Investigating the Extent to Which the Experienced Rate of Inflation Varies With Household Income

Abstract

This study explores the relationship between household income and experienced inflation in the UK in 2022. It leverages survey data on expenditure to construct household-specific indexes that measure the experienced rate of inflation (i.e., change in the cost of living) for over 5,000 households. A fixed-effects model and a multilevel model are then formulated to explore the relationship between the two variables. The results reveal that at the national level, low-income households experienced a higher rate of inflation than high-income households. However, estimates from the multilevel model also indicate that the relationship is not regionally consistent, pointing to additional complexities that cannot be captured at a national level.

Contents

1 Introduction

A prerequisite for successful monetary policy is a comprehensive underlying measure of inflation. Most economies - including the UK - rely on a consumer price index (CPI) to measure the average rate of change in the cost of a nationally representative basket of goods and services over a given time period. Relying on an index that subsumes variability in household expenditure by aggregating at a macroeconomic level is not inherently problematic. But if the measure systematically overestimates inflation for certain income groups and underestimates it for their counterparts, then it may obscure inequalities that should be taken into account when implementing monetary policy.

In the following work, I focus on evaluating the relationship between household income and experienced inflation in 2022 in the UK. The surge in inflation during the COVID-19 pandemic has drawn renewed attention to the issue. Indeed, the UK reported 10.1% inflation in 2022 (Honohan, 2024); assessing whether changes in the cost of living varied across the income distribution will provide insight into economic hardships that can be masked by a national CPI. To explore the relationship, I first derive the experienced rate of inflation for 5,000+ households surveyed by the Office for National Statistics (ONS) and then fit a linear regression to assess the overarching trend between the two variables, whilst accounting for various demographic controls that have also been linked to discrepancies in experienced inflation. To further evaluate the relationship at a subnational level I formulate a multilevel model to estimate the relationship between income and experienced inflation across 12 regions in the UK.

The work will find that there is a statistically significant relationship between income and experienced inflation, even when controlling for geography, household size, tenure and employment. But it will also show that the relationship is not consistent across the 12 regions. I will conclude by discussing the policy implications of these findings, arguing that more comprehensive monetary policy - especially during times of heightened inflation - will require developing indexes that can account for systematic variations in experienced inflation.

2 Literature Review

Considerable literature has been dedicated to studying systematic discrepancies in the experienced rate of inflation for different income groups. Traditional research generally finds that there is a negative correlation between the two variables; more specifically, researchers in this domain tend to construct household specific indexes with reference to microdata on expenditure and category specific rates of inflation (Michael, 1975; McGranahan and Paulson, 2005; Hobijn et al., 2009). Beyond the US, Gürer and Weichenrieder (2020) implemented a similar methodology to show that between 2001 and 2015 there was a 10.5 percentage point difference between the average annual rate of inflation experienced by the lowest earning decile and the highest earning decile across 25 European countries. Further, Baez Ramirez et al. (2021) reported persistent inflation inequality in Turkey between 2010 and 2020. Note that I will use the term “inflation inequality” to describe a systematic discrepancy in experienced inflation across the income distribution.

There is also a growing literature in this discourse that relies on Nielsen barcode scanner data. For instance, Argente and Lee (2021) have used this data to construct price indices for different income groups, finding that the average rate of inflation experienced by the highest income quartile was 0.59 percentage points lower than for the lowest income quartile; they attribute this difference to heightened inflation during the financial crisis. Similarly, Kaplan and Schulhofer-Wohl (2017) report a difference of nine percentage points between the rate of inflation experienced by the highest earning quintile and the lowest earning quintile between 2004 and 2012 in the US. With reference to these papers, it should be noted that although scanner data provides insights into both variations in the prices paid for a specific bundle by a given household and variations in bundle composition, it also accounts for merely 30% of household consumption Jaravel (2021).

Evidently, there is an emerging literature demonstrating that the burden of unequal inflation is substantial and generally borne by lower-income households. The most noteworthy exception is a study by Jaravel and O'Connell (2020) on inflation inequality in the UK in 2020, which found that inflation was actually slightly lower for low-income households than for high-income households. In the context of this discourse the following work makes two contributions. First, by using survey data it can account for income as a continuous variable – previous works generally grouped households into income brackets to cover larger time frames. Second, by leveraging granular data at the household level, I can account for confounding demographic attributes, which are generally disregarded by the above-described research.

3 Methodology

3.1 Data

In the following work I rely on two sets of data. First the 'Consumer price inflation basket of goods and services: 2022' published by the Office for National Statistics (2022a), which tracks the annual rate of inflation for the 84 product categories used in the national CPI. Second, the '2022 Living Costs and Food Survey' (LCF) conducted on an annual basis by the Office for National Statistics (2022b). The survey contains information on the detailed expenditure of roughly 6,000 households in the UK. By using multi-stage stratified random sampling the LCF is designed to be nationally representative in terms of geography and demography. A "full response" to the survey requires that (a) all individuals in the respective household co-operate with the interview, (b) no income question is refused and (c) all members of the household record their expenditure over two weeks.

For our purposes, income was equivalised to account for differences in household size/composition, but it was not normalized since weekly income was recorded with a cap at £2500. To maintain a representative sample, part-time workers were not removed since they are more likely to be in lower income brackets with less financial resilience (Warren, 2015). Responses from unemployed household representatives were included, but with any social security benefits accounted for as "income". The final sample included expenditure data on 1,531 goods and services for 5,628 households.

3.2 Measuring experienced inflation at the household-level

A price index measures the weighted average rate of change in the amount paid for a representative consumption bundle over a given time period. Aggregate price indexes use the national average mix of expenditure to construct consumption bundles. Deriving a household-level index therefore requires data on household specific consumption bundles. These can be constructed for each household included in the 'Living Costs and Food Survey', which tracks expenditure on 1,531 good and services (e.g., eggs, bananas, packaged holidays abroad and electricity top-ups). All items have a product code with which they can be linked to 84 broader product categories. The relative amount spent on each category by any given household can then be used to derive household specific consumption bundles as follows:

$$w_{h,c} = \frac{\sum_{i \in \text{items where } C(i)=c} E_{h,i}}{Y_h} \tag{1}$$

where $w_{h,c}$, represent the proportion of income spent by household h on a given product category c. $E_{h,i}$ denotes the expenditure of household h on item i and Y_h constitutes the household's total expenditure. Finally, $C(i)$ maps item i to its respective product category c. These bundles capture the relative spending habits of each household to the most granular extent possible, given the available data. The experienced rate of inflation, π_h, can then be derived with reference to information from the second dataset, containing category specific inflation as follows:

$$\pi_h = \sum_{c=1}^{84} w_{h,c} \cdot \pi_c \tag{2}$$

where π_c represents the rate of inflation for category c and $w_{h,c}$ the proportion of income spent by household h on category c, as derived in equation 1. By weighting category-specific rates of inflation to each household's unique purchasing patterns in 2022 the index can capture variations in experienced inflation at a very granular level. But since it measures experienced inflation with reference to heterogeneity in consumption bundles it cannot capture heterogeneity in the prices paid by different households for the selection of good or services in the index.

3.3 Controls

Variations in experienced inflation have been attributed to various factors. To derive comprehensive insights into inflation inequality, these variables must be controlled for in the regression analysis. The first attribute included is geography since previous research has found that household expenditure on goods and services varies systematically by region (Kaplan and Schulhofer-Wohl, 2017; Deryugina et al., 2019). I therefore control for 12 regions in the UK, as well as the difference between living in rural or urban neighbourhoods. Next, retirement status was included since studies have reported variations in the rate of inflation experienced by older households (Amble and Stewart, 1994, Jaravel, 2021). Further tenure was controlled for since rent is included in the household-specific index but mortgage payments are not - this is also the case for the national CPI.

It could be argued that controlling for tenure obscures the mechanism through which income influences experienced inflation, but the Variance inflation factor (VIF) derived when testing for multicollinearity between income and tenure was insignificant. Finally, household size is accounted for since Johannsen (2014) has documented considerable discrepancies in consumption bundles by household composition. For example, households with more than two members were found to spend proportionally more on education and child-care. All controls are constructed as dummy variables (with one category omitted as the reference group) to meet the assumptions underlying linear regression analysis.

Table 1: Variable Overview

Variable Name	**Variable Type**	**Range / Categories**	**Distribution (%)**
Equivalised_income	Continuous	0.00 to 2450.00	–
Location	Categorical	North East	3.64
		North West + Merseyside	14.49
		Yorkshire + the Humber	11.89
		East Midlands	10.38
		West Midlands	9.17
		Eastern	9.10
		London	8.52
		South East	8.20
		South West	7.93
		Wales	6.79
		Scotland	5.81
		Northern Ireland	4.07
Own_vs_rent	Categorical	Own	73.24
		Rent	26.76
Retired_vs_non-retired	Categorical	Retired	39.08
		Non-retired[1]	60.92
Urban_vs_rural	Categorical	Urban	78.70
		Rural	21.30
Household_size	Categorical	1 Member	28.16
		2 Members	40.01
		3 Members	14.20
		4 Members	12.75
		5+ Members	4.88
Experienced_inflation	Continuous	1.51 to 13.00	–

[1] *Note:* Includes households who are self-employed (11.5%), working full-time (69.7%), working part-time (16.8%), and unemployed (1.96%).

3.4 Statistical Models

3.4.1 Fixed-effects model

At a basic level the relationship between income and experienced inflation is estimated with an Ordinary Least Squares (OLS) regression:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{3}$$

where Y_i denotes the experienced rate of inflation for household i and X_i its respective income. β_1 is the coefficient for the relationship between income and experienced inflation, whilst β_0 represents the intercept (i.e., the experienced rate of inflation at income 0) and ε_i denotes residual errors. To account for the controls described above, a fixed-effects linear regression is then formulated as:

$$Y_i = \beta_0 + \beta_1 X_i + \sum_{j=1}^{11} \gamma_j Z_{ij} + \delta_1 W_i + \delta_2 T_i + \delta_3 O_i + \sum_{k=1}^{4} \theta_k H_{ik} + \varepsilon_i. \tag{4}$$

The summation $\sum_{j=1}^{11} \gamma_j Z_{ij}$ includes 11 regions (Z_{ij}) to account for confounding effects, each with its corresponding coefficient γ_j. The terms $\delta_1 W_i$, $\delta_2 T_i$, and $\delta_3 O_i$ denote urban living conditions, ownership of accommodation and a non-retired living status respectively. Finally, the summation $\sum_{k=1}^{4} \theta_k H_{ik}$ includes 4 controls for household size H_{ik}, each with coefficient θ_k and ε_i represents the error term to account for unexplained variation. This model can be used to determine if there is a meaningful correlation between income and experienced inflation when accounting for controls that may confound the relationship captured by equation 3.

3.4.2 Multilevel model

To capture differences in the regional baseline rate of inflation as well as the marginal effect of income on experienced inflation, I formulate a multilevel model with random slopes and random intercepts. This approach follows Snijders and Bosker (2011) who demonstrates that varying slopes and intercepts in multilevel models is appropriate when at least 30 observations are available for 10+ groups. In my case over 200 observations are available for all 12 groups, confirming the validity of the model. It can be denoted as follows:

$$Y_{ij} = \underbrace{\beta_0 + \beta_1 X_{ij} + \beta_2 W_{ij} + \beta_3 T_{ij} + \sum_{k=1}^{4} \theta_k H_{ijk}}_{\text{Fixed part}} + \underbrace{u_{0j} + u_{1j} X_{ij} + \varepsilon_{ij}}_{\text{Random part}} \tag{5}$$

where the fixed part remains largely unchanged, but slopes and intercepts are now fit at the regional level. The random part consists of u_{0j}, which captures region-specific deviations from the overall intercept, $u_{1j} X_{ij}$, which allows the effect of X_{ij} to vary across regions, and ε_{ij}, which represents the residual error for household i within region j.

4 Results

4.1 Fixed-effects model

In Table 2, model 1 is regressing experienced inflation on income and model 2 adds the controls. Coefficient estimates are shown with standard errors in parentheses and stars that represent the significance of the respective p-value. Note that standard errors - as opposed to robust standard errors - were favoured since a Breusch-Pegan test revelead that the assumptions of homoscedasticity is met; tests for all underlying assumptions are presented in section 4.3.

Table 2: Fixed-effects Model Results

	(1)	(2)
Income	-0.0009 (4.56e-05)***	-0.0006 (4.88e-05)***
Region		
North West + Merseyside		-0.0222 (0.115)
Yorkshire + the Humber		-0.0318 (0.117)
East Midlands		-0.0027 (0.121)
West Midlands		-0.1238 (0.118)
Eastern		0.0921 (0.115)
London		0.5151 (0.118)***
South East		0.0056 (0.112)
South West		0.1094 (0.114)
Wales		-0.0212 (0.134)
Northern Ireland		-0.0292 (0.124)
Household Size		
2 Members		-0.2109 (0.046)***
3 Members		-0.4970 (0.061)***
4 Members		-0.4374 (0.063)***
5+ Members		-0.4736 (0.092)***
Other		
Tenure_own		-0.7880 (0.044)***
Retired_yes		-0.3566 (0.044)***
Rural_yes		-0.2179 (0.047)***
Constant	9.1775 (0.039)***	9.0892 (0.107)***
R-squared	0.072	0.165
Adj. R-squared	0.071	0.163
Prob (F-statistic)	9.05e-93	1.60e-182
Observations	5628	5628

Note: SE, *p<0.1; **p<0.05, ***p<0.01

Model 1 shows that when regressing experienced inflation on income there is a statistically significant relationship between the two variables. The coefficient is significant, indicating that for every £1 increase in income, experienced inflation decreases by 0.0009 percentage points (i.e., earning an additional £100 is associated with a 0.09 percentage point decrease in experienced inflation). Nevertheless, an R^2 value of 0.072 suggests that there are other factors affecting the relationship that are not captured by the model. When accounting for controls in model 2 the R^2 more than doubles to 0.165 and although the coefficient decreases to 0.0006 it remains statistically significant.

Model 2 also reveals that the rate of inflation experienced by household in London was 0.51 percentage points higher than for the control and that households with more than 2 members experienced a much lower rate of inflation than households with one or two members. Additionally, Table 2 reveals that the average rate of inflation experienced by households who own their residence was 0.79 percentage points lower than for households who are renting. Finally households who are retired or located in rural areas also experience systematically lower rates of inflation. The intercept is very similar for both models, indicating that although controls help explain additional variations in experienced inflation, there is a core underlying rate experienced by all households.

4.2 Multilevel model

The results for the multilevel model are shown in Table 3. The statistical relevance of all controls remains similar at the regional level but the most notable difference is that although the coefficient for income is -0.001, indicating a more severe relationship than before, it is not statistically significant with a standard error or 0.401.

Table 3: Estimates for Multilevel Model

Effect	**Estimate (SE)**
Fixed Effects	
Intercept	9.513 (0.391)***
Equivalised Income	-0.001 (0.401)
Tenure_own	-0.788 (0.044)***
Retired_yes	-0.358 (0.043)***
Rural_yes	-0.219 (0.047)***
Household Size (2 members)	-0.180 (0.046)***
Household Size (3 members)	-0.364 (0.063)***
Household Size (4 members)	-0.257 (0.066)***
Household Size (5+ members)	-0.310 (0.093)***
Random Effects	
Variance of Random Intercepts ($\sigma^2_{u_0}$)	1.752
Variance of Random Slopes ($\sigma^2_{u_1}$)	1.920
Covariance of Random Intercepts and Slopes ($\sigma_{u_{01}}$)	0.000
Variance of Residuals (σ^2_{ε})	1.9148

Note: SE, *p<0.1; **p<0.05, ***p<0.01.

Regarding random effects, the variance of random intercepts ($\sigma^2_{u_0}$) is 1.758, while the variance of random slopes ($\sigma^2_{u_1}$) is slightly higher at 1.928. The covariance between random intercepts and slopes is effectively zero ($\sigma_{u_{01}} = 0.000$), revealing that there is no relationship between the variation in baseline levels of experienced inflation (random intercepts) and the variation in the effect of income on inflation (random slopes) for groups across the 12 regions. Finally, the residual variance (σ^2_{ε}) is 1.9189, indicating that some variability in experienced inflation remains unexplained. The VPC is approximately 0.478, meaning that roughly 47.8% of the total variance in experienced inflation is attributable to differences between groups (random effects). The remaining 52.2% of the variance is due to residual variability (within-group differences).

5 Discussion

First it should be mentioned that the average rate of inflation derived with reference to the household specific index was 8.8% - similar to the national CPI of 10.1% reported in 2022 - confirming the validity of the household-specific index I constructed. In addition, the results generally align with previous research. Indeed, the fixed-effects model indicates that in 2022 there was a significant relationship between income and experienced inflation, even when accounting for various controls. More specifically, the results in Table 2 reveal that earning an additional £100 per week decreases the experienced rate of inflation by 0.06 percentage points. Although this value may seem trivial in a single year, it would considerably compound discrepancies in the cost of living for low- and high-income households if prevalent over multiple years (Kaplan and Schulhofer-Wohl, 2017). Hobijn et al. (2009) have also uncovered a negative relationship between mean inflation and inflation inequality in the US, which would exacerbate the socio-economic relevance of this value.

Model 2 revealed that household size, home ownership, retirement and urban residency are all statistically significant indicators of experienced inflation. For regional controls only London was revealed to be a statistically significant predictor for experienced inflation, highlighting that Londoners spent systematically more on goods and services that were subject to higher inflation than households in other regions across the UK. The statistical significance of the controls reveals that the CPI also subsumes systematic discrepancies in experienced inflation that can be attributed to other demographic factors. Further when accounting for controls in model 2 the adj. R^2 increases to 0.163. Again, this value is not trivial; as demonstrated by Ozili (2023) an adj. R^2 value above 0.1 is meaningful for large survey data when most explanatory variables are significant.

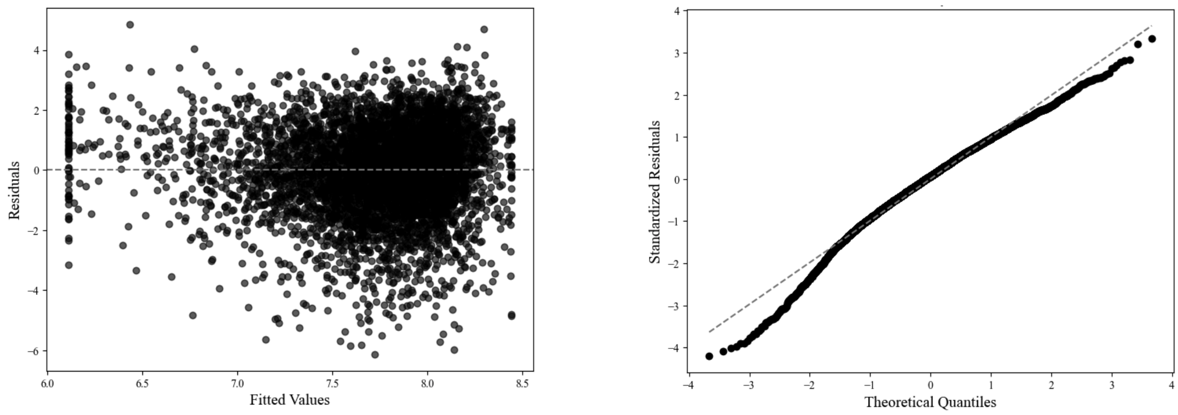
The multilevel model provides crucial insights into the relationship between income and experienced inflation by partitioning the variance into between-region and within-region components. Although it estimates a steeper slope (-0.001), the coefficient is no longer statistically significant ($SE = 0.401$) since a large portion of the variability in experienced inflation can be attributed to regional differences. This loss of significance can be attributed to the inclusion of random intercepts and slopes in the multilevel model, which accounts for unobserved heterogeneity across regions. Specifically, the variance of the random slopes ($\sigma^2_{u1} = 1.928$) indicates that there is substantial variation in how income relates to inflation across regions. This variation dilutes the overall statistical signal of income's effect. Further a large amount of variance remains unexplained within regions, as indicated by the residual variance ($\sigma_{\varepsilon}^2 = 1.9189$), indicating that while some regions exhibit a stronger or weaker income-inflation relationship, the lack of uniformity renders the overall slope less meaningful. The VPC also provides valuable insights in this regard, highlighting that 52.2% of the total variance in the outcome is attributable to differences between groups (random effects), while the remainder is attributable to within-region variability (residual variance).

The methodology I deploy highlights the importance of accounting for hierarchical structure in the data. This points to a key flaw in much of the literature on inflation inequality which generally formulates fixed-effect models that cannot go beyond dummy encoding to account for regional variations (Hobijn et al., 2009; McGranahan and Paulson, 2005). Given the extent to which these discrepancies are prevalent in the UK, it is not unlikely that larger countries like the US would be subject to similar if not greater regional heterogeneity. Nevertheless, the findings in Table 3 should not be interpreted as evidence against inflation inequality but rather as a testament to the importance of regional differences as an explanatory variable. Additional research would be required to understand how inflation inequality varies at the regional level and where it is most prevalent - ideally over a longer time frame.

Heterogeneity in experienced inflation - across the income distribution and by region - has considerable implications for social and economic policy. For instance social metrics such as the absolute poverty line are adjusted with reference to the UK's national CPI; if the experienced rate of inflation varies by region and income then doing so would invariably fail to capture real trends of poverty in certain places. This is not only problematic since policymakers subsequently operate under a false understanding of poverty dynamics, but also because there are social security programs for which eligibility hinges on the absolute poverty line. The CPI is also used to uprate social security programs such as child support, jobseeker's allowance and working tax credit. Policy makers may not be able to adequately safeguard the real value of these programs when using a national CPI for uprating purposes. A priority for statistical agencies should therefore be to obtain granular data on household specific expenditure shares, consumption patterns and prices to develop a measure of inflation that can capture systematic variations in the cost of living across the UK. These could be incorporated into governance frameworks to better inform social metrics and redistributive policies.

6 Model validity

There are various assumptions underlying the validity and reliability of linear regression analysis. The first is that it assumes a linear relationship between the outcome and each explanatory variable. Categorical variables always meet this condition but it must be tested for in the case of equivalised income, which can be done with reference to the scatter plot of residuals in Figure 1a. Not only does the figure indicate that the residuals randomly fall above and below 0, but a lack-of-fit test also revealed that the linearity assumption is met to a sufficient extent (Osborne and Waters, 2019).



(a) Residuals vs. fitted values (b) Q-Q Plot of Standardized Residuals

Figure 1: Plots for regression validity (relevant to assumptions one, three and five)

The second assumption requires that there is little to no multicollinearity between predictors; violating this assumption would result in inflated standard errors and unstable coefficient estimates (Osborne and Waters, 2019). Variance inflation factors (VIF) can be derived to quantify whether there is a correlation between any two predictors in a model. The results of this test can be found in Table 4 and they reveal that all VIFs are below five, indicating that the model satisfies the assumption of little to no multicollinearity (Farrar and Glauber, 1967). The third assumption is that the variance of the residuals is constant across all levels of the independent variables (homoscedasticity). Meaning that errors are not systematically related to the values of the predictors. The assumption can be verified visually with reference to Figure 1a, as well as a Breusch-Pagan test, which found no significant evidence of heteroscedasticity (p-value = 0.28).

The fourth assumption is that errors are independent of one another. The Durbin-Watson statistic was derived to test for this assumption and with a value of 1.96 it revealed that there is no meaningful autocorrelation between residuals. The last assumption is that the residuals are normally distributed. Both the Q-Q plot in figure 1b and a Shapiro-Wilk test ($W = 0.984$, $p < 0.001$) indicate that this assumption is not met. Nevertheless, the model was not adjusted in response since previous research has shown that regressions are generally robust to violations of this assumption when the sample size exceeds 100 observations (Alexopoulos, 2010). Also note that the Q-Q plot suggests that there are no outliers whose exclusion would meaningfully affect the significance of the model. Finally, it should be mentioned that although most demographic attributes believed to influence the composition of households' consumption bundle were accounted for, linear regressions generally cannot mitigate omitted variable bias under current data-constraints.

7 Limitations

The sample includes at least 200 observations for each category listed in Table 1 and it is generally representative of the population, with the exception of retired households who are overrepresented. But it only includes households who agreed to maintain detailed records of their expenditure; perhaps those who did have different innate characteristics to the population at large. Further, there are limitations to relying on weekly equivalised income since it does not include earnings from bonuses and stock options, as well as large inconsistencies in revenue streams for heads of households who are self-employed. Having merely focused on 2022 also makes it harder to generalize my findings. For instance, rising energy costs upon removal of the price cap by Ofgem strongly contributed to inflation. Since low-income households generally spend a larger proportion of their income on energy, it would not be surprising if they experienced a higher rate of inflation (Baltruszewicz et al., 2023). A comprehensive evaluation of inflation inequality would require assessing whether goods and services that low-income households spend proportionally more on are subject to systematically higher rates of inflation over longer time frames.

There are also limitations in the proposed methodology. In this study I use data on expenditure to first derive a household's consumption bundle and then measure its experienced rate of inflation with reference to category specific price indexes. The approach assumes that all household pay the same for any given good and that they purchase the same mix of goods within the 84 categories for which inflation is measured in the second dataset. My methodology therefore cannot account for the fact that expenditure shares within a given category also vary (e.g., spending on the 'fresh fruits' category could constitute 30 % on apples and 70 % on pears for one household and 100% on plums for another). More importantly, it also cannot account for variation in prices paid for the same good or service by different households. For example, it may be that low-income households purchase brands of toast were subject to a different rate of inflation than the brands purchased by wealthier households. As mentioned earlier, there has been research on how price heterogeneity contributes to inflation inequality, generally with reference to barcode scanner data. But current data constraints inhibit research that accounts for variations in expenditure patterns and prices.

8 Conclusion

In this study, I demonstrate that (i) in 2022 there was a statistically significant relationship between household income and experienced inflation (i.e., the percentage increase in a household's living costs) that (ii) there were considerable discrepancies in the baseline rate of inflation and the effect of income on inflation across regions in the UK. By formulating a fixed-effects model I followed the general status quo in the literature on inflation inequality, but by then fitting a multilevel model at the regional level I highlight that a large proportion of variability in experienced inflation can be attributed to geographic differences. These findings serve as a testament to the importance of studying heterogeneity in experienced inflation across hierarchical demographic data structures. The study and its limitations raise several questions for future research. First, heterogeneity in experienced inflation should be evaluated with reference to variations in expenditure patterns and specific product prices. Second, longer time frames must be considered - particularly in economies subject to higher rates of inflation - to evaluate whether this issue results in meaningful discrepancies over time. Third, how formulas designed to uprate redistribute social security programs could be adjusted to account for insights that an increasingly large amount of available data can provide. These findings are of considerable contemporary relevance; not only do they provide insights into the more nuanced socio-economic hardships that inflation has given rise to over the past three years, but they also draw attention to important target areas for policymakers seeking to mitigate the impacts of inflation.

References

Alexopoulos, E. C. (2010). Introduction to multivariate regression analysis. *Hippokratia*, *14*(Suppl 1), 23.

Amble, N., & Stewart, K. (1994). Experimental price index for elderly consumers. *Monthly Lab. Rev.*, *117*, 11.

Argente, D., & Lee, M. (2021). Cost of living inequality during the great recession. *Journal of the European Economic Association*, *19*(2), 913–952.

Baez Ramirez, J. E., Inan, O. K., & Nebiler, M. (2021). *Getting real? the uneven burden of inflation across households in turkey* (tech. rep.). The World Bank.

Baltruszewicz, M., Steinberger, J. K., Paavola, J., Ivanova, D., Brand-Correa, L. I., & Owen, A. (2023). Social outcomes of energy use in the united kingdom: Household energy footprints and their links to well-being. *Ecological Economics*, *205*, 107686.

Deryugina, E., Karlova, N., Ponomarenko, A., & Tsvetkova, A. (2019). The role of regional and sectoral factors in russian inflation developments. *Economic Change and Restructuring*, *52*(4), 453–474.

Farrar, D. E., & Glauber, R. R. (1967). Multicollinearity in regression analysis: The problem revisited. *The Review of Economic and Statistics*, 92–107.

Gürer, E., & Weichenrieder, A. (2020). Pro-rich inflation in europe: Implications for the measurement of inequality. *German Economic Review*, *21*(1), 107–138.

Hobijn, B., Mayer, K., Stennis, C., & Topa, G. (2009). Household inflation experiences in the us: A comprehensive approach, working paper 2009-19.

Honohan, P. (2024). The inflation surge in europe. *Peterson Institute for International Economics Policy Brief*, 24–2.

Jaravel, X. (2021). Inflation inequality: Measurement, causes, and policy implications. *Annual Review of Economics*, *13*(1), 599–629.

Jaravel, X., & O'Connell, M. (2020). High-frequency changes in shopping behaviours, promotions and the measurement of inflation: Evidence from the great lockdown. *Fiscal studies*, *41*(3), 733–755.

Johannsen, B. K. (2014). Inflation experience and inflation expectations: Dispersion and disagreement within demographic groups.

Kaplan, G., & Schulhofer-Wohl, S. (2017). Inflation at the household level. *Journal of Monetary Economics*, *91*, 19–38.

McGranahan, L., & Paulson, A. L. (2005). Constructing the chicago fed income based economic index-consumer price index: Inflation experiences by demographic group: 1983-2005, working paper 2005-20.

Michael, R. T. (1975). *Variation across households in the rate of inflation* (Working Paper). National Bureau of Economic Research.

Office for National Statistics. (2022a). Consumer price inflation basket of goods and services: 2022.

Office for National Statistics. (2022b). Living costs and food survey.

Osborne, J. W., & Waters, E. (2019). Four assumptions of multiple regression that researchers should always test. *Practical assessment, research, and evaluation*, *8*(1), 2.

Ozili, P. K. (2023). The acceptable r-square in empirical modelling for social science research. In *Social research methodology and publishing results: A guide to non-native english speakers* (pp. 134–143). IGI global.

Snijders, T. A., & Bosker, R. (2011). Multilevel analysis: An introduction to basic and advanced multilevel modeling.

Warren, T. (2015). Work-time underemployment and financial hardship: Class inequalities and recession in the uk. *Work, employment and society*, *29*(2), 191–212.

Appendix: VIF

Table 4: Variance Inflation Factor (VIF) Results

Variable	**VIF**
Equivalised Income	1.30
Tenure_own	1.11
Rural_yes	1.09
Retired_yes	1.36
North West + Merseyside	3.20
Yorkshire + the Humber	2.99
East Midlands	2.68
West Midlands	2.94
Eastern	3.19
London	3.13
South East	3.78
South West	3.47
Wales	2.04
Scotland	4.27
Northern Ireland	2.47
2 Members	1.51
3 Members	1.40
4 Members	1.44
5+ Members	1.18