billing company (ista GmbH) or property manager distributed the bills to building residents. I use the billing metering period as a proxy for the month of bill receipt which may be a noisy treatment indicator. Finally, data limitations did not allow me test for balance in household socioeconomic characteristics across billing dates. However, after controlling for all observable characteristics and location of the building, I find that there remain significant differences in consumption between billing months and that these differences are sensitive to the sum total of heating degree days in the first few months of the billing period. I use building-level consumption data and households, living in otherwise statistically identical buildings, with summer accounts versus winter accounts would not be systematically different on the aggregate (in income and preferences for heating, for example).

An important area of future research would be to quantify the extent to which consumer inattention affects energy demand from single-family homes. This would be important because close to half of the building stock (owned or rented) in Germany are one or two family houses (Destatis, 2016). Although the results in this paper refer to multi-apartment buildings, single family homes also receive energy bills once a year and thus the conclusion may apply to single-unit houses as well. The empirical approach used in the paper could also be applied to investigate the effectiveness of timing electricity bills as a means of curbing demand during peak summer months, characterized by high cooling degree days, in regions where energy supply constraints are particularly acute.

It is worth mentioning explicitly that this paper is unable to comment on the relative merits of annual versus more frequent billing in the German context. It may very well be that informing households about cumulative costs (on annual bills) elicits a stronger demand response than say information on incremental energy costs each month — i.e. monthly billing may be less salient. Would increasing the frequency of information (holding salience constant) lead to significantly more heat energy-savings? Results in this paper suggest that the delivery of bills should be timed during the winter heating season, if they are received once a year. Since increasing the frequency of bills may be associated with significant economic costs, further research would be required to determine what would be an optimal frequency of billing during the winter heating season for heat energy demand. Notwithstanding, considering the potential increase in energy poverty risk in Germany (Henger and Stockhausen, 2022), due to high energy prices and uncertain macroeconomic conditions, savings on energy costs are likely to become increasingly important for households.

In Germany, the heating sector is primarily powered by fossil-fuels and accounts for 25% of the final energy consumed, of which about 70% is consumed by the residential sector (AGEB, 2018). The results in this paper indicate that the current billing system that is used for the vast majority of buildings in Germany is not optimal for reaching energy and environmental policy targets. Ultimately, those households that want to save on bills or conserve energy must know the energy costs, with timely information or costs of attention to be as low as possible. This is likely to be increasingly important given the introduction of a CO_2 price on carbon emissions from heating fuels in Germany, and the difficulty of decarbonizing the heating technology in the building sector. Providing households with billing information during the peak of winter (relevant information at the relevant time) is arguably not more costly than status-quo, but it does have the high potential to reduce energy demand from the residential sector cost-effectively.

CRediT authorship contribution statement

Puja Singhal: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Robustness

A.1. Heterogeneity

In what follows, I test for heterogeneous effects by number of apartments and building quality.

Table A.1 presents evidence for pervasive salience bias in heat demand in the sample population. The first column replicates the main result that buildings with summer billing accounts consumed on average 7.5 percent more heat energy annually, compared to buildings with calendar year billing. This is provided here for comparison purposes. The second column shows that this effect of salience bias on heat consumption is homogeneous across all building sizes (measured by the number of apartments in a building). In the third column, I look at the interaction of summer billing with “WSVO 1995”, which captures whether all the observed energy-efficiency related components of the building meet the 1995 thermal insulation standards. With this specification, I seek to examine buildings that are as comparable as possible in terms of energy-efficiency investments and insulation performance. The coefficient estimate on the interaction term indicates that the rate of higher consumption does not vary significantly with energy standards of the building.

A.2. Water heating

In addition to space heating, heating bills also cover costs incurred for water heating for the majority of the buildings. Although energy consumed for hot water is a smaller share of total annual energy costs, households could react to costs on energy bills by adjusting the use of hot water instead. Residential demand for energy to heat water is less seasonal than that for space heating, however.

To test for consumer inattention, I have considered energy consumed for space heating independently thus far. Households that are indeed paying attention to heating costs during the summer months may react by adjusting (disproportionately) the amount of energy they consume for water heating, in the shower and in the kitchen, for example. This would potentially bias the main results had I considered total energy consumption (space plus water heating).

Table A.1
Heterogeneous effects.

	Dependent variable: ln (kWh/m^{2}a)		
	(1)	(2)	(3)
April to August	0.075***	0.074***	0.086***
	(0.009)	(0.012)	(0.015)
Cents per kWh	−0.040***	−0.040***	−0.036***
	(0.001)	(0.001)	(0.001)
Base omitted: 2 Apts			
May to July × 3 to 6 Apts		−0.007	
		(0.008)	
May to July × 7 to 12 Apts		−0.000	
		(0.009)	
May to July × 13 to 20 Apts		0.003	
		(0.010)	
May to July × 21+ Apts		0.004	
		(0.011)	
WSVO 1995 Dummy			−0.186***
			(0.011)
May to July × WSVO 1995			−0.012
			(0.013)
N	1,088,000	1,090,537	352,125
Adj R^2	0.532	0.360	0.655

Notes: The table reports regression estimates for the full sample of fuel types: heating oil, natural gas (high calorific), and district heating. The control group comprises buildings with calendar year billing (starting in January). Column 1 replicates the preferred specification. Column 2 reports coefficient estimates on the interaction between summer billing and building size. WSVO 1995 is a dummy variable indicating whether all building components related to energy efficiency (heating system, roof, loft, outer wall, windows, and the basement) meet the 1995 building standard. Column 3 reports coefficient estimates on the interaction between summer billing (starting the months of May to July) and WSVO 1995 building standard. All variables in any interacted terms were present in the regression equations independently. Columns 1 and 3 control for # of Apts X Zip Code FE, while the specifications in Column 2 controlled for Zip Code FE. All regressions included the following: Fuel Type × Year FE, Year of Construction FE, and controls for the price of energy and HDD. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2
Space versus water heating.

	Dependent variable: ln (kWh/m^{2}a)		
	Space	Space	Water
April to August	0.089***	0.069***	−0.022***
	(0.014)	(0.011)	(0.005)
Cents per kWh	−0.042***	−0.039***	−0.009***
	(0.001)	(0.001)	(0.001)
Sample	Space Only	Space + Water	Space + Water
N	293,368	793,644	793,644
Adj R^2	0.608	0.547	0.361

Notes: The table estimates Eq. (1) using the sample of all three main heating fuel sources. The omitted month is January, which corresponds to calendar year billing. The second and third columns only considers buildings that are billed for both space and water heating, while the first column only considers billing observations that do not report any energy consumed for water heating. All three regressions include the following controls: Fuel Type by Year FE, Year FE, # of Apts X Zip Code FE, Building Code FE, and the price of energy, year of construction, weather controls for the 12 month and 3 month HDD sums. Columns 3 tests for the potential spillover effect on the water consumption variable, the regression specification in Column 3 includes Year FE, # of Apts X Zip Code FE, the price of energy, year of construction FE, and HDD controls. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3
All billing months except January.

	Dependent variable: ln (kWh/m^{2}a)
February	0.023
	(0.015)
March	0.065***
	(0.016)
April	0.069***
	(0.017)
May	0.077***
	(0.017)
June	0.062***
	(0.016)
July	0.049***
	(0.015)
August	0.033**
	(0.016)
September	0.009
	(0.015)
October	0.002
	(0.012)
November	0.016
	(0.012)
Cents per kWh	−0.047***
	(0.001)
N	319,721
Adj R^2	0.524

Notes: The table estimates the preferred version of Eq. (1) with fixed effects for the construction year, using the sample of all three main heating fuel sources. The omitted billing month is December. The following controls were included: Year FE, Fuel Type × Year FE, # of Apts X Zip Code FE, Building Year FE, and controls for the price of energy and HDD. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4
By main fuel types.

	Dependent variable: ln (kWh/m^{2}a)		
	(1)	(2)	(3)
April to August	0.095***	0.030**	0.118***
	(0.014)	(0.015)	(0.026)
Cents per kWh	−0.046***	−0.009***	−0.042***
	(0.001)	(0.001)	(0.001)
Fuel type sample	Natural gas	Heating oil	District heating
N	662,922	286,462	136,858
Adj R^2	0.560	0.448	0.723

Notes: The table estimates the preferred version of Eq. (1) with fixed effects for the construction year, using the sample of each of the three main heating fuel sources separately. The control group is January. The following controls were included: Year FE, Fuel Type × Year FE, # of Apts X Zip Code FE, Building Year FE, and controls for the price of energy and HDD. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In the first column of Table A.2, I estimate the preferred Eq. (1) for buildings that are billed only for space heating to check the validity of the empirical results thus far. The estimate of close to 9 percent confirms the main quantitative findings for space heating.

Next, I check the extent of adjustments in heat demand via water heating. I limit the sample of buildings to only those that are billed for both space and water heating, and estimate the effect of salience bias on energy demanded for space and water heating separately. I continue to measure consumption in annual kilowatt hours consumed per square meter to credibly test the spillover mechanism. The third column of Table A.2 reports that buildings with summer billing consume on average 2 percent less heat energy for water compared to buildings with calendar year accounts. At the same time, I find that there is a weaker relationship between the energy price and the consumption variable for heat energy used for hot water. I interpret this as evidence of a spillover effect of non-salient space heating costs. Households billed during the summer billing months may be reducing heat consumption

Table B.1
Billing months by building size — Heating oil homes.

Starting month	Number of apartments/Household units								
of bill	2	3	4	5	6	7	8	9	10
January	39.3	40.4	45.9	51.5	57.6	59.2	62.7	61.2	66.9
February	2.2	1.6	1.5	1.1	0.8	0.9	0.4	0.6	0.6
March	2.3	1.6	1.6	1.4	0.6	0.9	0.8	0.6	0.4
April	3.6	3.1	2.3	2.0	1.8	1.7	1.5	1.2	0.7
May	5.3	5.0	4.3	4.1	3.7	4.3	4.0	5.3	5.3
June	23.2	27.5	26.4	22.9	22.2	19.7	17.9	18.3	14.5
July	8.2	8.1	7.2	7.0	6.2	6.3	6.6	6.7	6.6
August	3.3	2.5	2.1	1.8	1.5	1.2	1.2	0.8	1.0
September	3.2	2.6	2.1	2.1	1.0	1.2	1.2	0.9	1.2
October	5.2	4.3	3.6	3.8	2.6	2.8	1.6	2.4	1.5
November	2.6	2.0	1.7	1.3	0.9	1.1	1.2	1.1	0.6
December	1.6	1.4	1.3	1.0	0.8	0.7	0.8	0.9	0.5
May to July	36.6	40.6	38.0	34.0	32.1	30.3	28.6	30.3	26.5

Notes: The table shows the distribution of billing months observed in 2008 for all buildings with up to 10 apartments that use heating oil as fuel.

Table B.2
Billing months by building size — Natural gas homes.

Starting	Number of apartments/Household units								
month of bill	2	3	4	5	6	7	8	9	10
January	52.4	56.2	61.3	66.4	70.9	69.2	73.6	75.4	76.5
February	2.6	2.7	2.2	2.0	1.3	1.8	1.5	1.6	0.9
March	2.9	2.4	2.1	2.1	1.7	1.8	1.5	1.5	1.8
April	4.0	3.7	3.4	2.8	2.5	2.7	2.4	1.9	2.1
May	4.4	3.9	3.6	3.0	2.8	2.6	2.3	2.2	2.5
June	7.0	7.3	6.0	5.5	4.3	5.0	4.2	3.5	3.6
July	5.1	5.3	4.7	4.1	3.7	4.1	3.6	3.8	3.3
August	1.8	1.5	1.3	1.2	0.9	1.0	1.0	1.1	0.9
September	2.6	2.2	1.9	1.7	1.5	1.7	1.4	1.1	1.2
October	8.2	7.0	6.6	5.4	5.3	4.8	4.5	3.7	3.9
November	5.3	4.5	3.9	3.2	2.7	2.7	2.0	2.1	2.1
December	3.7	3.5	3.1	2.6	2.4	2.6	2.0	2.0	1.3
May to July	16.5	16.4	14.3	12.6	10.8	11.7	10.0	9.5	9.3

Notes: The table shows the distribution of billing months observed in 2008 for all buildings with up to 10 apartments that use natural gas as fuel.

for hot water in response to bills. Incidentally, this result also serves as a placebo test for the proposed salience mechanism at play in determining annual energy demand for space heating. If the residual differences in energy consumption for space heating between billing months is driven by socioeconomic characteristics of households, then one should expect the similar estimates for energy used for water heating — this is not the case.

A.3. Switching the control group & fuel-specific buildings

First, I extend the results in Section 5.3 and remove the large chunk of buildings billed for the calendar year. Now the control group of buildings are those billed during the month of December, also a winter month. The results below in Table A.3 highlight that the main results are not driven by selection bias characteristic of buildings with calendar year billing. Billing months that are not followed by the heating season continue to show higher rates of heat energy consumption compared to the December billing month, which is consistent with the lower salience of billing during summer months. For completeness, Table A.4 further shows that the main results in Table 6 by the main fuel types separately.

Appendix B. Additional tables

See Tables B.1–B.5.

Table B.3
Billing months by building size — District heating homes.

Starting	Number of apartments/Household units								
month of bill	2	3	4	5	6	7	8	9	10
January	67.8	64.8	68.9	69.9	71.8	73.7	70.6	68.2	66.8
February	1.7	3.	2.1	1.3	1.2	1.1	0.9	1.2	1.6
March	1.4	1.7	1.7	1.8	1.0	0.6	1.0	1.3	1.7
April	3.1	3.3	3.1	1.9	2.0	2.3	1.9	2.3	1.6
May	2.4	3.3	4.6	2.2	1.8	1.8	2.8	1.7	2.7
June	4.1	4.6	3.0	5.6	5.3	3.2	4.4	5.1	3.6
July	8.0	6.5	8.7	8.0	6.8	9.8	10.4	11.7	12.0
August	1.7	1.5	1.0	1.4	1.2	1.4	0.9	1.2	1.7
September	2.2	2.9	1.6	2.0	1.8	1.2	1.2	1.2	1.6
October	3.1	3.5	2.9	2.8	3.8	2.5	3.7	3.6	4.9
November	2.0	2.4	1.5	2.1	2.5	1.3	1.2	1.7	1.0
December	2.6	1.5	0.8	1.0	0.9	1.1	1.0	0.7	0.7
May to July	14.5	14.4	16.3	15.8	13.9	14.9	17.6	18.5	18.3

Notes: The table shows the distribution of billing months observed in 2008 for all buildings with up to 10 apartments that have district heating.

Table B.4
Standards for new construction.
Sources: Galvin and Sunikka-Blank (2013) and El-Shagi et al. (2017).

Year	Regulation	Max. per annum
Pre-1978	No regulation	
1978	Heat insulation (WSchV)	250 $\mathrm{kWh/m^2a}$
1984	Amendment of WSchV	220 $\mathrm{kWh/m^2a}$
1995	Amendment of WSchV	150 $\mathrm{kWh/m^2a}$
2002	Energy saving (EnEV)	100 $\mathrm{kWh/m^2a}$
2009	Amendment of EnEV	60 $\mathrm{kWh/m^2a}$
2016	Amendment of EnEV	45 $\mathrm{kWh/m^2a}$

Notes: The first column indicates the year in which the regulation became effective.

Table B.5
Untrimmed sample.

	Dependent variable: ln ($\mathrm{kWh/m^2a}$)
April to August	0.048***
	(0.011)
Cents per kWh	−0.000***
	(0.000)
N	1,101,010
Adj R^2	0.507

Notes: The table reports estimates for Eq. (1) for the full untrimmed sample of fuel types: heating oil, natural gas (high calorific), and district heating. The control group comprises buildings with calendar year billing. Standard errors in parentheses clustered at the building level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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