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Variation of gas use for space heating: cost implications when switching from gas to district heating

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ABSTRACT

For 35% of Dutch households, district heating (DH) is considered the least-cost option to phase out heating based on individual gas boilers. This outcome is grounded in neighbourhood averages that mask large differences in individual household heat demand, and leads to a risk that below-average heat consumers are worse off in terms of relative energy bill increase compared to above-average heat consumers. This study explores this risk by analysing household-level gas use variation and its impact on end-user costs under 2025 Dutch DH tariffs. We use 2019 and 2022 microdata from Statistics Netherlands for over 230,000 homes (>96% apartments) in 276 Amsterdam neighbourhoods for which DH is considered the least-cost option. We apply Kernel density estimation, Lorenz curves, Gini coefficients, and multinomial logistic regression to quantify the distribution of annual gas consumption, calculate percentage changes in energy bills if natural gas demand were replaced by DH, and characterize these households with building and household predictors of bill increases across four categories (<25%, 25-50%, 50-75%, >75% bill increase). Results reveal that there can be significant variation even within spatially homogeneous homes and 25% to 30% of the households would see their energy bill rise by more than 25% (of which 5% points would see a bill rise >75%). 23.3% (2022 data) to 25.7% (2019 data) of the Amsterdam households belong to the low-income group, and part of them are considered energy poor. 27% (2019 data) to 33% (2022 data) of the low-income households will face an energy bill increase of more than 25% when switching from individual gas heating to DH. Also, the results indicates that small apartments, high-insulated buildings, low-income households and commercial renters are at a heightened risk of a more than 75% bill rise. These findings demonstrate that leaning on average heat demand in least-cost calculations, and using fixed annual DH tariffs for all user categories disproportionately harm low-end heat consumers, including a significant share of low-income households, and households defined as energy poor. When striving for an equitable heat transition at the one hand and a viable business case for DH projects, this must not be overlooked.

Keywords

Residential heat transition. District heating. Energy bill. Household heterogeneity. Gini coefficient. Multinomial logistic regression.

Introduction

In the European Union (EU), heating accounted for 78.3% of final residential energy consumption in 2022, with district heating (DH) supplying 11% of the heat demanded.[1] Although most DH is still sourced from fossil fuels, the European Commission recognizes it as a key option for decarbonizing residential heat (Bacquet et al., 2022). The Heat Roadmap Europe (HRE) project, which mapped the economic potential of DH at a 1km² resolution across 14 European countries, estimated that up to 71% of total heat demand in 2015 could have been economically met by DH (Möller et al., 2019). For the Netherlands, one of the countries included in the study, this potential was even higher at 73%. While such country-level studies highlight the huge potential of DH it rarely tackles the neighbourhood and household challenge of retrofitting existing homes with DH instead of individual heating systems. Detailed, local level studies are therefore needed to show how and under what conditions DH can actually replace individual boilers. Without that local perspective, policymakers risk the practical guidance required to translate DH's theoretical potential into real-world implementation.

In the Dutch heat transition, municipalities play a central role by developing long-term neighbourhood-level plans that assess suitable heating strategies (Herreras Martínez et al., 2021). To support these local strategies, the Netherlands Environmental Assessment Agency (PBL) developed a "start-analysis[2]" using the Vesta Multi Actor Impact Simulation (Vesta MAIS)[3] model- an open-source techno-economic spatial energy model (Herreras Martínez et al., 2021). In March 2025, PBL released an updated start-analysis identifying the least-cost heating strategy for approximately 14,000 Dutch neighbourhoods (van Polen et al., 2025). The four primary strategies were 1) individual electric heat pumps, 2) medium- or high-temperature DH, 3) (very) low-temperature DH combined with electric heat pumps, and 4) hybrid heat pumps with green gas. According to the analysis, medium/high-temperature DH was the robust least-cost strategy for approximately 15% of Dutch households and low-temperature DH for 5%. "Robust" here is defined as having at least a 20% cost advantage over the next-best alternative. If all households for which DH was the least-cost strategy are included- also with less than 20% cost advantage- the share increases to 35% (van Polen et al., 2025).

Although the PBL's analysis provides greater detail than the earlier EU-level studies like HRE, it also reveals important challenges. One key concern is the dynamic nature of least-cost strategies: if too many households choose individual solutions, the viability of DH may diminish due to loss of scale (Van Polen et al., 2025). Another challenge is that the analysis focuses on societal costs, without yet considering the end-user perspective. What is least-cost for society may not be the most affordable or attractive option for households, as costs are distributed unevenly. Incorporating the end-user perspective is a critical (and planned) next step for refining the analysis and designing effective policies to accelerate the heat transition.

Jaffe & Stavins (1994) already noted that energy efficiency measures based on average energy use can be unattractive to below-average consumers. This concern is especially relevant for DH, which typically has higher fixed costs than individual gas-based heating systems (see Methods for details). If DH is deemed cost-effective based on average consumption, it will tend to benefit high-usage households more than low-usage ones; potentially jeopardizing collective viability.

Previous research has shown that building characteristics explain only around 40% of the variance in residential energy consumption. Adding household-level variables (e.g., household size, age, income) still leaves more than half of the variance unexplained (Guerra Santin et al., 2009; Huebner et al., 2015). Occupant behaviour accounts for a large part of this residual variance (Cuerda et al., 2019; Gram-Hanssen, 2010; Harputlugil & De

[1] Values derived from Eurostat (final household consumption by function) and Eurostat (final household consumption by fuel type).

[2] The Start Analysis outlines five non–natural gas heating approaches and serves as a resource for municipalities in crafting their Heat Transition Vision.

[3] Vesta MAIS is a spatial energy model for residential, commercial, and greenhouse sectors that explores pathways away from natural gas. It maps technical–economic potentials of building and regional measures, quantifies policy impacts on costs, energy use, and CO_2 emissions, visualizes costs outcomes for heating companies and users, and assesses infrastructure implications. The model operates at national and regional scales, integrating building-level data (e.g., energy labels, address registers) and local heat sources. Rather than optimize or predict a single outcome, Vesta MAIS serves as an exploratory tool to visualize cost-effectiveness of various heating and energy strategies.

Wilde, 2021). For instance, Liu et al. (forthcoming) demonstrate that behavioural differences in otherwise identical homes can result in nearly a fivefold difference in heat demand.

Corollary, the Vesta MAIS model uses reference buildings to represent clusters of homes with similar physical characteristics (e.g., building type, floor area, construction year), with the presumption of uniform energy consumption. To align with national statistics, modelled energy use is corrected at the neighbourhood level (van den Wijngaart et al., 2017). While this approach is suitable for estimating aggregate societal costs, it poses limitations when translating those costs to the household level, as it relies heavily on average values. Thus, this paper aims to inform policy development for the Dutch residential heat transition by analysing the implications of household-level heat demand variance in the context of DH as a key decarbonization strategy. We conduct a case study in the city of Amsterdam, where DH has been identified by PBL as the robust least-cost option for decarbonizing 77% of the housing stock. We address the following research questions: To what extent does the transition from natural gas to DH lead to a change in the energy bill of individual households, and how can these households be characterized? By examining these questions, the study contributes to a more equitable and data-driven approach to the heat transition, helping policymakers anticipate social impacts and design targeted support measures.

Data & Methods

Data

We used household-level data, sourced by Statistics Netherlands (CBS), to analyze gas consumption variation. We included a "normal" year (2019 data) and a year affected by high energy prices (2022 data) in the analyses. The heat demand used is corrected for temperature by CBS, where they normalize residential gas consumption to adjust for warmer and colder years. Table *1* provides the summary statistics for the Netherlands.

Table 1*:* Summary statistics of continuous variables for the residential sector at the national level

Variable	2019		2022	
	Mean	Standard deviation	Mean	Standard deviation
Gas use (m^3)	1313.295	730.054	1131.661	646.328
Floor area (m^2)	119.514	64.075	120.638	65.114
Disposable income (€)	47686.441	47645.757	53205.449	43874.712
Household size	2.243	1.254	2.217	1.246
Age	55.014	16.842	55.434	17.059

Note: Age of the reference person could either be the oldest person in the household or the male partner.
(N = 6,515,704 (2019) and 6,597,891 (2022))

For the case study, we used Amsterdam's PBL municipality files as the starting point[5]. These files contain information on the various strategies to achieve natural gas-free neighbourhoods. We focused on the 299 neighbourhoods where medium to high temperature DH[4] was identified by PBL as the robust and least-cost strategy (covering 77% of the city's housing stock, i.e., approximately 352,000 houses[5]). These neighbourhoods were then coupled, matching the neighbourhood codes, with CBS microdata. We obtained a dataset of 234,866 households in 2019 and 247,496 in 2022. The large difference is explained by several factors: the number of neighbourhoods in our dataset is 276 instead of 299. Additional neighbourhoods were assigned to the Municipality of Amsterdam in 2025 compared to 2019-2022. In the CBS dataset, multi-household dwellings, student housing and households living unusual dwellings like boats and caravans were excluded due to the lack

[4] Medium- to high temperature DH is indicated as Strategy 2 (S2) in the PBL-files.
[5] Derived from Gemeentedata | Startanalyse aardgasvrije buurten.

of autonomous income and(or) temporarily low incomes. Fig. 1 illustrates the 2019 data processing for the Amsterdam dataset (including additional data cleaning steps), and Table 2 the summary statistics.

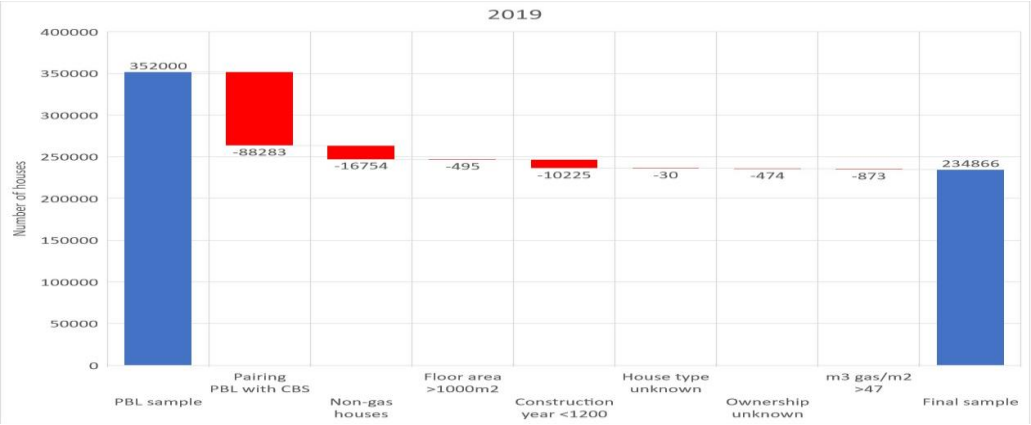

Fig. 1 Data processing for Amsterdam dataset.

Table 2: Statistics of continuous variables for Amsterdam houses for medium and high temperature DH

	2019		2022	
Variable	Mean	SD	Mean	SD
Gas use [m^3]	920.432	563.222	828.761	520.172
Floor area [m^2]	72.075	34.708	72.845	36.707
Disposable income (DY) [€]	45624.731	59648.315	52500.342	62477.171
Household size (HS)	1.866	1.149	1.838	1.114
	50.101	16.708	50.089	17.111

Note: Age of the reference person could either be the oldest person in the household or the male partner.
(N = 234,866 (2019) and 247,496 (2022))

Table 3 presents the summary statistics of the variables used for the Amsterdam case. It shows the descriptives of the variables that we used for defining housing archetypes: house type (detached, semi-detached & corner, terraced, apartment), ownership type (privately owned, social rent, commercial rent), and construction periods. Construction year and floor area are continuous variables in the data but were categorized into dichotomous variables for our analysis: six floor area categories (5-50 m^2, 50-75 m^2, 75-100 m^2, 100-150 m^2 and 150-250 m^2) and eight construction year groups (1200-1919, 1920-1945, 1946-1974, 1975-1982, 1983-1995, 1996-2000, 2001-2015 and 2015-2022). These bins were chosen to ensure as much homogeneity of the buildings as possible. More than 96% of the houses in the Amsterdam dataset are apartments, with a mix of privately owned apartments, commercial rent and social rent, but dominated by social rent. Most houses were constructed before 1995.

Table 3: Statistics of categorical variables for the Amsterdam dataset

		2019				2022			
Variable	Categories	Freq.	%	Mean	SD	Freq.	%	Mean	SD
House type	Detached	241	0.1	3027.79	1304.58	250	0.1	2472.75	1127.15
	Semi-detached & corner	1429	0.61	1702.37	856.62	1451	0.59	1529.68	804.66
	Terraced	6665	2.84	1481.06	744.65	7452	3.01	1370.29	709.68
	Apartments	226531	96.45	896.76	536.43	238343	96.3	805.84	494.41
Ownership type	Social rental	108029	46	863.60	501.54	106588	43.07	779.89	471.83
	Own home	68785	29.29	1013.33	645.48	71856	29.03	927.15	599.31
	Commercial rental	58052	24.72	916.11	552.62	69052	27.9	801.82	487.78
Construction year (CY)	1200-1919	57.779	24.60	955.45	595.43	67778	27.39	875.27	552.84
	1920-1945	63.018	26.83	1003.25	537.09	64431	26.03	891.81	497.69
	1946-1974	44.692	19.03	902.13	631.95	43597	17.62	803.04	562.66
	1975-1982	14.193	6.04	1029.90	560.53	14336	5.79	912.62	542.28
	1983-1995	34.653	14.75	818.38	461.40	35081	14.17	742.31	442.53
	1996-2000	6.933	2.95	634.64	465.70	6925	2.8	600.15	443.93
	2001-2015	10.917	4.65	779.80	448.71	11412	4.61	696.79	415.53
	2015-2022	2.681	1.14	575.36	337.28	3936	1.59	530.67	304.89

Note: Mean is the mean of gas used in cubic meters per year; SD is the standard deviation.

Methods

We followed a three-step approach

- Step 1: We quantified and compared variations/differences in household gas consumption at three spatial scales: the national level, the 276 Amsterdam neighbourhoods together, and specific neighbourhoods within Amsterdam.
- Step 2: We examined how these variations in gas usage affect end-user costs when transitioning from individual gas-based heating systems to DH.
- Step 3: We applied logistic regression analysis to statistically characterize these households based on building and household characteristics.

Step 1: Gas use variance

First, we plotted the data in Kernel density plots and Lorenz curves for the national case and the selected neighbourhoods in Amsterdam to show 1) the variance in gas consumption based on m^3 and m^3/m^2 (Kernel density plots), and 2) the aggregate Gini coefficients (Lorenz curves). In the Lorenz curves, we also computed the national distribution of income and compare this to gas distribution in the Netherlands. Second, to control the heterogeneity that exists across households, we grouped households into housing archetypes based on building characteristics that are relevant for the heat transition: house type, ownership, construction year and floor area. For each housing archetype, we calculated the Gini coefficient to show the variance at archetype level. We did this for the national sample, the Amsterdam sample, and the three largest Amsterdam neighbourhoods. Our hypothesis was that an increasing level of homogeneity of the archetypes would lead to less variance in gas consumption.

Lorenz curve and Gini coefficient

We employed the Lorenz curve and Gini coefficient to quantify differences in gas use across building archetypes. The Lorenz curve is a graphical tool used that illustrate the distribution of income or wealth within a population (Jacobson et al., 2005). It is commonly applied to income distribution. The curve shows what share of total income is held by a percentage of households, highlighting the degree of inequality as the curve deviates from a diagonal. The Gini coefficient quantifies this deviation by comparing the actual distribution to a perfectly equal one (Jacobson et al., 2005). The Gini coefficient is widely recognized for assessing income inequality but it has also been applied to evaluate disparities in environmental and social contexts, such as water access, food distribution, and urban development (Tian et al., 2024; Yuan et al., 2017; Zhang et al., 2020). The Gini coefficient calculated in equation (2) is a measure of statistical dispersion representing the variation within a group. It quantifies variability on a scale from 0 to 1, where 0 signifies perfect equality (every household within a group consumes the same amount of gas) and 1 indicates perfect inequality (where one household consumes all the gas). We adopt this measure of variance because it is an easy-to-grasp concept, which works well for small and large populations such as in our case. Because the same Gini-score can result from very different distribution patterns, both the Lorenz curve and the Gini coefficient are reported (Jacobson et al., 2005).

$$Gini\ coefficient = 1 - \sum_{i=1}^{N} [(X_{i+1} - X_i)(Y_{i+1} - Y_i)] \quad (1)$$

Where *Xi* is the cumulative proportion of households (with $X_N = 1$). *Xi* is measured as the number of gas users *i* divided by total population with *Xi* indexed in an increasing order. *Yi* is the cumulative proportion of gas consumption. *Yi* is measured as the quantity of gas used by household *i* divided by total gas use, with *Yi* ordered from lowest to highest gas consumption.

Step 2: Exploring the impact of gas use variance on end-user costs when moving from individual heating to DH

In this step, we analyzed the change in energy bill as a result of shifting from natural gas-based heating to DH in each of the 276 neighbourhoods in Amsterdam. Currently, the situation in the Netherlands is such that district heating consumers do not pay more for their heat than they would have if they had a gas boiler. The Dutch Authority for Consumers and Markets (ACM) annually calculates the maximum tariff price for a GJ heat, and a maximum annual fixed tariff, both based on a natural gas reference. For our calculations, we used the 2025 prices and tariffs applicable in Amsterdam.[6]

The data in Table *4* allowed us to calculate the annual gas bill of an Amsterdam household, and the DH bill, assuming an equivalent amount of natural gas and DH use. We assumed no change in behavior and no change in the energy performance of the house. The relation between DH consumption and the difference in energy bill compared to the natural gas reference is illustrated in Fig. 2. In our subsequent analysis, we focused on the three categories identified in Fig. 2. For each neighbourhood, we identified the households that face up to 25%, 25-50%, 50-75% or >75% increase in the energy bill. This increase in bills corresponds to households that consume between more than 540 m^3, 540 - 283 m^3, 283 - 120 m^3 and less than 120 m^3, respectively.

[6] Two remarks: 1) the reference gas price is the gas price used by ACM to calculate the maximum DH price. As this reference price is the average price of a one-year fixed gas contract concluded on January 1, 2025, many Amsterdam households will pay a different gas price in 2025; 2) The fixed fee for gas delivery is also the average used by ACM. Depending on which energy company delivers gas to individual Amsterdam household, this number can also vary.

Table 4: Parameters used for end-use cost calculations (prices including 21% VAT).

Description	Value	Source
Reference gas price: Average price of a one-year fixed contract on January 1, 2025	€1.3636/m^3	ACM factsheet DH tariff 2025 ACM DH tariff calculation sheet
DH price : Maximum 2025 tariff & tariff set by the Amsterdam DH supplier	€43.79/GJ	ACM.nl - maximum tariff DH 2025 Vattenfall - DH tariffs 2025
Fixed fee gas delivery: Average for energy companies	€101.48	ACM.nl - maximum tariff DH 2025
Fixed tariff gas (Grid Management): • Households that consume <500 m3/year • Households that consume 500-4000 m3/year	 €176.92/yr €239.46/yr	Liander-annual_network_costs-gas-2025.pdf
Fixed tariff DH: Maximum 2025 tariff & fixed tariff set by the Amsterdam DH supplier - including the DH delivery set	€760.77/yr	ACM.nl - maximum tariff DH 2025
Fixed tariff DH: Maximum 2025 tariff - excluding the DH delivery set	€610.28/yr*	Vattenfall - DH tariffs 2025
Conversion factor GJ -> m^3: Accounting for share space heating (71%) and hot water 29%), the efficiencies of space heating production (94%) and hot water production (68%), and using higher heating value of gas (35.17 MJ/m^3)	32.11 GJ/m^3	ACM DH tariff calculation sheet

* We used this figure in our calculation to simplify. By excluding the costs for the DH delivery set, we also excluded the costs of the reference gas boiler (CAPEX and maintenance).

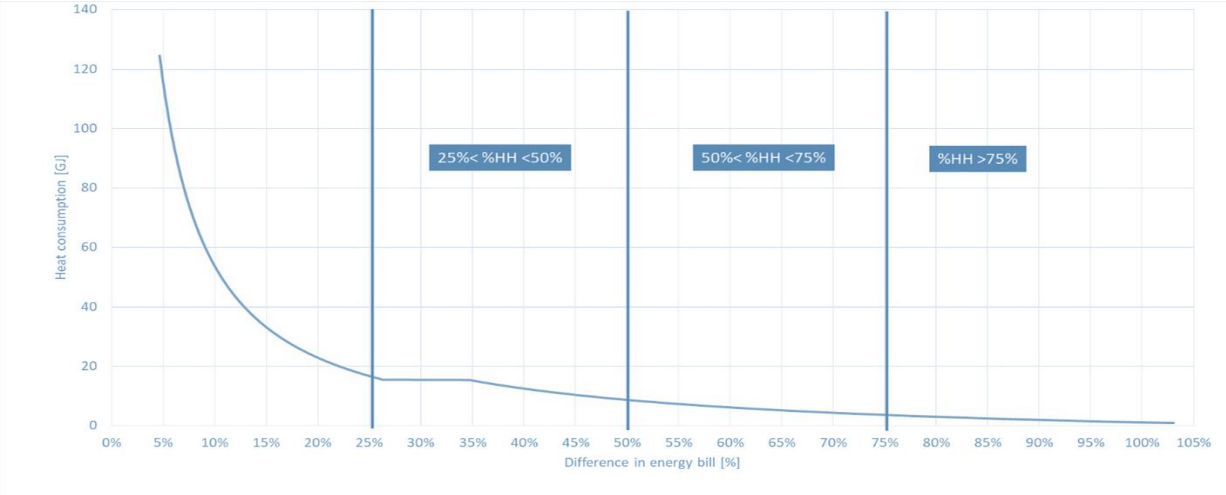

Fig. 2 DH consumption and the difference in energy bill compared to the natural gas reference.[7]

[7] The flat part in the curve between 15.5 and 15.6 GJ DH is due to a change in the fixed tariff of natural gas to the tariff for small consumers (<500 m^3/yr), see Table 4

In the results, we provide further descriptives (building characteristics & socio-economic variables) of the households belonging to each of these categories.

Step 3: Determining characteristics of households that face a higher energy bill

In this step, we run a MLR to further characterize the identified bill change groups and investigate the extent building and household factors affect exposure to tariff changes. Here, we add explanatory power and predictive insights to the descriptives in Step 2. With this regression analysis, we are able to quantify the effect of variables while controlling for others and tests the significance of predictors.

Multinomial Logistic Regression (MLR)

Logistic regression is a statistical technique used to model the probability of a binary outcome based on one or more predictor variables. It estimates the log-odds of the dependent variable as a linear combination of the independent variables, making it suitable for situations where the response variable is dichotomous. When the dependent variable encompasses more than two nominal categories, the model extends to MLR. MLR is particularly valuable in analyzing categorical outcomes with three or more categories and without inherent order (Hosmer et al., 2013). The explanatory variables in a logistic regression analysis can take any form because logistic regression makes no assumption about their distribution. They can include a mix of continuous and categorical variables. For our case study, we employed logistic regression to investigate the characteristics that predict a household's risk of facing a high energy bill based on building and household characteristics if it transitions to DH. The theoretical model of the multinomial logit model allows each household *i* to be faced with *j* different bill increases at time *t*. MLR extends binary logistic regression to handle a nominal dependent variable with K[8] > 2 categories by modeling the log-odds of each non-reference outcome relative to a chosen base category as a linear function of explanatory variables (Hashimoto et al., 2019). Specifically, the model is:

$$DEH_{ijt} = \alpha_{ij} + \beta_j X_{it} + \varepsilon_{ijt} \quad (2)$$

Where DEH_{ijt} is the group category *j* of the *ith* household to experience an increase in their energy bills by more than 75%, between 50 to75%, between 50 to 25% and less than 25% if they switch to district heating at each time *t*. X_{it} is a vector of housing and household variables such as house type, building age, ownership type, income and age. α_{ij} is the time-invariant unobserved household heterogeneity and ε_{ijt} is the random error term that is independently and identically distributed. β_j is the coefficients for the vector of the explanatory variables. The coefficients β_j are not intuitively interpretable as they represent the change in the risk ratio of a one-unit increase in the independent variables and not a change in likelihood. Thus, we report the relative risk ratios (RRR represented by *P*) are obtained by exponentiating the multinomial logit coefficients specified in equation (3) and the likelihood that the *ith* household is faced with a high energy bill expressed in equation (4).

:

$$\log\left(\frac{P_{i\theta}}{P_{iK}}\right) = \beta_j X_{it} + \varepsilon_{ijt}\ i = (1, \dots, n), \theta(1, \dots, K-1) \quad (3)$$

$$P_{i\theta} = \Pr(\beta_j = 1) = \frac{\exp(\beta_j X_{it})}{\sum_{k=1}^{k} \exp(\beta_j X_{it})}, \theta(1, \dots, K-1) \quad (4)$$

[8] K is this case is the number of levels of our dependent variable. In our case K=4.

To run (3), we performed an additional variable transformation. Specifically, we recategorized the insulation variable by combining the 'very low' and 'low' insulation levels into a single category 'low insulation' because the 'very low' group included fewer than 10 households, raising potential privacy concerns.

Results

Step 1: Gas-use variance

Fig. 3 shows the distribution of annual consumption in cubic meters (m^3) and cubic meters per square meter for the Netherlands and for the 276 Amsterdam neighbourhoods. The distribution of gas consumption is skewed to the right with a long tail indicating that households can vary significantly in their consumption. Looking at the tails, a small percentage of the households consume more than 4000m^3/year (0.87% for the Netherlands and only 0.04%of the houses in the Amsterdam dataset). When comparing the highest point of the distribution (the mode) with the data from Table 1 and 2, it shows that most households' consumption falls below the mean.We also observe more variation in the distribution for gas use in cubic meters than gas use in cubic meters per square meter showing that floor area plays a huge role in explaining gas use variation.

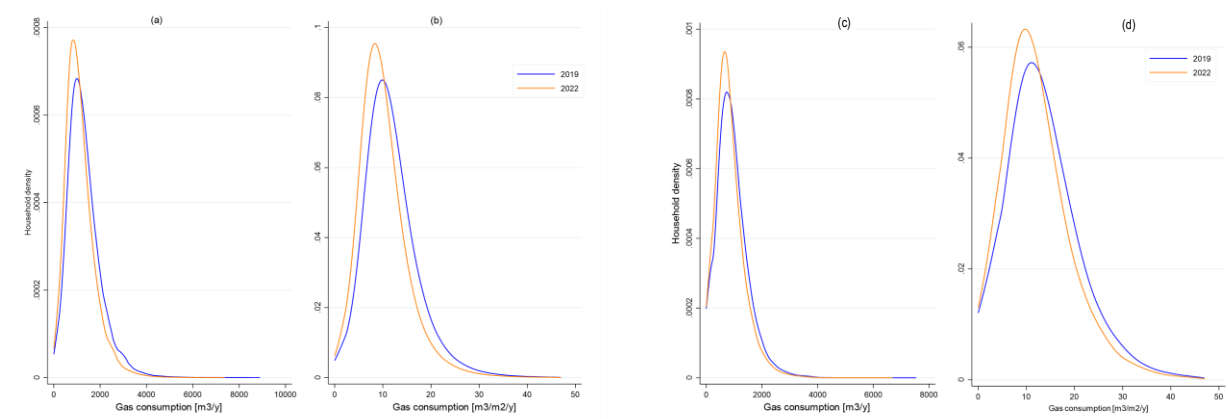

Fig. 3 Distribution of annual gas consumption in cubic meters per year and cubic meters per square meter per year of households. Frames a & b are for the national sample while c & d are for the Amsterdam dataset. Note: graphs have different scales.

The Lorenz curves as well as the associated Gini ratios of **Fig. 4** indicate that variation in gas use is greater in the Amsterdam case sample compared to the national level. The figure shows that gas use variations are small compared to income variation despite experiencing a slight increase from 2019 to 2022. This increase illustrates that even though mean gas use fell in 2022 due to high energy prices, the variation in gas use across households increased.

Although Amsterdam's housing archetypes are likely more homogeneous than those at the national level, we observe greater variation in gas consumption within them. This is counterintuitive, as greater homogeneity would typically suggest less variation. A key reason is the dominance of apartments, which vary considerably in orientation and position within buildings—factors not captured in the microdata, where all apartments are grouped together regardless of their exposure to external walls or other heat-loss-related features.

Fig. 5 compares Gini coefficients for the dominant housing archetypes in three large Amsterdam neighborhoods, to further investigate the impact of spatial homogeneity on variation in gas consumption. It shows that increasing spatial homogeneity does not necessarily reduce variation. For privately owned and commercial rental housing, this may reflect greater variation in energy efficiency upgrades (decided upon individually by the property owner). However, the high variation observed in social housing suggests that even with detailed archetypes, incorporating construction year, floor area, ownership, and housing type, important

intra-building differences, especially among apartments, explain variation, next to differences in occupant behavior.

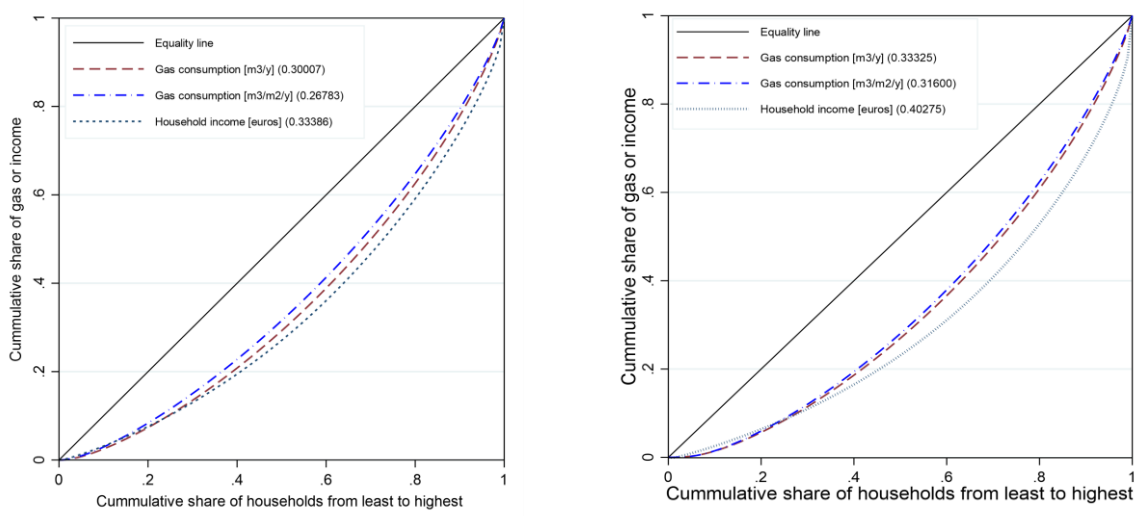

Fig. 4 Lorenz curves of residential gas use versus income variation. The left frame is for the national level and Amsterdam sample is on the right. The Gini indexes are in parentheses. Note: the total Ginis for both years are used in Figure 3, however, the Gini coefficient for the national case was 0.2935 in 2019 and 0.3013 in 2022. Also, it was 0.3288 in 2019 and 0.3341 in 2022 for the Amsterdam sample.

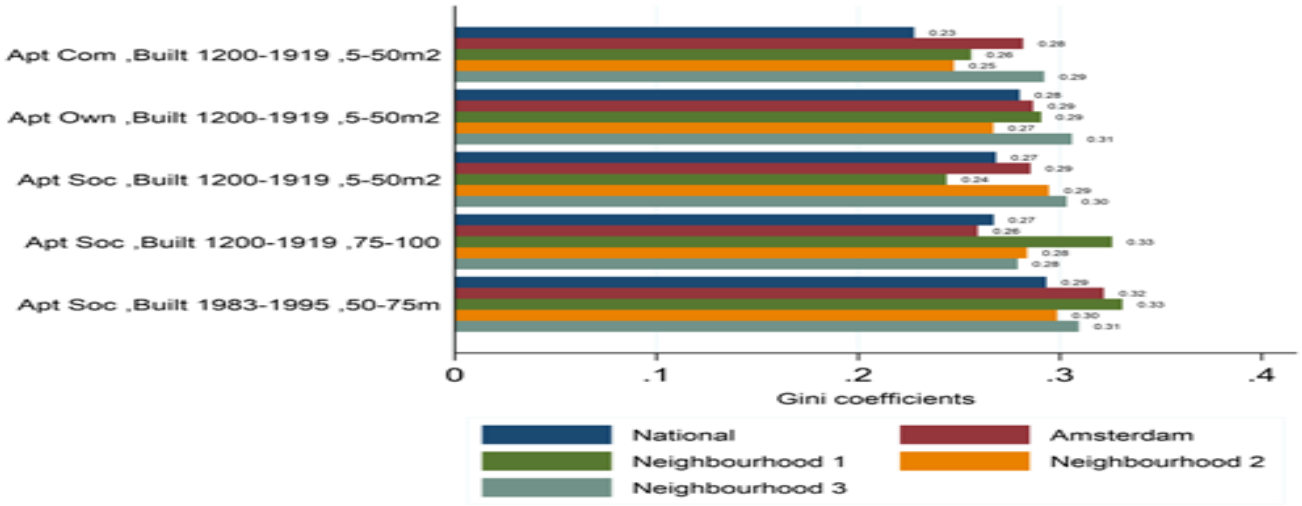

Fig. 5 Variation of same archetype under different levels of homogeneity. Note that the plot is based on the year 2022

Step 2: Exploring the impact of gas use variance on end-user costs when moving from individual heating to DH

We saw in step 1 that spatially homogeneous buildings still show considerable variation in gas consumption. In this step, we analyze how this variation impacts the end-user costs when moving from individual gas-based heating to DH, assuming no change in consumption and behavior. Fig.6 plots the percentage increase in bill of the switch for the 276 Amsterdam neighbourhoods. The percentage increase of energy bills is largely independent of the years 2019 and 2022. In the majority of the neighbourhoods, most households experience and increase of up to 25%, but the 25-50% increase is also substantial. We observe that 75% (2019 data) to 70%

(2022 data) of the Amsterdam sample would face a moderate-high bill increase (MHIB; 0-25%), 15% (2019 data) to 19% (2022 data) a high bill increase (HIB; 25-50%), 4% (2019 data) to 6% (2022 data) a very-high increase in bill (VHIB; 50-75%) and 5% (2019 and 2022 data) an extremely-high-bill increase (EHIB; >75%).

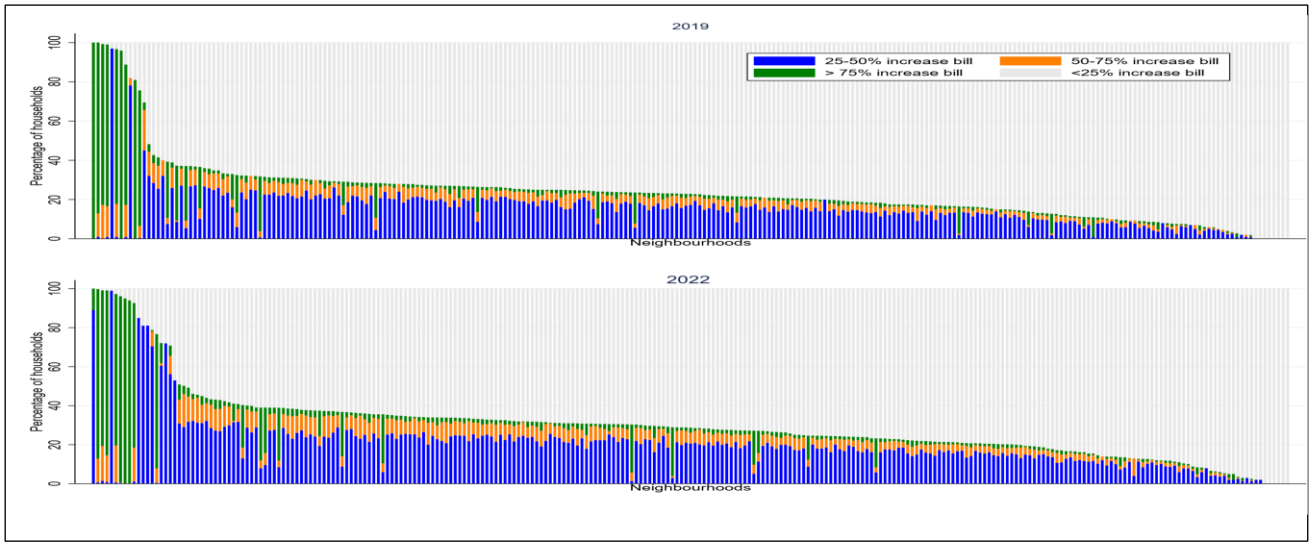

Fig. 6 Percentage of households that experience an increase in energy bill by neighbourhoods in Amsterdam if they switch to DH. Note: (a) are for the year 2019 and (b) are for the year 2022. Neighbourhoods that had less than 10 houses in a group were excluded from the plots to ensure compliance with privacy standards.

In Table 4 we present the descriptives of the households belonging to the four bill increase categories. For all categories, apartments dominate. 23.3% (2022 data) to 25.7% (2019 data) of the Amsterdam households belong to the low-income group, and part of them are considered energy poor. 27% (2019 data) to 33% (2022 data) of the low-income households will face an energy bill increase of more than 25% when switching from individual gas heating to DH. Compared to the first two categories, households in the last two categories (EHIB and VHIB) tend to have a higher share of low-income households, a higher percentage of social ownership but also higher insulation levels. Our results suggest therefore suggest that a significant group of low-income households, even those with better insulation, would be affected by an energy bill increase should they switch to district heating. While these descriptives are informative, they are not conclusive in characterizing the households to experience an increase in bill.

Table 5: Population, mean, and sd of certain characteristics energy change groups.

Household to experience	# of HH	Energy Poor		Low-income HH		Mean statistic				Housetype	Ownership	Insulation	Energy labels
		#	%	#	%	SA	Cy	HH size	Age				
2019:													
Moderate high increase in bill (MHIB; 0-25%)	177102	16690	9	44230	25	75.13	1943	1. 982	50.76	96% apart.	45% social rent	54% high	50% not labeled & 15% label C
High relative increase in bill (HIB; (25-50%)	35339	2516	7	8871	25	59.07	1947	1. 469	46. 127	98% apart.	46% social rent	69% high	43% not labeled & 12% label B
Very high increase in bill (VHIB; 50-75%)	10285	826	8	3331	32	60.15	1952	1.396	49.433	99% apart.	55% social rent	72% high	43% not labeled & 19% label C
Extremely high Increase in bill (EHIB; >75%)	12140	692	6	3832	32	75.42	1966	1.74	52. 624	99% apart	50% social rent	79% high	42% not labeled & 25% label C
Total	**234866**	**20724**	**9**	**60264**	**26**								
2022:													
Moderate high increase in bill (MHIB; 0-25%)	172939	11185	7	38905	23	77.41	1937	1.98	50.94	96% apart.	42% social rent	69% high	44% not labeled & 15% label B
High increase in bill (HIB; 25-50%)	47453	2297	5	10750	23	59.62	1943	1. 507	46. 158	99% apart.	43% social rent	77% high	37% not labeled & 17% label B
Very high increase in bill (VHIB; 50-75%)	14286	811	6	4195	29	60.5	1948	1. 367	49. 628	99% apart.	51% social rent	79% high	37% not labeled & 19% label C
Extremely high Increase in bill (EHIB; >75%)	12818	614	5	3859	30	73.95	1963	1. 673	53. 671	95% apart.	49% social rent	82% high	34% not labeled & 25% label B
Total	**247496**	**14907**	**6**	**57709**	**23**								

Note: Energy-poor is defined in the data as low incomes and low insulation (Mulder et al., 2023).

Step 3: Characterization of households

Fig. 7 shows the results from the multinomial logistic regression (MLR), where relative risk ratios (RRRs) measures the likelihood and the extent of certain characteristics determining a bill rise if a household switched to district heating (DH). An RRR below 1 means the risk is lower, above 1 means the risk is higher, and an RRR of 1 means no change.

The age of the building shows strikingly divergent effects. Houses built between 1946-1974 and 1996-2000 are ten times more likely to incur an EHIB than a MHIB (RRR = 10.627 and RRR=10.407). A similar less extreme, pattern holds for the 1975-1982 houses when compared to builds between 2015 to 2022. These findings hint at heterogeneity within the midcentury stock, perhaps tied to variations in renovation history or original construction standards, that magnifies the risk of higher relative bill increases. In contrast, the oldest homes (pre-1945) show comparatively reduced likelihoods. The heterogeneity suggests that construction period in itself is not a very good predictor but in itself dependent on better predictors such as floor area and insulation level (see below).

The results show that, holding all other parameters constant, each additional square meter marginally raises the risk for only the EHIB group (RRR = 1.005, $p < 0.01$) than the MHIB group. In contrast, an additional square meter floor area reduces the likelihood bill rise for the other groups. In practical terms, this pattern suggests that very small homes mainly found in the EHIB group are disproportionately vulnerable to a high percentage increase in the energy bill. This relation can be explained: the smaller the floor area of a house, the lower (ceteris paribus) the heat demand, the more exposed to a higher relative energy bill increase when switching from gas to DH (see Fig. 2).

Insulation quality emerges as an even more powerful predictor of cost exposure. Relative to homes with low insulation, those with high insulation face an increased risk of higher relative bill rises. Interestingly, the increased risk is 3.7 times stronger for the EHIB group. The strong relation between insulation and relative bill increase can be explained: the higher the level of insulation, the lower (ceteris paribus) the heat demand, the more exposed to a higher relative energy bill increase when switching from gas to DH (see Figure 2); and vice versa: the lower the level of insulation, the higher (ceteris paribus) the heat demand, the less exposed to a higher relative bill increase (see Fig. 2).

Ownership and household composition further shape cost outcomes. Owner-occupied homes are roughly 12 to 18 percent more likely to face any of the larger increases than social-housing. Private renters, meanwhile, face slightly lower odds of the HIB and VHIB groups but nearly double the odds of the EHIB group (RRR = 2.037, $p < 0.01$), indicating different levels of vulnerability that may reflect diverse stock quality in the private-rental sector.

Furthermore, the effect of household size is consistent across all categories when compared to the MHIB group but the effect is reduced for the EHBI group. Larger households systematically experience smaller relative bill increases: each additional member cuts the risk of a high increase by 34 percent, a very-high increase by 40 percent, and an extremely-high increase by 25 percent (RRRs = 0.658, 0.601, and 0.749; all $p < 0.01$). A plausible explanation is that larger households either live in larger houses with more floor area or that they heat more rooms. Both lead (ceteris paribus) to higher heat demand and therefore less exposure to a higher relative energy bill increase when switching from gas to DH (see Fig. 2).

Additionally, low-income as well as energy-poor households are more likely to face all types of bill increases especially extremely high increases. The plausible explanation here is that low-income households often live in smaller houses. When these houses are owned by social housing corporations, the level of insulation is on average higher than for privately owned or privately rented houses. Part of the low-income houses may also under consume (hidden energy poverty), automatically exposing them to high relative bill increases when

moving from gas to DH. Since energy poverty is defined as low income and low insulation, the households in this group are likely found in the smaller houses.

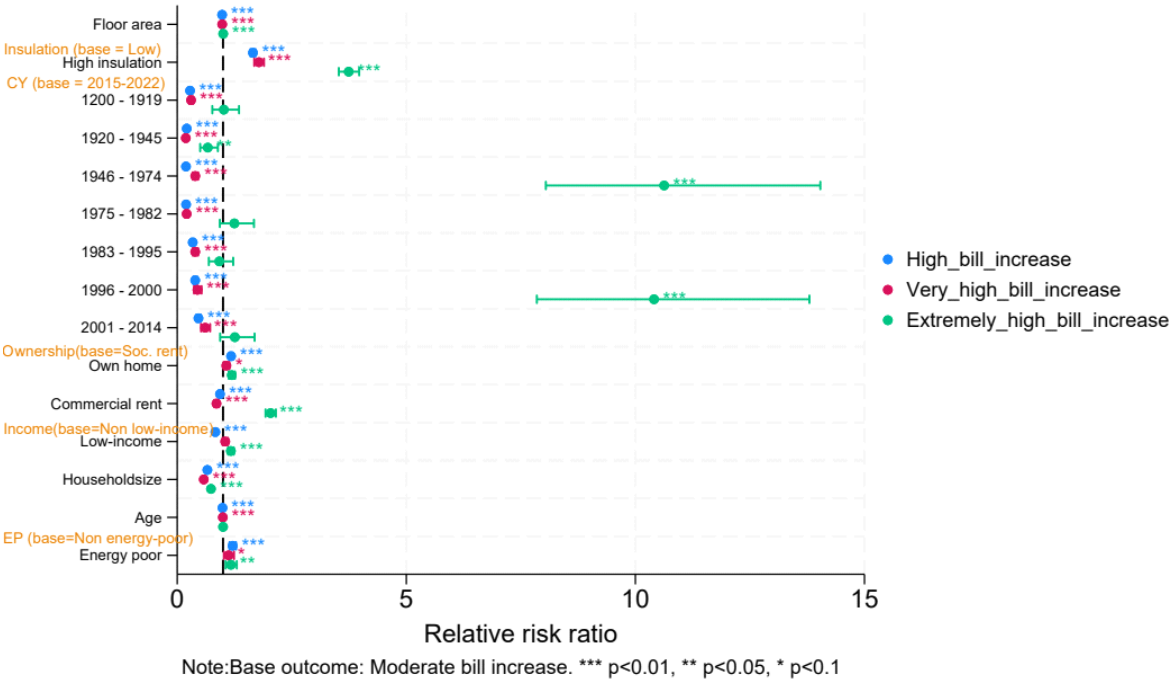

Fig. 7 Multinomial logistic results for bill increase groups in Amsterdam for 2019

Discussion

Contribution

We applied a new approach of measuring variance in residential gas use which we took from the inequality literature: Lorentz curves and Gini coefficients. Our results confirm that significant gas-use variation persists even in Amsterdam's relatively uniform neighbourhoods. Contrary to intuition, making building stock more homogeneous did not eliminate variability. Amsterdam's gas demand distribution remains as skewed as the national pattern, with large differences in consumption. This echoes prior studies showing that building characteristics (type, size, building age) typically explain only nearly 40% of consumption variance (and up to 50% including household characteristics). In Amsterdam, the dominance of diverse multi-family apartments, with differing orientation, floor level and heat-loss profiles, and wide income disparities mean even similar homes use very different amounts of heat. Our study reveals that apartments are a relatively coarse housing category in the context of analyzing energy consumption. Unlike terraced houses, where a distinction is made between mid-terraced and corner houses, apartments are not broken down into more specific types such as corner units, ground-floor, or top-floor apartments. However, these apartment subtypes differ significantly in their heat loss area, meaning that grouping all apartments together can obscure important differences in energy performance. Our findings suggest that solving the limitations of using apartments as housing type, may increase the explanation of variance to some extent. However occupant behavior likely drives much of the residual variance (Guerra Santin et al., 2009; Gram-Hanssen, 2010; Liu et al., forthcoming).

Our results echo the work from Jaffe and Stavins (1994) who already indicated that an average household does not exist. In our study, this means that a shift from gas to DH leads to high relative energy bill increases for low-end consumers. Among these consumers are commercial renters, residents of apartments, energy-poor

households, and those with low incomes, also identified before by Woods et al. (2024). Our study stresses there is a key difference between social costs for residential heat transition, average end-use costs for residential heat transition, and end-use costs for individual households. Most existing studies focus on social cost and/or average end-use costs, a choice which is almost exclusively driven by data availability. The premise of using microdata, in our study provided by Statistics Netherlands, is the ability to unhide cost implications for individual households. While existing studies often emphasize broad societal acceptance as sufficient for enabling the energy transition (Faure et al., 2022; Onencan et al., 2024), they frequently overlook the individual-level consequences, which may be critical for a successful heat transition.

Limitations and further research

A note of caution is warranted as our analysis of shifting from gas to DH assumes no change in behavior and building efficiency. In practice, switching to DH may induce behavioral changes, particularly in response to changed tariff structures. Future studies could do a scenario analysis to incorporate behavioral feedback to better estimate post-switch heat consumption. In addition, it must be noted that we used 2025 price data and the 2025 DH tariff structure to carry out our analysis. The tariff structure of future DH projects will not use the price of natural gas as reference but actual project costs. Whether these actual project costs lead to higher or lower DH prices compared to today is unknown. However, this does not change the fact one must look into the impact of the heat price and tariff structure on low-end heat consumers.

Whereas the PBL file identifies 299 Amsterdam neighbourhoods and approximately 352,000 houses for which DH is the least-cost heat transition option, our analysis using CBS microdata was based on 276 neighbourhoods and more than 230,000 houses. Although the difference can be explained, it means that we were not able to do our analysis for all houses identified by PBL.

Another limitation is that our gas consumption data contains gas used for space heating, hot water, and cooking. These end-uses cannot be disaggregated in the microdata. Moreover, gas consumption data are based on historical meter readings provided by suppliers and operators. These readings are often taken at irregular intervals, sometimes exceeding 12 months, and adjusted using weather and calorific correction factors. Such adjustments, while standard practice, can introduce estimation error especially when reference periods do not align with the calendar year. Future research could address this limitation by employing high-frequency smart meter data to disaggregate end uses and more precisely align energy use with actual periods of consumption.

In our analysis for Amsterdam neighbourhoods, we were not able to identify free riders, households that consume little gas as their home is heated with the heat losses from the neighboring apartments. Future research could focus on disaggregating the extent to which free-riding influence consumption. This is, e.g., important for energy poverty studies where it is critical to distinguish free riders from households that under consume because of energy poverty.

The definition of the insulation variable we used (the “LEK” variable in the CBS microdata) includes broader aspects than insulation performance (e.g., the presence of solar panels). Still, it turned out to be a stronger variable in our analysis than the energy label which is not available for many Dutch houses or outdated. An interesting avenue for future research is to investigate household gas use with up-to-date energy labels to enhance predictive accuracy.

While we control for a wide range of household and building attributes, behavioral drivers like thermostat settings, occupancy patterns, heating preferences during absences, and cooking habits- all plausible contributors to gas use variance. Their omission may introduce omitted-variable bias. Further research using real-time monitoring could help isolate these behavioral effects and clarify their role in shaping household vulnerability to DH cost changes.

Conclusions and policy implications

This paper investigated gas use variation, the extent to which a switch to DH leads to a change in energy bills and attempts to characterize these households. For this purpose, it combines two datasets from CBS and PBL. Using Kernel density estimation, Lorenz curves, Gini coefficients, and multinomial logistic regression, we find that there are significant variation even in similar building archetypes. Particularly, increasing the level of spatial homogeneity did not reduce the variation the exist in gas consumption. These findings challenge assumptions embedded in techno-economic spatial models and policy tools like PBL's study, which optimize at the societal level but abstract away from end-user heterogeneity. While such models correctly identify where DH is cost-optimal on average, they may obscure the distributional effects at the household level.

Our research questions were the following To what extent does the transition from natural gas to DH lead to a change in the energy bill of individual households, and how can these households be characterized?

Using 2025 prices and the 2025 DH tariff structure, 25% to 30% (based on 2019 or 2022 data) of the households would see their energy bill rise by more than 25% (of which 5%-points a bill rise >75%). 23.3% (2022 data) to 25.7% (2019 data) of the Amsterdam households belong to the low-income group, and part of them are considered energy poor. 27% (2019 data) to 33% (2022 data) of the low-income households will face an energy bill increase of more than 25% when switching from individual gas heating to DH. Since the high relative energy bill increase is found for low-end users, houses with a small floor area and well-insulated houses are good but not exclusive predictors for households to belong to one of the high relative bill increase groups.

These findings demonstrate that leaning on average heat demand in least-cost calculations, and using fixed annual DH tariffs for all user categories disproportionately harm low-end heat consumers, including a significant share of low-income households, and households defined as energy poor. When striving for an equitable heat transition at the one hand and a healthy business case for DH projects, policy makers must not overlook the cost impact of heat transition strategies on individual households. In the case of future Dutch DH projects, the possibility of a tariff structure based on different levels of heat consumption (which is common for natural gas) should be explored.

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Appendix

Table A1: Data cleaning steps

Sequential exclusion	# of cases	Characteristics of dropped observation	Justification
Non-gas heated houses	952,149		Our study focused on gas consumption
Floor area above 1000m^2	16,290		This floor area is considered unrealistic
Houses built before 1200	12,411	96% of these buildings were built in the year 1005 (according to the micro data)	
House type unknown	6,992		According to CBS this data does not contain sufficient detail to assign one of the standard house type classifications.
Ownership type unknown	16,649		These are owner-occupied homes that were uninhabited and had non-living function at the time of data collection
Gas m^3/m^2 > 47	16,627	Houses with annual consumption of more than six standard deviations from the national mean.	This annual consumption m^3/m^2 square was considered extreme.
Total cases excluded	1,021,118		

* The dropped cases are based on 2019 data. These cases were also excluded for the 2022 analysis.

Table A2: Descriptives of categorical variables for the Dutch residential sector

		2019				2022			
Variable	Categories	Freq.	%	Mean	SD	Freq.	%	Mean	SD
House type	Detached	903654	13.9	2144.36	932.09	915534	13.88	1819.9	835.92
	Semi-det & corner	1526977	23.4	1516.19	612.23	1542262	23.38	1295.9	561.12
	Terraced	2032774	31.2	1221.88	512.29	2046690	31.02	1054.35	470.32
	Apartments	2052299	31.5	886.95	495.96	2093405	31.73	785.24	458.16
Ownership type	Social rental	1911764	29.3	957.07	468.57	1869261	28.33	837.27	428.34
	Own home	3987119	61.2	1506.82	768.11	4042863	61.28	1290.62	681.09
	Comm. rental	616821	9.47	1166.43	692.07	685767	10.39	996.99	617.21
Construction year	1200-1919	458798	7.04	1580.45	936.14	479727	7.27	1350.41	820.25
	1920-1945	743355	11.4	1599.08	840.25	746449	11.31	1369.41	744.58
	1946-1974	2165078	33.2	1354.87	716.72	2136013	32.37	1157.43	632.84
	1975-1982	812154	12.5	1361.65	688.89	811598	12.3	1172.68	616.32
	1983-1995	1150049	17.7	1150.86	601.49	1151428	17.45	1007.31	547.08
	1996-2000	369925	5.68	1167.24	618.15	370421	5.61	1029.05	565.97
	2001-2015	680381	10.4	1063.69	612.91	680785	10.32	952.91	562.36
	2015-2022	135964	2.09	918.86	502.73	221470	3.36	825.23	451.45

Note: Mean is the mean of gas used in cubic meters per year

Table A3: Descriptives of archetype groups in Fig. 5

Archetype groups	Spatial aspect	Sample	Gini coef.	mean_GAS	sd_GAS	mean_DY	sd_DY	mean_NC	sd_NC	mean_AGE	sd_AGE
Apt Com ,Built 1200-1919 ,5-50m2	National	22398	0.22	749.37	306.46	30155.89	17413.89	1	1	36	13
		29124	0.23	668.67	284.05	34668.77	24405.11	1	1	36	13
	Amsterdam	6939	0.28	668.40	339.17	35396.20	22464.26	1	1	39	15
		9515	0.28	612.00	315.56	40743.16	32712.12	1	1	39	15
	Neighbourhood 1	464	0.24	718.72	315.10	38692.88	22371.70	1	1	39	14
		478	0.26	648.86	309.40	42172.92	23195.54	1	1	39	15
	Neighbourhood 2	38	0.23	713.82	311.55	33874.97	13856.44	2	1	42	14
		41	0.25	598.46	288.15	41315.83	20788.79	2	1	39	15
	Neighbourhood 3	472	0.31	595.35	334.54	35281.09	28857.36	1	1	38	14
		517	0.29	546.66	294.86	38735.69	22047.70	1	1	37	15
Apt Own ,Built 1200-1919 ,5-50m2	National	6191	0.27	678.20	334.91	48634.55	32151.60	1	1	40	12
		6325	0.28	612.61	314.55	56623.06	37895.91	1	1	41	13
	Amsterdam	4608	0.28	642.65	321.92	51012.90	34396.45	1	1	39	10
		4716	0.29	584.95	306.45	59385.22	39512.40	1	1	41	12
	Neighbourhood 1	252	0.26	736.40	350.73	56844.59	37533.66	1	1	40	11
		218	0.29	650.67	347.17	67028.92	40192.16	2	1	40	11
	Neighbourhood 2	47	0.23	655.75	269.20	47863.91	20060.40	1	1	37	8
		44	0.27	582.94	282.72	55197.84	18334.44	1	1	39	8
	Neighbourhood 3	160	0.31	594.55	333.80	52040.54	32484.16	1	1	38	11
		152	0.31	540.17	304.73	60462.36	43353.87	1	1	39	12
Apt Soc ,Built 1200-1919 ,5-50m2	National	13589	0.27	701.21	339.24	22844.02	16096.99	1	1	45	15
		14157	0.27	636.40	312.65	26134.51	13823.57	1	1	45	16
	Amsterdam	8349	0.28	690.41	350.75	23507.14	13418.00	1	1	47	15
		8693	0.29	626.12	325.48	26829.65	14603.97	1	1	49	15
	Neighbourhood 1	194	0.25	735.58	332.46	23156.03	15434.00	1	1	50	14
		184	0.24	699.03	312.06	25084.82	12641.94	1	1	51	14
	Neighbourhood 2	55	0.29	782.27	406.38	23376.20	13360.29	2	1	49	13
		64	0.29	734.38	417.14	27659.63	17821.99	2	1	50	12
	Neighbourhood 3	143	0.28	608.67	316.97	20787.87	11168.88	1	0	46	16
		152	0.30	543.88	304.46	24814.63	12445.95	1	0	46	16

Table A4 continued

Archetype groups	Spatial aspect	Sample	Gini	mean_GAS	sd_GAS	mean_DY	sd_DY	mean_HS	sd_HS	mean_AGE	sd_AGE
Apt Soc ,Built 1200-1919 ,75-100m2	National	9666	0.27	1005.46	490.28	31153.72	23077.10	2	1	52	16
		9158	0.27	912.87	448.82	36021.63	20972.18	2	1	53	16
	Amsterdam	2075	0.27	1042.13	512.17	38971.81	37438.49	2	1	55	15
		1935	0.26	956.59	462.14	43593.57	25414.13	2	1	55	15
	Neighbourhood 1	51	0.30	949.01	513.70	50041.80	30332.05	2	1	49	14
		50	0.33	769.70	464.39	50022.38	25715.26	2	1	51	15
	Neighbourhood 2	19	0.26	1024.57	523.81	66468.05	47824.71	3	1	40	10
		18	0.28	953.20	559.69	63929.61	49213.94	3	2	44	13
	Neighbourhood 3	18	0.28	977.21	502.31	31585.61	21229.56	2	1	57	10
		29	0.28	926.74	479.55	31223.90	22789.59	2	1	59	11
Apt Soc ,Built 1983-1995 ,50-75m2	National	136373	0.2748	718.42	361.18	22598.91	9710.16	1	1	61	19
		137492	0.29329	647.40	350.33	25723.66	11162.65	1	1	61	19
	Amsterdam	12198	0.30183	790.09	434.36	26005.79	15255.88	2	1	58	15
		11918	0.32177	725.65	430.97	29735.23	18962.28	2	1	59	15
	Neighbourhood 1	39	0.33674	776.01	466.88	28278.72	20375.45	1	1	59	13
		31	0.33101	662.93	424.51	29291.68	15239.31	1	0	59	14
	Neighbourhood 2	348	0.28516	797.31	413.88	25542.23	14758.21	2	1	56	16
		345	0.29856	749.95	408.85	30976.29	16837.74	2	1	57	16
	Neighbourhood 3	86	0.27456	726.65	359.36	24611.76	16855.93	1	1	58	14
		80	0.30934	655.29	367.40	28932.84	18837.83	1	1	58	13

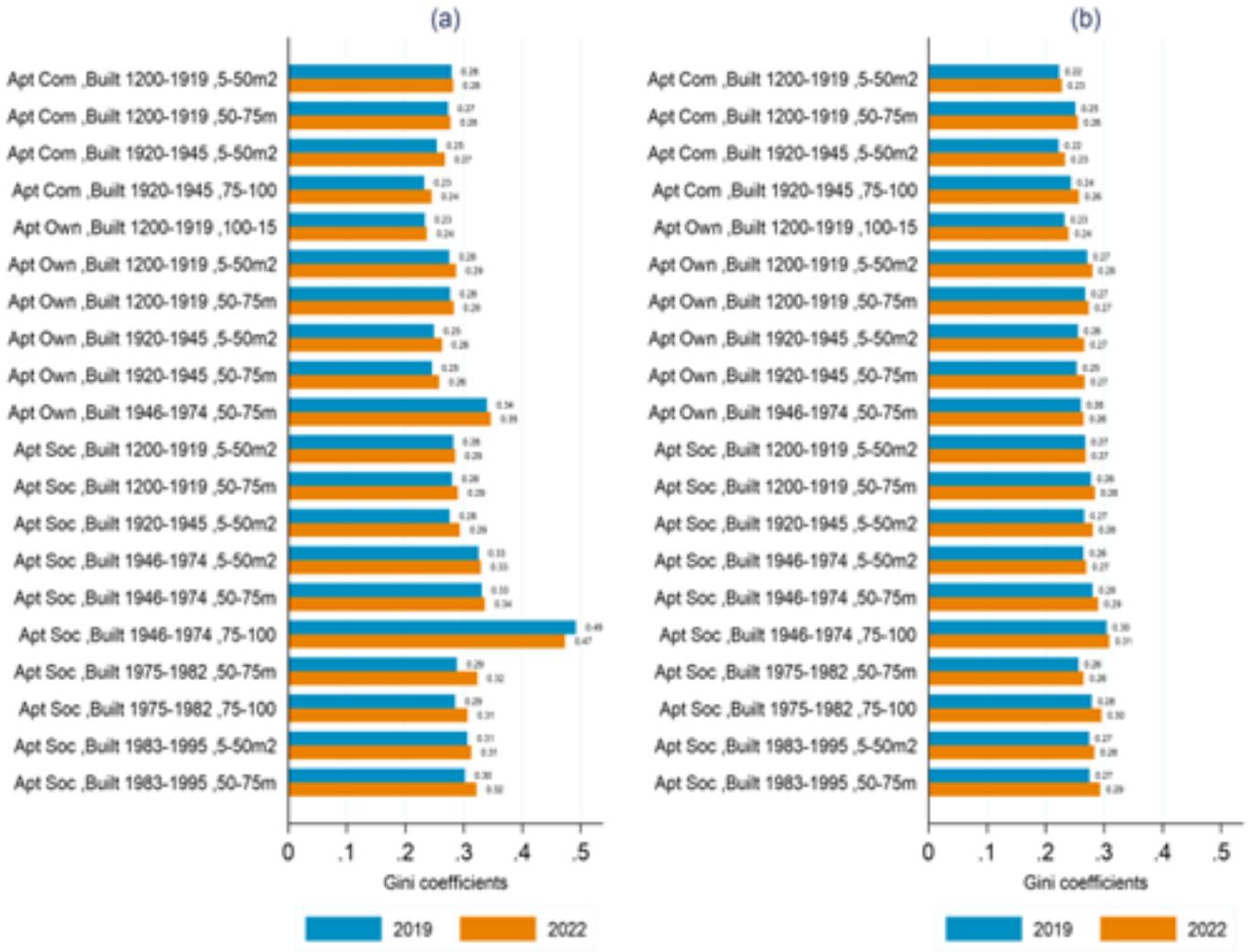

Fig A1 Comparison of gas use variation between archetype groups in Amsterdam and the National level. (a) represents the National case while (b) is Amsterdam. Archetype groups with fewer than ten dwellings as an outlier and excluded it from analysis; the plots therefore display the results for the twenty largest archetype groups in Amsterdam paired with the national cases.

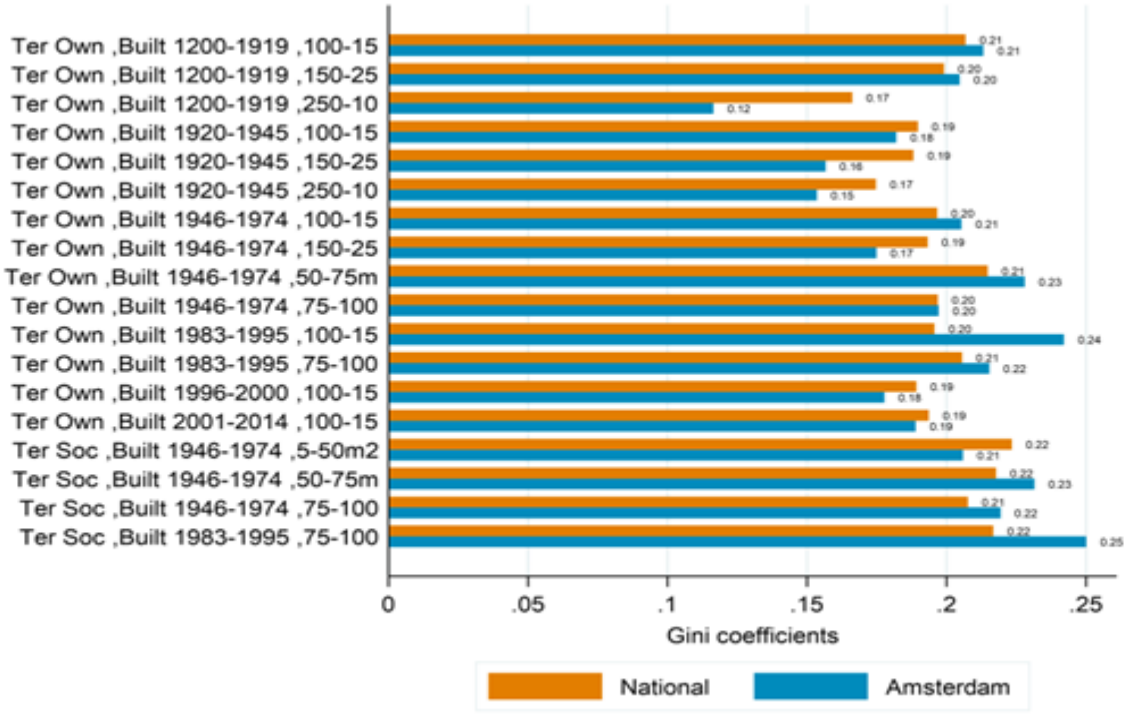

Fig A2 Comparison of gas use variation between archetypes for terraced groups. Note: Plot based on only 2019 data.

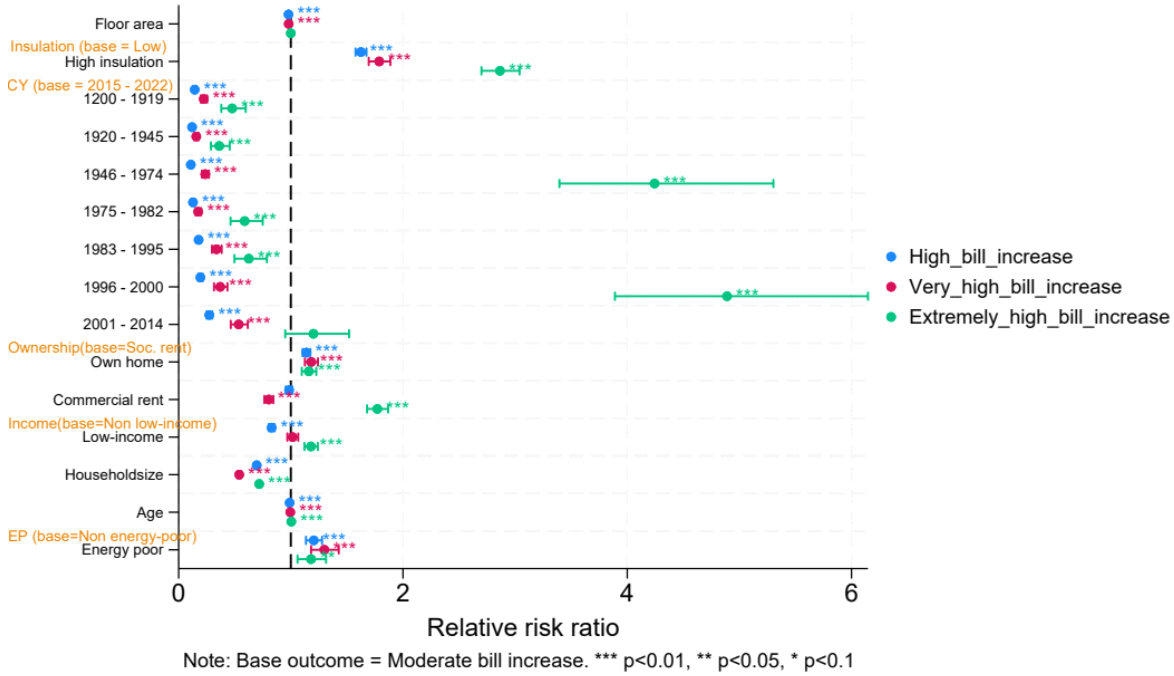

Fig A3 Multinomial logistic results for bill increase groups in Amsterdam for 2022.