Understanding the Impact of Unemployment on Antidepressant Prescriptions - An English Local Authority Investigation

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Abstract

Utilising the English Prescribing Dataset (EPD) and several Office for National Statistics (ONS) surveys, this study investigates the impact of unemployment on antidepressant (AD) prescriptions in England at a local authority (LA) level. Through OLS and fixed-effects (FE) estimations, this study found that unemployment was not associated with levels of AD prescribing in England. Additionally, this study highlighted that unobserved heterogeneous variables may create wide discrepancies in AD prescribing across LAs. Although this study was unable to guarantee causation or robustness of its findings, its model results suggest that labour market policy interventions may not be appropriate or effective in combatting issues associated with AD prescribing. However, it may be beneficial to further disentangle prescribing determinants at the LA level.

1 Introduction

1.1 Antidepressant Classifications

This study sets out to clarify the influence of unemployment as a labour market determinant of antidepressant (AD) prescriptions in England. When describing AD data in England, this study refers to the British National Formulary classification, (BNF section 04.03 – Antidepressants (Joint Formulary Committee, 2020)) which is the de facto standard used by the NHS and UK-focused literature. Based on mechanisms of action, ADs can generally be broken down into six main types: (NHS, 2021)

- Selective serotonin reuptake inhibitors (SSRIs)
- Serotonin-norepinephrine reuptake inhibitors (SNRIs)
- Serotonin antagonists and reuptake inhibitors (SARIs)
- Noradrenaline and specific serotonergic antidepressants (NASSAs)
- Monoamine oxidase inhibitors (MAOIs)
- Tricyclic antidepressants (TCAs)

Despite what the categorisation might imply, ADs are used to treat a wide range of mental health conditions beyond depressive disorders. Not only are these drugs frequently prescribed for common disorders such as anorexia nervosa, generalised anxiety disorder and obsessive-compulsive disorder, but they are also co-prescribed alongside other specialised psychotropic medications to treat and manage less common disorders such as psychosis (NHS, 2021).

1.2 Antidepressant Trends, Dangers, and Study Motivation

On 6th July 2023, the NHS released a report on mental health medicine for the financial year 2022-2023. The report detailed that within this financial year, 86 million AD items were prescribed to approximately 8.6 million unique adult patients in England, representing about 15% of the total population and nearly 20% of all adults (Davies et al., 2023; NHSBSA, 2023). These staggering findings expand on an extensive body of research, which shows a substantial increase in global usage of ADs in recent decades. Even before the spike in mental health conditions attributed to Covid-19 (Rabeea et al., 2021), NHS reports indicated that the ADs citalopram, sertraline, and amitriptyline consistently ranked among the top 20 most prescribed pharmaceuticals, with over £200 million spent on ADs in 2019 (NHSBSA, 2020). Iacobucci (2019) found that in just ten years from 2008 to 2018, AD prescriptions almost doubled from 36 million to 71 million. Lalji, McGrogan, and Bailey (2021) noted that between 2015 to 2019, the top ten most prescribed ADs saw prescriptions rise by 25%.

Whilst there is no denying that ADs have a positive impact on the lives of many that receive them, there is little evidence that rising AD prescriptions are linked to improved mental health outcomes at a population level (Middleton and Moncrieff, 2011). Additionally, many ADs are known to have several side-effects including violent tendencies, suicidal ideation, sexual dysfunction, and weight gain (Davies and Read, 2018; Rabeea et al., 2021). Many of these side-effects worsen over prolonged periods of use; additionally, a significant proportion of individuals struggle to come off ADs due to withdrawal symptoms, leading to chronic dependency (Davies and Read, 2018; Read et al., 2019). Rising rates of AD prescription point to a social phenomenon known as overmedicalisation - the overuse of pharmaceutical interventions in everyday life. Considering the risks associated with ADs, unnecessary prescriptions may have negative consequences on both an individual and societal level.

Several studies have investigated the socio-economic determinants of AD usage within and outside of England (Heald et al., 2020b; Katolik and Oswald, 2017). However, there is a significant gap within the economic literature, with few papers attempting to establish the influence of potential labour market determinants of ADs in England; this forms the motivation for this study. In studying the effect of unemployment on AD prescriptions in England, this study will build on existing literature, aiding in determining whether labour market policy could remedy overmedicalisation. Additionally, this study will evaluate this relationship at the LA level, which may serve as a launchpad for further qualitative regional analysis.

1.3 Economic Theory

The determinants of AD prescribing are wide-ranging and complex. This study will utilise a multidisciplinary set of economic theory to contextualise the role of ADs within the wider economic landscape, forming a basis for the potential mechanisms in which unemployment may impact AD prescriptions.

Supply and demand theory

ADs are a commodity; as such they are influenced by the market forces of supply and demand. Those without deteriorating mental health are unlikely to seek or be recommended ADs, as they offer no benefit. Conversely, those with mental health conditions may seek and receive AD prescriptions. As will be discussed in the following literature review, unemployment is associated with a range of negative life outcomes and can negatively impact an individual's mental health through both financial and non-financial mechanisms. From this, unemployment can reasonably be expected to influence mental health decline in a population. Applying this to a simple demand and supply model, increases in unemployment can be expected to exacerbate mental health conditions, consequently increasing demand for AD prescriptions. Assuming supply to be constant, this would shift the demand curve to the right, generating a new, higher equilibrium price and quantity for AD prescriptions consumed.

When applying this to a real-world population, various external factors may disrupt this relationship. For example, the assumption of consumer rationality may not hold true for all agents in the economy, leading to decisions contrary to their best interests. For instance, individuals may choose not to take ADs when it could benefit their well-being, or they may opt for ADs when an alternative therapy would be more appropriate. The latter scenario may be increasingly common through the overmedicalisation of daily life. Consequently, we cannot guarantee that increases in mental health decline would have a proportional or positive effect on the demand for ADs.

When considering the English population, a significant proportion of citizens either do not pay, or pay less for their NHS prescriptions. Consequently, this distortion in the price factor of demand lowers the cost barrier of entry for AD prescriptions, likely resulting in increased accessibility and demand. As consumers are paying a lower price, one would expect the supply line to decline, resulting in a higher equilibrium price. However, this is not the case, as pharmaceutical firms are still paid in full, with the NHS shouldering the loss. For many consumers there are no substitutable goods for ADs, so they will assume the role of price takers. Therefore, AD prescriptions will likely have a strong downward price elasticity of demand but be relatively inelastic to increases in prices.

Human capital productivity

The role of ADs can be better understood through the utilisation of human capital theory, which dictates that earnings are determined by productivity, influenced by an individual's traits and skills (Mincer, 1958). One such trait acknowledged as being essential to productivity is health. It follows that individuals with poor health will not be able to work as efficiently, thus being less productive. A number of studies have demonstrated that those with poor mental health perform worse in the labour market and experience losses in personal income due to lost productivity (Rice et al., 1985; Harwood et al., 1992; Kessler et al., 2008). This theory highlights the potential value of ADs in the labour market. In alleviating symptoms of mental health conditions, ADs can enhance productivity, resulting in improved employability and wages. These significant returns make ADs a desirable commodity, for which individuals are willing to pay a high price (Katolik and Oswald, 2017). However, some ADs are associated with side effects which could reduce labour market productivity, such as reduced cognitive function or fatigue (Read et al., 2019). Taken together, it is therefore reasonable to assume that there is a link between the labour market and AD prescriptions.

Happiness and the Easterlin Paradox

Mental health conditions are well-known for their ability to restrict an individual's quality of life. As such, ADs are naturally intertwined with the economics of happiness. First described by Easterlin (1974), the Easterlin Paradox states that at a given point in time, happiness will vary directly with income, but the growth rates of happiness and income are not significantly related over time (Easterlin and O'Connor, 2022). Within the literature, two behavioural phenomena have been offered as explanations of the Easterlin Paradox.

The first phenomenon which we can draw upon is social comparison. Social comparison asserts that within a society, individuals are constantly comparing themselves to their peers. Regarding income, this implies that those with higher incomes tend to be happier as they compare themselves to those with lower incomes, while those with lower incomes may feel unhappier as they compare themselves to those with higher incomes. While this theory may seem crude, numerous studies on different populations such as that of Knight, Song and Gunatilaka (2007) have found that it does indeed hold.

The second phenomenon is that of hedonic adaptation, which explains that whilst people may initially feel shocks to happiness from changes in circumstances, they will quickly adapt to their new situation, effectively rebasing their baseline living expectations. Using income as an example, an individual that receives a positive income shock may temporarily experience an increase in happiness as they compare themselves to their previous situation, but they will not feel this into the long run as they adjust to their new living expectations (Clark, 2016).

Both phenomena may help to predict AD usage in a population. Social comparison suggests that those who are unemployed will be less happy relative to their employed counterparts and thus may be more inclined to receiving a course of ADs. On the other hand, hedonic adaptation may suggest that unemployment and will not have much of an effect on happiness or AD usage over a long enough period of time, as individuals adapt to their new circumstances. Equally, this theory may suggest that increases in income over the long term do not affect AD prescriptions.

2 Literature Review

2.1 Mental health and the Labour Market

In investigating the relationship between unemployment and AD prescriptions, it is essential to recognize that the primary determinant for ADs is individuals' mental health. Regardless of socio-economic factors, individuals without a mental health condition (diagnosed or otherwise) are far less likely to receive an AD. Therefore, it is prudent to initially examine the broader literature on mental health and the labour market before delving into how focusing on AD specifically alters the factors at play.

There is now a wealth of evidence that demonstrates that a decline in one's mental health is associated with several negative life outcomes such as relationship difficulties, homelessness, or crime (Bartel and Taubman, 1986, Katolik and Oswald, 2017). Furthermore, economic investigations into mental health and labour market outcomes, such as wages or participation, have demonstrated that there is an unmistakable association between the two, however the magnitude of the relationship varies considerably between studies.

A study by Kessler et al. (2008), found that in the US between 2001-2003, those with severe mental illness earned approximately $16,000 less annually than those without mental illness. They also found that there was a significant gender disparity in earnings, with men suffering from mental illness seeing near to a three-fold earnings loss compared to women suffering from mental illness. This study corroborated the earlier findings of Rice et al. (1985) and Harwood et al. (1992) which found that mental conditions are associated with large losses in human capital productivity (Kessler et al., 2008).

Frijters, Johnston and Shields (2010) made important contributions to the literature through emphasising the empirical difficulties of measuring the causal relationship between mental illness and labour market outcomes and exemplifying best practice in modelling. Through their extensive modelling of Australian household data, they calculated that a decrease of one standard deviation in mental health decreases the probability of participation in the labour market by seventeen percentage points.

While these studies offer valuable insights into the connection between mental health and the labour market, what is of greater relevance to this paper is the inverse relationship: the impact of labour outcomes on mental health. Specifically focusing on unemployment, several studies have addressed this

Within the literature, employment is generally recognized to have a two-pronged effect on mental health. Firstly, it is believed to influence mental well-being through financial benefits: employed individuals are more likely to have a steady income stream that supports the necessities for a good quality of life. Conversely, unemployed individuals may experience higher levels of stress and anxiety due to concerns about meeting the costs of living in modern society. Secondly, it is associated with a range of non-financial benefits such as social status and self-esteem (Artazcoz et al., 2004, Warr, 1987). Those who are unemployed may feel undervalued or have greater concerns over feeling “good enough” when compared to those who are employed.

However, as noted by Ezzy (1993), there is great social nuance to unemployment. Assuming that ‘work is good’ and ‘unemployment is bad’ is too simplistic, and in some cases, well-being may even increase after unemployment. Moreover, Ezzy (1993) reasons that the experiences of those that are unemployed are heavily intertwined with a variety of factors, such as: “gender, age, income, social support, reasons for job loss, commitment to employment [and] length of employment”. Indeed, this is echoed throughout the literature with many studies estimating unemployment alongside a variety of socio-economic control variables.

Artazcoz et al. (2004) estimated the effects of unemployment on mental health in Catalonia with a focus on gender, family roles and social class. They found that when controlling for these variables in cross-sectional analysis, poor mental health was consistently higher for men than women and for those that previously worked in manual jobs. They found that mental health decline was greater among individuals that were unemployed and not receiving benefits compared to those who were, stressing that employment status should be considered a 3-category variable: employed, unemployed with benefits, and unemployed without benefits. These findings are in line with other studies such as Backhans and Hemmingsson (2011) and Paul and Moser (2009), which found that those who are unemployed face higher mental distress and psychological problems compared to the employed. Many other studies have found covariates such as age, marital status, household composition, ethnicity, and length of unemployment to be significant in the estimations of these models, however, there is a great inconsistency within the literature as to their significance and magnitude (Paul and Moser, 2009, Leinonen et al., 2017).

While the majority of literature finds that unemployment is associated with declines in mental health, a small handful of studies do not support this conclusion. These include Salm (2009) who found that job loss did not have a causal effect on mental health in an American panel of workers. Similarly, Böcker and Ilmakunnas (2009) found, in a five-year Finnish household panel, that unemployment was not causally related to self-assessed health at any level. Nevertheless, the literature indicates that there is a high likelihood of finding a relationship between these variables.

2.2 AD Prescriptions and the Labour Market

Whilst the literature on mental health and labour market outcomes continues to garner interest and expand, a notable gap exists in the economic literature on ADs. Considering the rising consumption and prominence of ADs in daily life, this gap is unexpected. Nonetheless, it opens avenues for further literature development.

Unlike mental health conditions, ADs are commodities borne externally of the individual. Thus, while they likely share many covariates with mental health conditions; prescriptions are potentially subject to additional exogenous factors. These may include, but are not limited to (Katolik and Oswald, 2017):

- New releases of safer and more effective ADs
- Increased cultural awareness of treatment options
- Changes in prescribing protocols
- Cultural stigma towards ADs
- The cost of alternative therapies

Such factors pose a challenge to the literature, as in many cases there are no available measurements to account for them. Of the small handful of papers that examine the relationship between unemployment and ADs, two studies stand out in trying to control for the unobserved heterogeneity that arises from omitted variable bias through regional analysis.

The first study, Buffel, Dereuddre and Bracke (2015) utilised gender-split country fixed effects models to analyse Eurobarometer data from 27 European countries. In addition to including a suite of employment statuses, they also incorporated a broad range of covariates.

In doing so, they found that ADs had a positive relationship with unemployment and was further linked with gender, job security, urbanisation, financial difficulties, and GP/psychiatrist consultations. Importantly, they found no significant difference between countries. One of their explanations for this being that working at a country-level is simply too broad to capture significant differences.

The second study, Cherrie et al. (2021), investigated the effects of post-recession labour market trajectories on AD prescriptions at a LA level in Scotland. They observed AD usage for a period following the Great Recession (2009-2015) and utilized a suite of socio-economic controls typical of the literature. Unlike Buffel, Dereuddre and Bracke (2015), they found significant regional differences; LAs that had weak post-recession labour market recoveries were associated with growing AD usage.

In the literature, there is an apparent scarcity of papers which explore the relationship between unemployment and ADs within the UK. Within studies of trends within UK prescription databases, authors often only make light attempts to associate ADs with regional economic indicators (for example Lalji, McGrogan and Bailey (2021), which uses the index of multiple deprivation). Analysis in these studies is often limited by available data geography, specifically NHS Clinical Commissioning Groups (CCGs), a common level supplied with NHS outputs. Despite their utility, CCGs are incompatible with most official UK statistics. Drawing on the use of LAs in Cherrie et al. (2021), this paper will be the first to examine ADs in England at a LA level, enabling comparison between of a variety of official statistics from the ONS.

2.3 Empirical Difficulties

As shown in the literature review, the link between mental health and labour market outcomes is bi-directional. Individuals with mental health issues may face difficulties in work, resulting in lower wages or job loss. Concurrently, unemployment can worsen mental health. This phenomenon, termed reverse causality, poses a significant empirical challenge in the literature. Compounding this, there is also a high likelihood of unobserved variables which may jointly determine labour and mental health outcomes, threatening omitted variable bias. The AD literature suffers especially from the dangers of omitted variable bias, as the commodities are further influenced by a host of nigh-immeasurable characteristics. Taken together, these two factors mean that most studies are not able to draw causation from their findings and are instead relegated to the realm of correlational inference. This matter is of great importance, as without causation, it will be far harder to confidently estimate the efficacy and impact of current and future mental health policies.

In discussing these empirical difficulties, Frijters, Johnston and Shields (2010) describe three main trends in modelling approaches used within the literature:

- Controlling for a wide range of variables
- Controlling for fixed individual characteristics
- Utilising Instrumental Variables (IVs)

The most basic of these methods is that of controlling for a wide range of variables. In capturing a wide spectrum of observable variables to assess the relationship between labour market outcomes and mental health, the assumption that there are unobserved heterogeneities within the model can be relaxed, removing omitted variable bias. Examples of such studies include Artazcoz et al. (2004) and Kessler et al. (2008).

A technical step up from this method is the utilisation of panel data over periods of time to model fixed-effects. In using dummies to control for specific time-invariant individual characteristics, time-varying effects, or both, one can capture the unobserved heterogeneities of the model within these dummies (Wooldridge, 2010). Examples of this include the previously mentioned Cherrie et al. (2021), or Björklund (1995) which controlled for individuals of the Swedish Level of Living Survey when modelling the effects of unemployment on mental health.

While both methods can tackle unobserved heterogeneity with varying degrees of success, they generally fall short in being able to account for reverse causality. For this reason, many studies have chosen to utilise IVs in their models. A good IV is one that can influence the independent variable of interest, without influencing the dependent variable except through said independent variable (Frijters, Johnston and Shields, 2010). Studies that estimate the effect of unemployment on health outcomes have come up with a few IVs for unemployment: these are generally exogenous unemployment events such as plant/business closures (Salm, 2009; Schmitz, 2011) or unemployment transitions (Gathergood, 2012). These instruments have shown mixed results, with studies such as Salm (2009) finding that there was no causal relationship between unemployment and mental health, whereas Gathergood (2012) found that the onset of unemployment can lead to significant decline in mental health. Thus far, there has been no significant use of IVs in the unemployment and AD literature.

3 Data

3.1 Data Sources

This study makes use of a panel dataset constructed with prescription data from the EPD and various survey data from the ONS.

English Prescribing Dataset

The EPD is a monthly compilation of all recorded prescriptions items that have been prescribed and subsequently dispensed in England. It includes data on a number of prescription characteristics, such as the number of items prescribed (e.g. one pack of sertraline), the quantity of medicine (the number of individual pills within the pack) and the cost of the prescription. It also records the geography of the prescription at a practice, address, postcode, and CCG level (NHSBSA, 2024).

For two reasons, this study will be observing data from the years 2014-2019. First and foremost, Covid-19 created a large surge in mental health conditions across England from 2020 (Rabeea et al., 2021). This exogenous shock saw large increases in ADs prescribed, which may lead to a break in economic relationships that may otherwise have been captured over this period. Secondly, lengthening the time series element of our panel data will increase the risk of introducing or exacerbating challenges associated with timeseries data such as serial autocorrelation. Thus, to try and keep the scope of modelling manageable for this study, a shorter panel is desirable.

In order to make the millions of unique prescription observations compatible with ONS data, a number of data transformation processes had to be undertaken in R Studio. These primarily include:

- Aggregating monthly data into the six years of 2014-2019.
- Aggregating unique AD prescriptions to the '04.03: Antidepressant' BNF code level (Joint Formulary Committee, 2020).
- Crossmatching the postcodes associated with each unique prescription with the ONS Postcode Directory (ONS, 2023a), allowing for prescriptions to be reassigned to a LA and regional level.

ONS

The ONS is the independent body responsible for producing the largest proportion of official UK statistics. Several Datasets from the following data sources were used to extract variables for modelling:

- The 2021 Census (ONS, 2023e)
- The Annual Population Survey (ONS, 2023b)
- The Business Register and Employment Survey (ONS, 2023d)
- Business Counts (ONS, 2023c)
- The Labour Force Survey (ONS, 2023f)
- Regional Accounts (ONS, 2023g)

Data from these individual sources were joined by LA; a small portion of LAs with an incomplete series of data were excluded.

3.2 Variables

This study makes use of both dynamic (2014-2019) and static variables (2021). Appendix A1 contains a shorthand summary of all variables.

Dependent Variable

Antidepressants per capita (ADpc) – This is the total quantity of individual AD pills prescribed annually at a LA level, divided by 2021 LA population estimates to allow for comparability across authorities. This metric is superior to simply capturing the count of prescriptions, as it can also account for the absolute volume of ADs prescribed. Across the six years of reported data there were approximately 13.5 billion individual AD pills prescribed. Table 3A below contains summary statistics for ADpc aggregated to a national level. The average ADpc was 44.6; equivalent to the entire population taking one AD pill a day for almost 45 days a year.

Table 3A: National England ADpc Summary Statistics

ADpc	National			
	Mean	**Median**	**Min / Max**	**Std. Dev**
2014	39.2	39.4	10.7 / 75.8	10.5
2015	41.5	41.7	11.2 / 78.7	11.1
2016	43.8	44.3	11.6 / 81.2	11.7
2017	45.4	46.2	12.1 / 83.4	12.2
2018	47.5	48.2	12.8 / 86.0	12.8
2019	49.9	50.8	13.5 / 89.9	13.4
All Year	44.6	44.6	10.7 / 89.9	12.5

Explanatory Variable

Unemployment Rate (UR) – This is a model-based estimate of unemployment annually at the LA level. Table 3B below contains descriptive statistics of the UR aggregated to a national level.

Table 3B: National England UR Summary Statistics

UR	National			
	Mean	**Median**	**Min / Max**	**Std. Dev**
2014	5.8	5.4	2.4 / 12.5	2.0
2015	4.8	4.5	2.0 / 11.0	1.7
2016	4.5	4.3	2.1 / 9.0	1.4
2017	4.1	3.9	2.0 / 10.1	1.4
2018	3.9	3.8	1.9 / 9.0	1.1
2019	3.7	3.5	1.7 / 8.2	1.2
All Year	4.5	4.1	1.7 / 12.5	1.7

Control Variables – Dynamic

Antidepressant Cost (ADC) – This is cost per AD pill prescribed annually by LA. This variable may capture changes in the relative costs of ADs over time, which may be a factor in a GP's willingness to prescribe an AD (Heald et al., 2020b).

Prescribing Density (PD) – This is a count of unique postcodes that ADs were prescribed from annually by LA, divided by 2021 estimates of LA population density. This variable acts as an imperfect proxy for healthcare accessibility. Areas with greater accessibility to healthcare may have higher rates of prescribing (Heald et al., 2020b). A PD value of 0.03 would mean that there are 0.03 prescribing postcodes available per person per square kilometre.

Gross Disposable Household Income per capita (GDHIpc) – This is GDHI divided by 2021 LA population estimates. This measure captures changes in material wealth in households between local authorities (ONS, 2023g) and will represent the effect of income on the dependent variable.

Control variables – Static

Local Authority – This is a geographic level used frequently in sub-national official UK statistics. A near-complete sample of 277 English LAs are included, capturing a vast majority of the English population. This variable will be fixed in FE modelling.

A series of census variables have also been included to control for population demographics. Numerous papers have found that these demographics can affect mental health (Blanchflower and Oswald, 2008; Katolik and Oswald, 2017; Heald et al., 2020b) and thus they may also have an impact on AD prescribing. These are summarised within Appendix A1, and summary statistics for all control variables can be found in Table 3C below.

Table 3C: National England Control Variable Summary Statistics (2014-2019 Aggregate)

National 2014-2019 Aggregate	Mean	Median	Min / Max	Std. Dev
AD Cost	11.4	10.9	6.0 / 19.6	2.7
Prescribing Location Density	0.0	0.0	0.0 / 0.6	0.1
GDHI per capita (£)	20156.1	18973.0	12021.0 / 54307.0	5318.7
Disability or Health Condition (%)	24.5	24.7	15.2 / 32.2	3.5
Non-white Ethnicity (%)	13.6	7.7	1.5 / 64.4	13.5
Religion (%)	8.7	4.2	1.1 / 51.4	10.2
Divorced/Separated (%)	11.5	11.6	7.0 / 15.6	1.5
No Qualification (%)	17.9	17.6	9.1 / 28.9	4.0
Female (%)	51.1	51.0	48.7 / 53.1	0.6
Average Age	40.7	40.8	31.6 / 49.2	3.1

3.3 Data Limitations

Before discussing the methodology and modelling, it is important to highlight the limitations of the data used:

ADpc values do not account for the relative strength or type of AD prescription; a ten-pack of 10mg sertraline pills will have the same count as a ten-pack of 30mg citalopram pills.

However, for the purposes of this study this is not an important issue, as the main motivation is in the number of people taking ADs as opposed to the relative intensity of mental health and ADs.

The UR uses model-based estimates and while measures have been taken by the ONS to improve accuracy, the levels of confidence in the estimates vary between authorities (ONS, 2023b). This will mean that if too many LA estimates are incorrect, then model results are likely to be spurious.

Prescribing Density only accounts for prescribing at a postcode level, and therefore does not account for the existence of multiple prescribing locations within a postcode. As a result, this variable may mischaracterise healthcare accessibility in some LAs.

The census variables used are estimates for 2021. This means that they may not always be good representations of the population from 2014-2019 and will also be less effective in capturing the influence of the control variables.

The LA level geography is updated on a regular basis and different vintages are used across ONS publications. As a result of this, there may be some mismatches of data, as some geographic LAs may be redefined and boundaries reallocated over time. This may lead to a misrepresentation of any LAs that have had significant boundary changes between the 2021-2023 vintages.

Finally, as has been demonstrated in papers such as Artazcoz et al. (2004), there is great value in including a host of employment statuses alongside unemployment. This was not possible as only a handful of LAs had a complete timeseries of employment variables. While this may still be preferable, it is the hope of this study that more model validity can be drawn from including a near-full LA sample instead.

4 Modelling and Analysis

4.1 Methodology

Drawing on the work of Frijters, Johnston and Shields (2010) who provide a solid framework for modelling the relationships between the labour market and mental health and Cherrie et al. (2021), who utilise a LA FE model for their analysis, two models will be employed.

The first model, a pooled OLS, will allow for the control for several observable variables that may influence ADs, capturing heterogeneity and reducing the chance of omitted variable bias. As has been previously mentioned, there are a number of unobservable factors that may influence ADs that simply cannot be measured. The second model will account for this using FEs to capture the unobserved heterogeneity within individual LAs, reducing endogeneity.

In experimenting with early versions of these models, Wooldridge tests for autocorrelation repeatedly signalled the presence of first-order autocorrelation (p-value < 0.05). This was compounded by Durbin-Watson (DW) values close to 0 indicating strong positive autocorrelation. In an attempt to correct for this and increase model validity, final model estimations will include a 1-year lag of the dependent variable (ADpc-1; further lags not included to avoid overfitting of the model)[1]. This decision may be reconciled through the knowledge that a considerable portion of AD users will be chronic users (Read et al., 2019), with ongoing treatment plans that renew annually, thus a portion of prescriptions in a given year will be partially predicated on the number of chronic users in the previous year.

Furthermore, a number of variables, including the explanatory variable UR, were logged to normalise the distribution of their observations. Age was squared to better represent the 'U-shape' of age on mental health proposed by Blanchflower and Oswald (2008).

All modelling and robustness checks will be performed in the statistical software package Gretl.

4.2 Model Specifications

Model 1f - Autoregressive Pooled OLS

The functional form of the pooled OLS model is as follows:

$$ADpc_{it} = a + B_1 \ln{(UR_{it})} + B_2 C_{it} + B_3 ADpc_{it-1} + e_{it}$$

Where:

- i represents the individual LA
- t represents the year (2014-2019)
- C represents the controls (linear and non-linear)

Model 2f – Autoregressive LA FE

[1] See Appendix A2 for test statistics of intermediary models that do not include ADpc-1 (Model 1i and 2i)

The functional form of the LA FE model is as follows[2]:

$$ADpc_{it} = B_1 \ln(UR_{it}) + B_2 C_{it} + B_3 ADpc_{it-1} + \sum_{i=1}^{277} a_i DLA_i + e_{it}$$

Where:

- i represents the individual LA
- t represents the year (2014-2019)
- C represents the controls (linear and non-linear)
- a represents the LA fixed effects
- DLA represents a dummy variable for each LA

As this model fixes for time-invariant unobserved effects, the time-invariant (2021) controls must be discarded, as they will otherwise introduce perfect collinearity into the model.

4.3 Robustness Checks

To assess the robustness of each model, consistent test statistics were generated[3]:

To test for the presence of heteroscedasticity, White's test was used:
$(H_0: model\ is\ homoscedastic \mid H_1: heteroscedasticity\ is\ present)$

To test for the presence of first-order autocorrelation (FOA), Wooldridge's test was used:
$(H_0: No\ FOA \mid H_1: FOA\ is\ present)$

To test for a normally distributed error, a normality test of residuals was used:
$(H_0: error\ distribution\ is\ normal \mid H_1: error\ distribution\ is\ not\ normal)$

To test for multicollinearity, the variance inflation factor (VIF) of each variable was analysed (a VIF > 10 suggests a collinearity issue).

4.4 Model 1: Pooled OLS

Given the importance of robustness checks in refining the final model specifications, the robustness checks of intermediary models that did not include ADpc-1 have been included[4].

<u>*Model 1 Final (Model 1f)*</u>

[2] Dummy variables 1-277 included, constant therefore excluded to avoid dummy variable trap
[3] See Appendix A2 for test statistics; Appendix A3 for VIF checks
[4] See Appendix A2 for Model 1i and 2i test statistics; Appendix A3 for VIF checks

Informed by the intermediary Model 1i, whose robustness tests demonstrated prevalent heteroscedasticity, autocorrelation, a skewed error distribution and a collinear variable (DLHC). Model 1f was estimated with robust standard errors to address heteroscedasticity, ADpc-1 was included to mitigate autocorrelation, and DLHC was excluded to reduce the likelihood of multicollinearity. Since several log transformations had already been applied to improve the distribution, no further direct action was taken to address normality in any of the models.

Table 4a – Model 1f

Model 1f: Pooled OLS, 1662 observations Cross-sectional units = 277 Time-series length = 5 Dependent variable: ADpc Robust Standard Errors			
Variable	**coefficient**	**p-value**	**sig.**
const	3.5963	0.2471	
log_UR	0.2298	0.0735	*
log_ADC	0.0796	0.5491	
log_PD	0.0411	0.2171	
GHDIpc	-0.0000	0.1673	
NWE	-0.0272	0.0000	***
DS	-0.0132	0.6506	
Female	0.0094	0.8576	
log_Religion	-0.8935	0.0085	***
log_NQ	0.7225	0.0135	**
Age_Squared	-0.0004	0.0567	*
ADpc-1	1.0161	0.0000	***
p-value (F)		0.0000	
R-squared		0.9952	
Adjusted R-squared		0.9952	
Durbin-Watson		1.4284	

The R-squared is near to 1, indicating that the model explains nearly all the variation in the dependent variable. This value likely suggests overfitting due to the inclusion of ADpc-1. When accounting for a lag in the dependent variable, we find that few variables are significant in explaining ADpc.

The explanatory variable was found to be mildly significant, with a coefficient of 0.23 suggesting that a 10% increase in the UR is associated with an increase in prescriptions of approximately 0.023 ADpc. This relationship is weaker than what is typically found in similar models in the mental health literature. One reason for this may be that the additional heterogeneity ADs are subject to in comparison to mental health diminish the role of unemployment. Compounding this, the inclusion of ADpc-1 may further reduce the explanatory power of variables within the model. Another reason may be data selection; studies typically use longitudinal household surveys, which enable employment status to be linked to individuals with ADs more accurately than the population aggregates used in this study.

Of the original control variables, NWE, Religion, NQ, and Age were significant to varying degrees. The direction of each coefficient generally aligns with what has been found in the literature, although as has been mentioned there no great consensus on the exact contributions of these variables. GDHIpc having no significance could lend credence to the concept of hedonic adaptation nullifying the mental health effects of income.

The dependent variable lag was found to be the most significant variable informing the relationship. The coefficient of 1.02 implies that a 1 unit increase in ADpc in the previous time period can predict a 1.02 increase in ADpc the next period – effectively a 1:1 relationship. This suggests that chronic usage may be a systemic reason as to why AD prescriptions continue to increase, although it is an unrealistic estimate. As a result of this, less inference can be drawn from the variables that may actually induce the need for a new AD prescription.

When inspecting the robustness checks of the model, several observations stand out. Firstly, the p-value of the White's test is 0.04, indicating reduced heteroscedasticity. Similarly, the p-value for the Wooldridge test is 0.01, suggesting decreased autocorrelation. This is supported by the Durbin-Watson (DW) value of 1.43, implying lingering positive autocorrelation. Additionally, all variables have variance inflation factors (VIFs) of less than 10, indicating no problematic collinearity.

4.5 Fixed Effects

The robustness checks of Model 2i were used to inform the final specification. To assess the validity of a FE approach, two additional tests were used:

To test whether a random-effects (RE) model should be used over an FE model, the Hausman test was employed on a parallel RE model of the same specification[5]:

$(H_0\text{: } consistent\ GLS\ estimates \mid H_1\text{: } inconsistent\ GLS\ estimates)$

The test p-value was able to reject the null, suggesting that the RE model estimates were inconsistent and FE would therefore be superior model.

A test for differing group intercepts was then employed:

$(H_0\text{: } entities\ have\ common\ intercepts \mid H_1\text{: } entitites\ have\ differing\ intercepts)$

The p-value returned was 0, rejecting the null hypothesis and validifying the approach of fixing for the individual intercepts of the LA entities.

The robustness test statistics all yielded p-values significantly lower than the 0.05 threshold, indicating the presence of heteroscedasticity, a skewed error distribution, and autocorrelation. A Durbin-Watson test further signalled the presence of positive autocorrelation[6]. The VIF for each variable demonstrated that GDHIpc and log PD had substantial collinearity problems.

Model 2 Final (Model 2f)

This model was estimated with heteroscedastic robust standard errors, ADpc-1 was included to tackle autocorrelation, GDHI and log PD were excluded to reduce the likelihood of multicollinearity. Table 4d details significant LA dummies with the 5 highest and lowest coefficients.

[5] Appendix A4
[6] Appendix A5

Table 4b – Model 2f

Model 2f: Fixed-Effects, 1662 observations **Cross-sectional units = 277** **Time-series length = 5** **Dependent variable: ADpc** **Robust Standard Errors**			
Variable	**coefficient**	**p-value**	**sig.**
log_UR	-0.350411441	0.1748	
log_ADC	1.049322040	0.0026	***
ADpc-1	0.9089382707	0.0000	***
p-value (F)		0.0000	
LSDV R-squared		0.9966	
Adjusted R-squared		0.9461	
Durbin-Watson		1.8757	

Table 4c – Model 2f LA dummy variable significance

Model 2f	**Significance**			
	*	**	***	**Total**
Dummy LA	5	12	244	261

Table 4d – Model 2f LA dummy variable coefficients

Top 5 Highest Coefficients		
Region	**LA**	**Coefficient**
East Midlands	Bolsover	9.19
North West	Blackpool	8.16
East Midlands	Chesterfield	8.05
East Midlands	Mansfield	7.95
East Midlands	East Lindsey	7.52

Top 5 Lowest Coefficients		
Region	**LA**	**Coefficient**
South West	South Hams	1.65
South East	Sevenoaks	1.74
East of England	St. Albans	1.81
South East	Epsom and Ewell	1.85
South East	Elmbridge	1.86

The LSDV R-squared is near to 1, indicating that the model explains nearly all of the variation in the dependent variable. Like Model 1f, this suggests that the model has been overfitted with the inclusion of ADpc-1.

When accounting for unobserved heterogeneity across LAs, the explanatory variable UR is no longer found to be significant. This contrasts with the majority of mental health literature, which typically finds significance in FE models, as well as the findings of Cherrie et al. (2021). Broadly, the explanations applied to Model 1f can be applied here. However, the lack of significance could suggest that the aforementioned data challenges of confidence in UR estimates, may be interfering with the results. In such a case, a smaller panel consisting only of LAs with high-confidence UR estimates may be preferable.

Unlike Model 1f, the control variable log ADC was found to be significant; the coefficient suggests that a 1% increase in ADC increases AD usage per capita by 0.01. This relationship is not what one would expect, as we would assume increases in prices to decrease demand. One reason for this may be a possible distortion of the price-demand relationship through the NHS. Alternatively, as the AD category is made up of several differently costed drugs, whose relative proportions change with each observation, ADC is unable to accurately reflect true changes in costs, leading to a spurious result.

ADpc-1 remained an important variable in determining ADpc, however, compared to Model 1f it had a weaker effect: a 1 unit increase in ADpc in the previous year predicts a 0.91 unit increase in the next year.

Out of 277 LA dummy variables, 261 showed significant coefficients. The largest coefficient, for Bolsover, suggests an average 9.2 unit increase in AD usage per capita. The smallest coefficient, for South Hams, suggests an average 1.7 unit increase in ADpc. This indicates the presence of strong unobserved heterogeneity across LAs. Unfortunately, as socio-economic control variables could not be used in this model, we can expect a portion of the heterogeneity created by them to be captured in the LA dummies, making it less clear to what extent unobserved variables beyond socio-economic controls influence ADs. Despite this limitation, however, this model provides a clear incentive to qualitatively investigate and compare LAs to further determine the driving forces of ADs.

Despite using heteroscedastic robust standard errors, the p-value for the White's test was significantly less than the 0.05 threshold required to reject the null hypothesis, indicating that the model suffers from heteroscedasticity. The p-value for the Wooldridge test was 0.04, indicating that autocorrelation was still present (although improved on model 1f). The p-value of a follow-up DW test for positive autocorrelation was 0.01, indicating the presence of positive autocorrelation. The VIF for ADpc-1 was 70.95, implying a strong collinearity problem, however, this is likely still more favourable than not addressing autocorrelation.

From these robustness tests we can assume that the estimates of both Models 1f and 2f are biased and inconsistent. Whilst a number of measures have been taken to improve model validity, great caution must be taken in drawing inference from these results.

5 Limitations and Future Improvements

As has been demonstrated, the dependent variable suffers from serial autocorrelation, and attempts to remedy this within modelling may stifle the explanatory power of both observed and unobserved independent variables within the model. This problem appears to be novel within the literature, and future studies using the EPD should account for this within their technical planning.

Crucially, the methodology used was unable to control for the effects of reverse causality, and for this reason, the limited inference drawn from the models can only be seen as association, not causation. While it was the hope of this study to include a third panel IV model, this was not possible due to data constraints, with only one suitable IV for unemployment being found. As the order condition of IVs states that you cannot have more independent variables than instruments, early estimations of IV models were not found to be useful for inference.

With this and the aforementioned data challenges in mind, future investigations would benefit greatly from research into unemployment IVs at the LA level. Furthermore, procurement of a suite of time-varying socio-demographic variables would be of great benefit to this strand of research; this would allow for increased accuracy in pooled OLS models and could increase the extraction of unobserved heterogeneous variables in regional FE models. The discovery and inclusion of additional employment covariates may also help bring to light more conclusive unemployment findings.

6 Conclusion

The number of antidepressants prescribed to individuals both nationally and globally has been climbing radically. Within England, several papers have found AD prescriptions to be doubling on the decade, and recent reports have shown that a substantial portion of the population has now received AD treatments (Davies et al., 2023; NHSBSA, 2023). These trends point to the overuse of pharmaceutical interventions in everyday life, which may create large social and economic costs. Drawing on the literature that dissects the impacts of labour market outcomes on AD prescriptions, and more broadly mental health, this study has estimated two models.

The pooled OLS model found that in England, a 10% increase in the rate of unemployment was associated with an increase of approximately 0.023 ADpc. This is an insignificant relationship given that the average ADpc across the 2014-2019 period was 44.6.

The FE model, which improved on the pooled OLS estimates by fixing for unobserved heterogeneity across LAs, found that unemployment was not significant in determining AD prescriptions. There was, however, significant variation across LAs in England, suggesting that there is indeed value in further analysing the determinants of AD prescriptions across LAs.

Most of the model findings counter those of the literature, with positive relationships between employment and mental health or ADs being found in several papers (e.g. Gathergood, 2012; Buffel, Dereuddre and Bracke, 2015; Cherrie et al., 2021). Still, a number of adjacent mental health papers like that of Salm (2009) have found no causal link between employment statuses and mental health.

This study has also highlighted the issues of autocorrelation with English prescribing data, which may be driven partially by chronic users of ADs. This appears to be a novel problem that has not yet been encountered or addressed within the sparse literature on this topic.

It is crucial to highlight that this study is unable to draw causal inference from results, primarily because of reverse causality. Furthermore, a number of test statistics show that neither model is profoundly robust. Consequently, the findings of this study may be at best considerably biased and inconsistent, and at worst completely spurious. From this the potential implications on policy are limited. Assuming some level of model validity, however, it would seem evident that employment-focused labour market policies will be unable to address the challenges of overmedicalisation. Therefore, any attention given to this issue would best be turned towards the unobserved variables that may have been captured across the fixed LAs, such as prescribing protocols. Nevertheless, there is still much opportunity within this area for experimentation; building upon the findings of this study through addressing the discussed challenges may yield valuable insights into this matter.

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Appendix

A1: Variable Summary

<table>
<tr><th>Variable</th><th>Model Tag</th><th>Description</th><th>Data Source</th><th>Year</th></tr>
<tr><td>ADs per capita</td><td>ADpc</td><td>Total ADs / 2021 population</td><td>EPD (NHSBSA, 2023); ONS, 2023e</td><td rowspan="5">2014-2019</td></tr>
<tr><td>AD Cost</td><td>ADC</td><td>Total ADs / Total AD cost</td><td>EPD (NHSBSA, 2023)</td></tr>
<tr><td>Unemployment Rate</td><td>UR</td><td>Model based unemployment estimates</td><td>ONS, 2023b; ONS, 2023f</td></tr>
<tr><td>Prescribing Location Density</td><td>PD</td><td>Total unique postcodes / population density</td><td>EPD (NHSBSA, 2023); ONS, 2023e</td></tr>
<tr><td>GDHI per capita</td><td>GDHIpc</td><td>Gross Domestic Household Income per capita</td><td>ONS, 2023g</td></tr>
<tr><td>Disability or Long-term Health Condition</td><td>DLHC</td><td>Proportion of the population that has a disability or long-term health condition</td><td>ONS, 2023e</td><td>2021</td></tr>
</table>

Non-white Ethnicity	NWE	Proportion of the population that is of a non-white ethnic background		
Religion	Religion	Proportion of the population that follows a religion		
Divorced/Separated	DS	Proportion of the population that has a divorced/separated partnership		
No Qualification	NQ	Proportion of the population with no qualification		
Female	Female	Proportion of the population that is female		
Average Age	Age	Mean age of population		

A2: Consistent Robustness Checks

	p-value			
Test	**Model 1i**	**Model 1f**	**Model 2i**	**Model 2f**
Normality Test	0.0000	0.0000	0.0000	0.0000
Wooldridge Test (Autocorrelation)	0.0000	0.0115	0.0000	0.0306
White's Test	0.0000	0.0390	0.0000	0.0000

A3: VIF Table

Variation Inflation Factors (Min. value = 1; Value > 10 indicates collinearity problem)				
Variable	**Model 1i**	**Model 1f**	**Model 2i**	**Model 2f**
log_UR	3.61	2.92	8.93	9.34
log_ADC	1.51	1.43	4.24	6.51
log_PD	1.90	1.92	354.32	
GHDIpc	3.73	3.17	80.43	
NWE	6.40	6.10		
DLHC	13.65			
DS	3.35	3.36		
Female	1.55	1.55		
log_Religion	2.70	2.59		

log_NQ	4.09	4.34		
Age_Squared	6.31	5.16		
Adpc-1		3.13		70.95

A4: RE Hausman Test

Random-effects	**p-value**
Hausman Test	1.43E-15

A5: Model 2 DW Test

	p-value	
Durbin-Watson Test	**Model 2i**	**Model 2f**
H1: positive autocorrelation	0.0000	0.0096
H1: negative autocorrelation	1	0.9904