The Effect of Socioeconomic Status on the Prescription of Drugs in English Regions

700037484

Introduction

One of the most notable phenomena of COVID-19 was the socioeconomic disparity of impact, providing further evidence for addressing healthcare inequality in the UK. Healthcare inequality by socioeconomic status (SES) has long been documented before COVID-19 with prominent research beginning in 1999. (Gunning-Schepers and Stronks 1999) Since it's initial introduction, SES/income has been classified as a determinant of health, directly correlated to life expectancy, quality of life, and disease risk. (Kivimäki et al. 2020) Further research has built on this by identifying drug-specific or disease-specific relationships with SES, namely cardiovascular disease, kidney disease, diabetes, cancer, and more. (Schultz et al. (2018), Dalstra et al. (2005))

Although there have been macroscopic analyses done on SES and various common diseases, there has been little broad-spectrum research on SES and drug prescriptions. Currently, it is not fully understood how SES can impact the incidence or prescribing of different drugs. Therefore, this study aims to investigate the nine English regions for the effect of SES on the regional profile of antibiotic, diabetes, hypertension, mental health, or painkiller drug prescriptions. Furthermore, it also attempts to identify if any pre-existing socioeconomic inequalities in prescriptions were exacerbated after COVID, by comparing 2018 and 2021 data.

Methods

Data Sources

Following the 2019 UK local authority restructuring, drug prescription data was compared between the 9 official UK regions: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East and the South West. Socioeconomic status of each region was determined through a proximal measure of Gross Domestic Product (GDP) per capita, indicating relative average income of region residents. Regional GDP data was taken from the 1998 to 2021 edition of the Regional Gross Domestic Product: Local Authorities dataset, published by the UK Office for National Statistics, filtering out all but the 2018 and 2021 data. GDP per capita was then calculated by importing regional population data from the Mid-2018 (2019 LA boundaries) and Mid-2021 editions of the Estimates of the population for the UK, England, Wales, Scotland and Northern Ireland dataset, also published by the Office for National Statistics.

Prescription data was taken from the December 2018 and December 2021 editions of the English Prescribing Dataset (EPD), published by the NHSBSA. The EPD applies the Practice Detailed Prescribing Information data structuring guidance on an updated version of the Practice Level Prescribing dataset, intending to become the primary public practice-level prescription dataset in the future.

The EPD dataset was formatted to categorise all prescriptions into the nine selected UK regions, using the EPD-native postcode data, and an external postcode lookup table from the December 7th version of the National Statistics Postcode Lookup UK dataset, published by Open Data Camden.

Variables and analysis

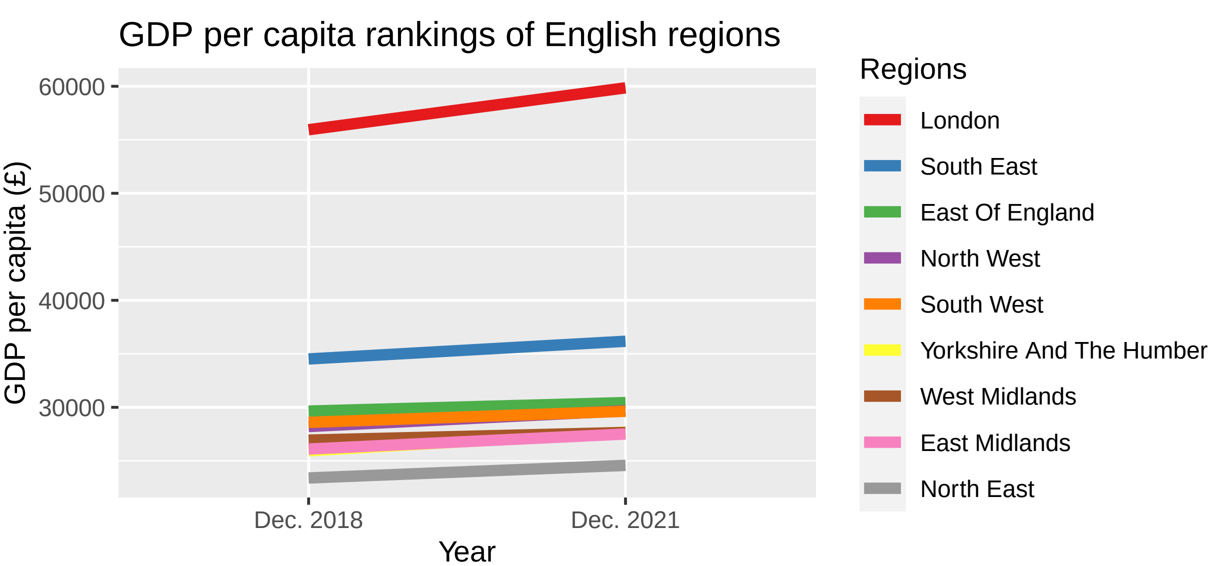
In line with similar disease-specific SES studies, practice prescriptions were categorised into common disease categories, including: antibiotics, diabetes, hypertension, mental health and painkillers. Antivirals were also initially captured, but due to low numbers of observed prescriptions were ultimately removed. Prescriptions were captured using a custom matching algorithm, where string-based prescription descriptions were scanned against a custom lookup table of the most commonly prescribed drugs used in each disease category. For a full breakdown of captured drugs and corresponding categories, see Supplementary Table 1. Data was excluded if the prescription could not be classified into any of the five groups, or the nine English regions.

All analysis was done using R version 2023.06.1+524. Descriptive analysis was done on 3 levels of the prescription data, comparing drugs by the nine English regions, comparing December 2018 to December 2021, and comparing drug categories. GDP per capita was seen to display significant right skew, but as this accurately represents the distribution of wealth in the UK, no further data was collected to investigate or correct this distribution. Drug category was seen to have a significant confounding effect on prescriptions, so a multiple linear regression using GDP per capita and drug category was developed to predict prescription count per 100,000 residents. Linearity was investigated, and due to the small sample size there was some leverage present by outlying data points, however data remained mostly linear. Although this regression model is unlikely to accurately explain the complex nature behind SES and prescription behaviour, it provides a novel insight into the unmapped relationship.

Results

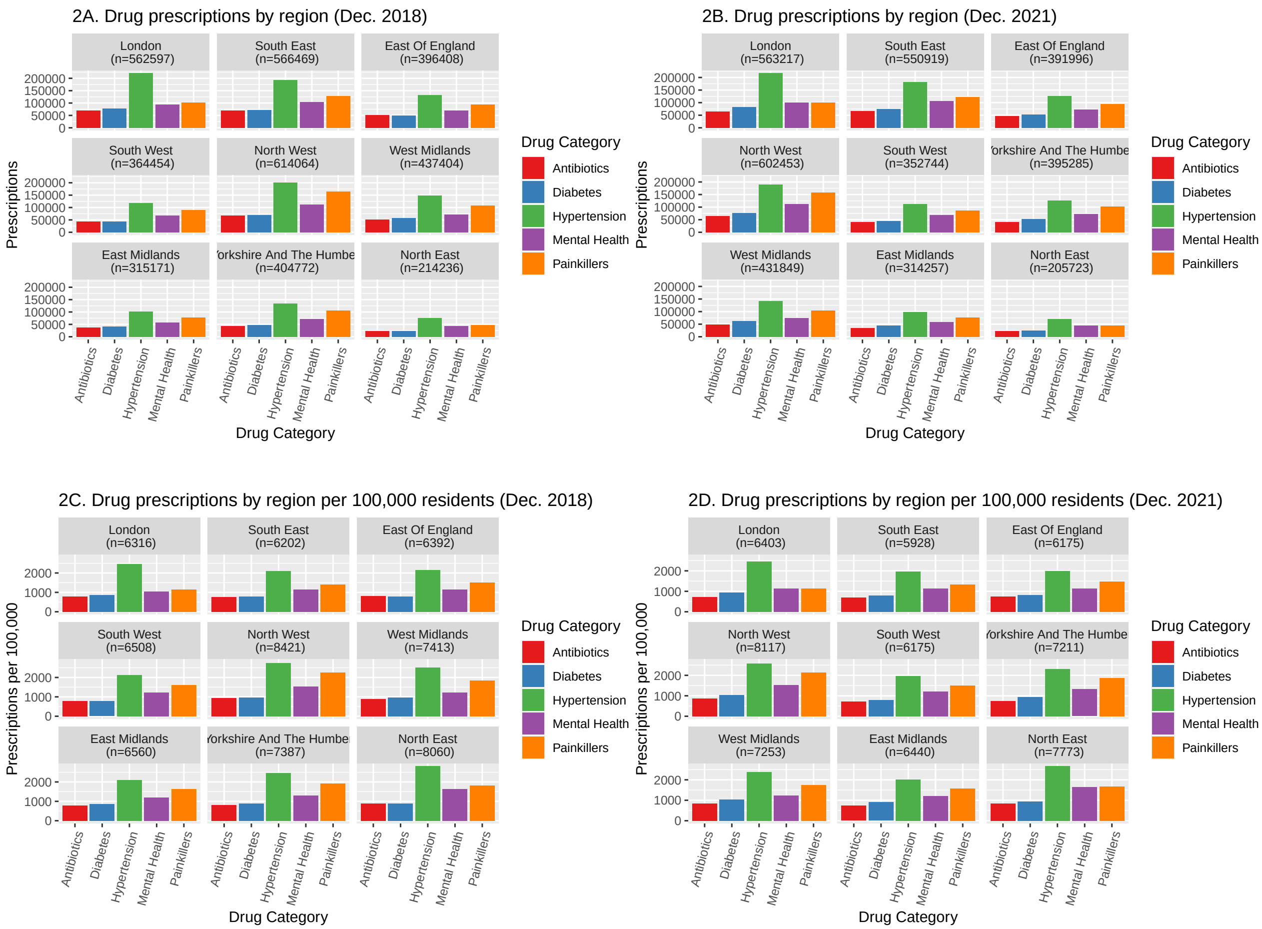
Of the 17,819,185 observations in the December 2018 EPD dataset, 3,875,575 were successfully categorised into the five drug categories and nine regions. Similarly, 3,808,443 prescriptions were captured in the December 2019 EPD dataset out of 17,678,769 observations. The vast majority of data loss was attributed to non-relevant prescriptions being filtered, as the 2018 EPD dataset only incurred 143,106 lost observations due to incorrect/missing regional categorisation, and 56,684 for 2021.

Figure 1. GDP per capita tracked over 2018 and 2021 for the nine English regions



The GDP per capita of regions seen in Figure 1 shows some heterogeneity, where some regions like London, the South East, and the North West show significant growth from 2018 to 2021, while other regions like the West Midlands and East show limited growth. Although growth differs between regions, the rankings of regions remain relatively unchanged, with the most prominent change coming from Yorkshire, marginally overtaking both East and West Midlands in GDP per capita. There is unequal spread of the GDP per capita data, as majority of the regions sit between ~£20,000 to ~£30,000, where London is the only region with a GDP per capita over £40,000, likely impacting the accuracy of later modelling.

Figure 2. 4-part figure of the number of prescriptions by region, year and drug category.

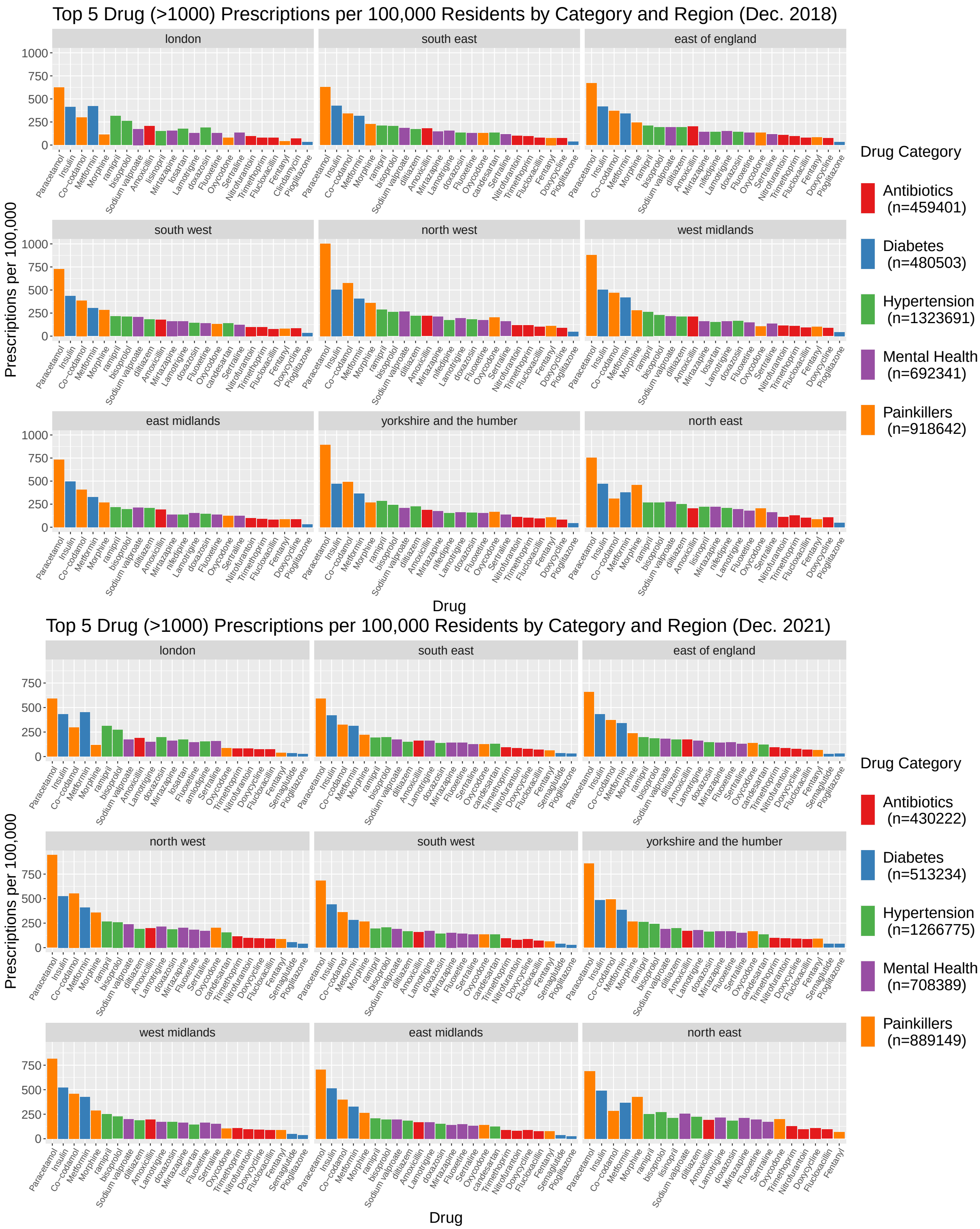


The number of prescriptions in December 2018 and 2021 is compared by region and drug category in the 4-part plot Figure 2. Regions are ordered by GDP per capita, where the first plot (London) has the highest socioeconomic ranking, and the last plot (North East) has the lowest. As population is a confounder for number of prescriptions, Figure 2A and 2B show prescriptions unadjusted for population, while 2C and 2D adjust the number of prescriptions per 100,000 residents.

All regions observed a decrease in total prescriptions from December 2018 to 2021, shown in Figure 2A and 2B. When population-adjusted in figures 2C and 2D, this decrease from 2018 to 2021 remains true with the single exception of the South West. Across all regions and both years, Hypertension drugs were the most frequently prescribed per 100,000 residents, followed by painkillers, and then closely thereafter by mental health drugs. Diabetes and antibiotics were the second least and least frequently prescribed drugs, respectively. Interestingly, the North West is an outlier in all 4 graphs, with disproportionately high unadjusted and population-adjusted prescriptions across categories.

Antibiotics and diabetes prescriptions per 100,000 residents remains relatively constant between regions, regardless of SES in both December 2019 and 2021, seen in Figure 2C. The opposite is true for hypertension, painkiller, and mental health drugs which can be seen to increase as SES decreases in 2018. Furthermore, the total number of prescriptions per 100,000 residents (regional n numbers) increases as SES decreases in 2018, suggesting that there may be an inversely proportional relationship between SES and population-adjusted drug prescriptions. However, in December 2021 these relationships are less clear, as Hypertension, mental health and painkiller prescriptions cannot clearly be seen steadily increasing as SES decreases. Similarly, the inversely proportional relationship between socioeconomic status and population-adjusted prescription count is less clear in 2021.

Figure 3. A 2-part detailed breakdown of the 5 most commonly prescribed drugs with at least 1,000 prescriptions by region and category for December 2018 and 2021



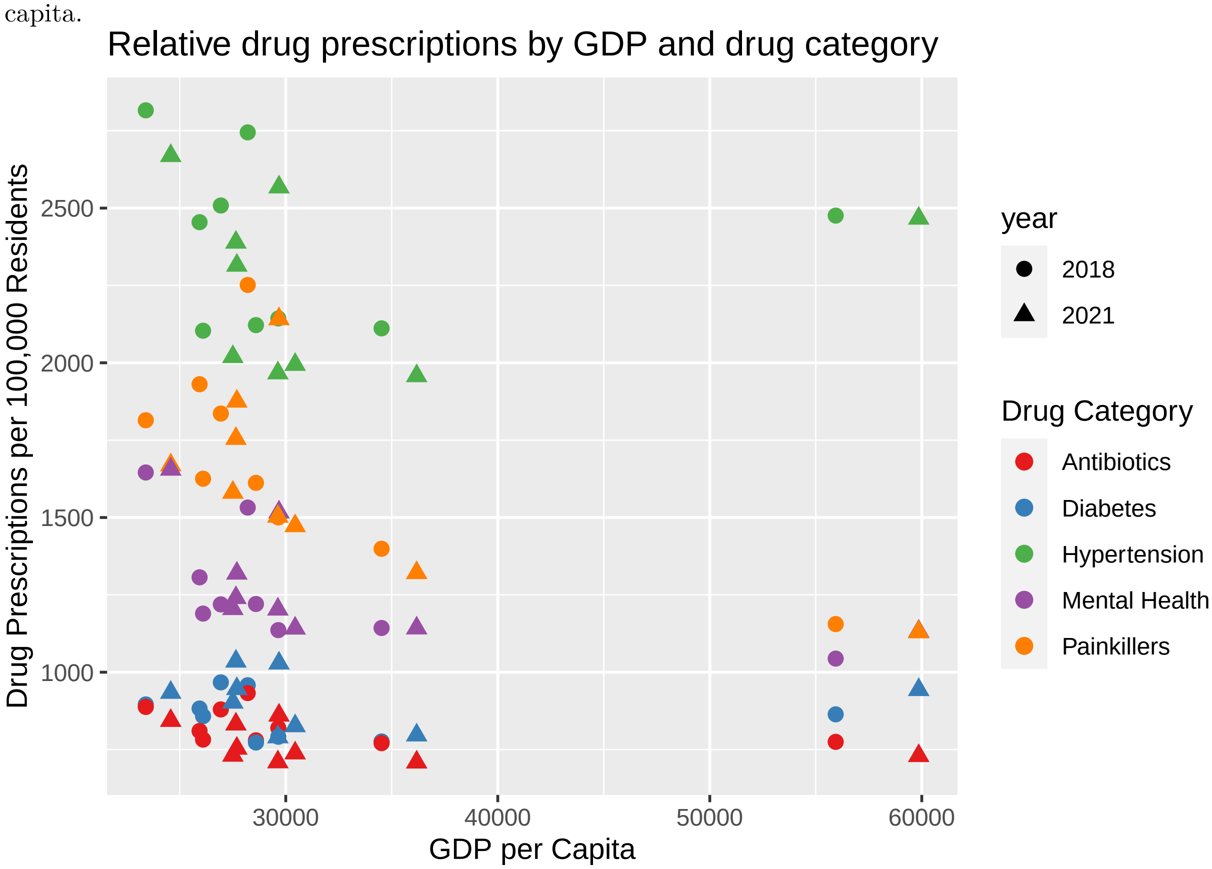
The detailed drug category breakdown in Supplementary Table 1 shows that drug categories are heterogenous in their prescription distribution. Some categories like diabetes and painkillers have the majority of their total prescriptions composed from their few most prescribed drugs, while other categories such as antibiotics and hypertension drugs have prescriptions more evenly distributed amongst all drugs. This can be visualised in Figure 3, which shows the 5 most commonly prescribed drugs (with at least 1,000 prescriptions) per 100,000 residents.

The most frequently prescribed drugs remain generally similar across regions, with painkillers such as Paracetamol and Co-codamol being among the most frequently prescribed, along with diabetes-categorised insulin and Metformin. The 5 most frequently prescribed hypertension and mental health drugs are commonly seen directly thereafter, followed by antibiotics. This pattern generally holds true across regions, however, at the extremes of SES (London and North East, highest and lowest respectively), prescriptions show deviation from the pattern. London shows elevated diabetes and hypertension prescriptions, with a noticeable decrease in painkiller prescriptions, particularly Morphine. Conversely, the North East has elevated hypertension, mental health, and painkiller prescriptions compared to its SES-similar regions. Interestingly, Morphine is seen to positively deviate in the North East, suggesting a potential inversely proportional relationship between Morphine and socioeconomic status - an area that has not yet been deeply researched.

The data and prescription patterns remain relatively consistent comparing December 2018 to December 2021, except for two important differences. Firstly, mental health prescriptions can be seen to be elevated in London in 2021 relative to 2018. Secondly, the North East can be seen further deviating from the general prescription profiles, with fewer Co-codamol prescriptions and elevated hypertension prescriptions.

Linear Modelling

Figure 4. Scatterplot visualising population-adjusted drug category prescription data by year and GDP per capita.



In line with figures 2 and 3, Figure 4 visualises that drug categories are prescribed differently, regardless of GDP per capita of the region. Hypertension is consistently seen as the most frequently prescribed drug, followed by painkillers and mental health drugs, and finally by antibiotics and diabetes drugs. Since there is a clear confounding affect by drug category on prescriptions, this was factored into our model and a multiple linear model predicting drug prescriptions using GDP per capita of the region and drug category was created. Due to the confounding of population on prescription count, we used GDP per capita to automatically capture this relationship, and prevent intra-model coefficient confounding between population and GDP.

Table 1. Coefficients and values from the multiple linear model predicting drug prescriptions

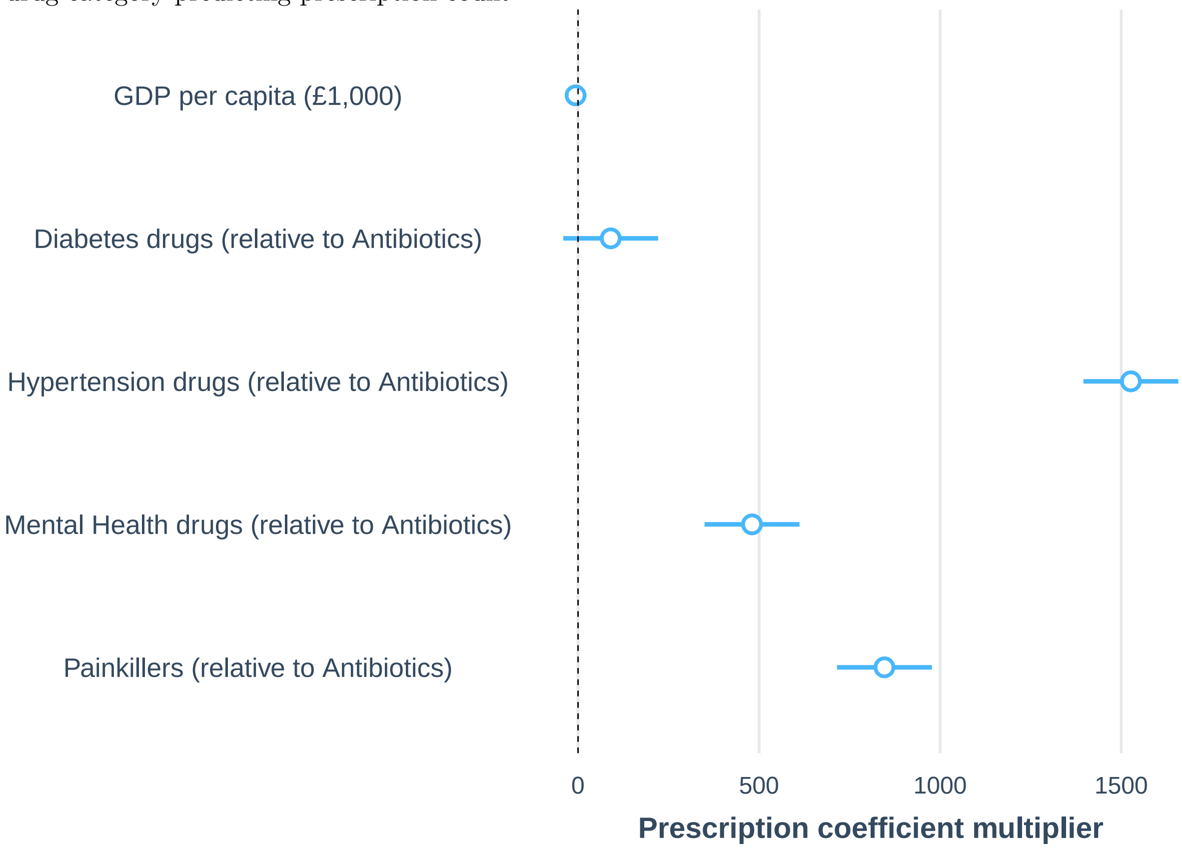
	Prescription coefficient multiplier
GDP per capita (£1,000)	-6.77 **
	[-11.03, -2.51]
Diabetes drugs (relative to Antibiotics)	90.22
	[-40.84, 221.29]
Hypertension drugs (relative to Antibiotics)	1526.66 ***
	[1395.59, 1657.72]
Mental Health drugs (relative to Antibiotics)	480.48 ***
	[349.42, 611.55]
Painkillers (relative to Antibiotics)	846.07 ***
	[715.00, 977.13]
N	90
R2	0.90

*** p < 0.001; ** p < 0.01; * p < 0.05.

$$\begin{aligned}\widehat{\text{count\_per\_hundredthousand}} = 1012.224768 &- \\ &6.769054(\text{gdp\_per\_capita}) + \\ &90.224742(\text{drug\_category}_{\text{Diabetes}}) + \\ &1526.659622(\text{drug\_category}_{\text{Hypertension}}) + \\ &480.481048(\text{drug\_category}_{\text{Mental Health}}) + \\ &846.068173(\text{drug\_category}_{\text{Painkillers}})\end{aligned} \tag{1}$$

The first coefficient in the equation which is not shown in the table is the intercept, indicating that a region with all other variables set to 0 (0 population, £0 GDP per capita, and an antibiotic drug) will prescribe ~1,012 antibiotics per 100,000 residents. As linear models function only with binary categorical variables, each drug category was converted into binary outcomes, and coefficients were generated relative to the baseline category, antibiotics. The GDP per capita coefficient is relative to £1,000 changes, meaning a £1,000 GDP per capita increase would result in ~6.8 less antibiotics prescribed per 100,000 residents. The diabetes coefficient has confidence intervals which cross 0, indicating that there is not enough evidence to evaluate if there will be more diabetes prescriptions than antibiotics per 100,000 residents. This is consistent with our previous findings, where antibiotics and diabetes were similarly prescribed across regions and years. The coefficients of the remaining three drug categories (hypertension, mental health, and painkillers) present significant P values, narrow confidence intervals and very high coefficients relative to antibiotics. These largely positive coefficients are consistent with previous findings, where prescriptions of any of these 3 drugs were found to be much higher than antibiotics, across regions and years. The correlation coefficient of the data to the multiple linear model can be seen presented at the end of Table 1 as well, indicating a very strong fit of $R^2 = 0.90$. All of the coefficients from Table 1 can visually be compared in the following Figure 5.

Figure 5. Forest plot comparing coefficients from multiple linear model of GDP per capita, population, and drug category predicting prescription count



Limitations

Although the study provides some insight into the relationship between the prescription profile of various socioeconomic English regions, any relationship identified is purely observational. Furthermore, as only 2 months of prescription data were captured (2018 December and 2021 December), the observational relationships are subject to temporal resolution, as some drugs are affected by seasonal changes, and may not accurately represent year-round prescription patterns. Future studies should focus on incorporating more plentiful, high granularity data, such as authority or county level data, and should track prescriptions year-round to minimise temporal/spatial constraints. Once stronger observational relationships have been identified, causal research should attempt more sophisticated statistical analysis, such as instrumental variable analysis or mixed effects modelling, as both drug prescriptions and socioeconomic status are by nature, highly confounded variables.

This study presented various other areas that can be improved upon in future research. Firstly, only about 18% of prescriptions were captured from the datasets. Implementing a more sophisticated capturing algorithm, either by increasing the number of key terms/drugs used, or by considering other drug categories/classifications, would greatly reduce data loss. Secondly, as antivirals were expected to have a large change from 2018 to 2021, finding an alternative dataset which can be incorporated into the analysis would greatly improve discussion and inter-drug comparisons. Furthermore, GDP per capita was used as a proxy measurement for socioeconomic status, however this is an unrefined definition, and much more complex rankings can be used such as pre-calculated deprivation indexes from the English Indices of Deprivation 2019 dataset published by GOV UK. Finally, only prescription data at practice-level was included through the selected datasets. Incorporating hospital or over-the-counter data has been done in similar studies, and could provide more accurate data on drug prescriptions within a region.

Conclusion

Socioeconomic status, measured by-proxy through GDP per capita, was seen to have an inversely proportional relationship with population-adjusted prescription count of drugs. This was strongly observed in December 2018, and visible in 2021, across all 5 drug categories (antibiotics, diabetes, hypertension, mental health and painkillers). This relationship was then quantified with a multiple linear model, which showed strong correlation of the data, and confirmed a significantly inversely proportional relationship. Interestingly, hypertension drugs and painkillers were the most prescribed, while antibiotics and diabetes drugs were the least prescribed per 100,000 residents, across all regions and both years. Furthermore, some drug categories, like hypertension drugs, saw relatively even prescription between all captured drugs, while other categories like painkillers saw the majority of prescriptions from a few prominent drugs, like Paracetamol and Co-codamol. Most regions showed similar prescription profiles, with similar proportions of drug categories prescribed across both 2018 and 2021. However, the highest and lowest socioeconomic regions (London and North East, respectively) were shown to have the highest deviance from this standard prescription profile of other regions. Morphine was a particular drug of interest, as there was significantly elevated or reduced prescriptions in the highest and lowest socioeconomic regions, respectively. Finally, the North West had disproportionately high prescriptions, even when adjusted per 100,000 residents, and also slightly deviated from the prescription profile of most other regions. This study presents a novel insight into the relationship between socioeconomic status and drug prescriptions, however subsequent research is required involving more sophisticated statistical and confounder analyses in order to better understand the observational relationship.

Supplementary

Supplementary Table 1. Drug categories broken down by captured prescribed drugs, and their relative percentages by year

Drug Category	Drug	% prescrpiptions (2018)	% prescrpiptions (2021)	% prescrpiptions (total)
Antibiotics				
	Amoxicillin	24.10	23.38	23.75
	Trimethoprim	12.15	12.81	12.47
	Nitrofurantoin	12.90	11.58	12.26
	Doxycycline	9.92	11.24	10.56
	Flucloxacillin	10.47	10.39	10.43
	Clarithromycin	8.54	8.56	8.55
	Clindamycin	7.64	7.98	7.80
	Co-amoxiclav	7.32	7.46	7.39
	Ciprofloxacin	6.33	5.88	6.11
	Levofloxacin	0.46	0.54	0.50
	Vancomycin	0.07	0.11	0.09
	Cefuroxime	0.07	0.05	0.06
	tazocin	0.02	0.02	0.02
	Ceftazidime	0.00	0.00	0.00
	Meropenem	0.00	0.00	0.00
	Piperacillin	0.00	0.00	0.00
	Tazobacta	0.00	0.00	0.00
Diabetes				
	Insulin	53.00	51.50	52.23
	Metformin	42.54	40.77	41.63
	Pioglitazone	4.46	3.50	3.96
	Semaglutide	0.00	4.23	2.19
Hypertension				
	ramipril	10.73	10.66	10.70
	bisoprolol	9.66	10.15	9.90
	diltiazem	8.12	7.56	7.85
	doxazosin	6.76	7.31	7.03
	candesartan	5.84	6.16	6.00
	losartan	5.95	5.92	5.93
	lisinopril	6.00	5.80	5.90
	nifedipine	6.05	4.98	5.53
	amlodipine	4.89	5.34	5.11
	perindopril	5.01	4.83	4.92
	atenolol	4.89	4.41	4.66
	spironolactone	3.24	3.70	3.47
	felodipine	3.26	3.36	3.31
	indapamide	3.14	3.22	3.18
	enalapril	3.17	3.03	3.10
	irbesartan	3.08	2.87	2.98
	valsartan	2.26	3.47	2.85
	verapamil	2.54	2.41	2.48
	bendroflumethiazide	2.45	2.22	2.34
	amiloride	1.95	1.56	1.76
	olmesartan	0.98	1.03	1.00
Mental Health				

(continued)

Drug Category	Drug	% prescrpiptions (2018)	% prescrpiptions (2021)	% prescrpiptions (total)
	Sodium valproate	16.95	15.55	16.24
	Lamotrigine	12.89	13.85	13.38
	Mirtazapine	13.32	12.83	13.08
	Fluoxetine	11.64	12.41	12.03
	Sertraline	10.73	11.57	11.15
	Duloxetine	7.14	7.96	7.55
	Paroxetine	6.48	6.20	6.34
	Trazodone	4.81	5.03	4.92
	Lithium	4.66	4.41	4.54
	Escitalopram	4.09	4.66	4.38
	Temazepam	3.83	3.06	3.44
	Dosulepin	3.44	2.47	2.95
Painkillers				
	Paracetamol	46.20	45.67	45.94
	Co-codamol	24.62	25.03	24.82
	Morphine	15.75	16.12	15.93
	Oxycodone	8.30	8.76	8.52
	Fentanyl	5.09	4.40	4.76
	Ibuprofen	0.02	0.01	0.01
	Ketamine	0.01	0.01	0.01

References

Dalstra, JAA, AE Kunst, C Borrell, E Breeze, E Cambois, G Costa, JJM Geurts, et al. 2005. "Socioeconomic Differences in the Prevalence of Common Chronic Diseases: An Overview of Eight European Countries." *International Journal of Epidemiology* 34 (2): 316–26. https://doi.org/https://doi.org/10.1093/ije/dyh386.

Gunning-Schepers, Louise J., and Karien Stronks. 1999. "Inequalities in Health: Future Threats to Equity." *Acta Oncologica* 38 (1): 57–61. https://doi.org/https://doi.org/10.1080/028418699431807.

Kivimäki, Mika, G David Batty, Jaana Pentti, Martin J Shipley, Pyry N Sipilä, Solja T Nyberg, Sakari B Suominen, et al. 2020. "Association Between Socioeconomic Status and the Development of Mental and Physical Health Conditions in Adulthood: A Multi-Cohort Study." *The Lancet Public Health* 5 (3). https://doi.org/https://doi.org/10.1016/s2468-2667(19)30248-8.

Schultz, William M., Heval M. Kelli, John C. Lisko, Tina Varghese, Jia Shen, Pratik Sandesara, Arshed A. Quyyumi, et al. 2018. "Socioeconomic Status and Cardiovascular Outcomes." *Circulation* 137 (20): 2166–78. https://doi.org/https://doi.org/10.1161/circulationaha.117.029652.