Some Socio-Economic Determinants of Antidepressant Use: Province Level Evidence from Turkey

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Abstract

This paper studies the socio-economic determinants of antidepressant use in Turkey using province level panel data for the period 2012-2017. We build a simple theoretical model, which implies that total utility is augmented by antidepressant consumption, per capita antidepressant use increases by income per capita, and contrary to a priori expectation, a higher unemployment rate decreases antidepressant use. The dataset allows us to test three different models: first, a model that uses monthly sales data to test for seasonality in sales, second, a panel data model on province level annual data, and third, a dynamic panel data model, again on province level annual data. We find a fall in antidepressant sales in the spring and summer and an increase at the end of the summer, which indicate a seasonal pattern as seen in other parts of the world. The estimation of the two panel data models shows us that several socio-economic variables are indeed correlated with antidepressant sales in the provinces: The share of the elderly (ages 65+), the number of divorces per capita, the share of university graduates are found to have a positive and statistically significant effect; the number of unemployed people have a small and negative effect on antidepressant sales. Moreover, evidence suggests that the government decree, released in March 2013, which warns pharmacies not to sell antidepressants without a valid prescription may have reduced or have controlled the surge in antidepressant sales.

Keywords: Antidepressants, Panel data, Turkey

JEL classification: I10, I15, I18, I19

1. Introduction

Antidepressants, initially developed in the 1950s, are psychiatric medications used for the treatment of major depressive disorder and other conditions including dysthymia, anxiety disorders, obsessive compulsive disorder, eating disorders, chronic pain, neuropathic pain and, in some cases, dysmenorrhoea, snoring, migraine, attention-deficit hyperactivity disorder (ADHD), addiction, dependence, and sleep disorders. Antidepressants may be prescribed alone or in combination with other medications.

The use of antidepressants has become progressively more common over the last three decades. Many studies in the medical literature assessed both the incidence and the prevalence of antidepressant use in the United States and Europe and have shown that the use of antidepressants significantly increased over the past three decades. In the United States, for instance, prescription rates for antidepressants increased over 4-fold between the years 1985-1999 (Grunebaum et al., 2004) and continued to rise significantly among youths and adults (Pirraglia et al., 2003; Olfson and Marcus, 2009; Marcus and Olfson, 2010). They are the most commonly prescribed medications for the treatment of anxiety, depression, mood disorders, and adjustment disorders (Olfson et al., 2002; Olfson et al., 2004; Olfson and Marcus, 2009). Most studies also revealed that antidepressant prescription and use is higher for females compared to males. For example, Mojtabai and Olfson (2011), using the data from the 1996–2007 National Ambulatory Medical Care Surveys, showed that antidepressant visits were higher for female patients compared to male ones. Mojtabai and Olfson (2011) also report that antidepressants are the third most commonly prescribed class of medications in the United States over the past two decades. The picture is no different in many European countries. The antidepressant-use increased rapidly in UK (Middleton et al., 2001; Moore et al., 2009; Martín-Merino et al., 2010), in Italy (Poluzzi et al., 2004; Guaiana et al., 2005), in Netherlands (Meijer et al., 2004; Aarts et al., 2014; Huijbregts et al., 2017), and in the Nordic countries (Isacsson et al., 1999; Rosholm et al., 2001). Vilhelmsson (2013) report that sales of antidepressants in the Nordic countries have increased up to fourfold since the mid-1990s and reached 74.1 DDD/1000 inhabitants per day in 2009, which is considerably higher than the OECD average (52.5 DDD/1000 inhabitants per day in 2009). Gasquet et al. (2005) evaluate annual prevalence of psychotropic drugs based on a transversal survey carried out between 2001 and 2003 in France and in other five European countries (Germany, Belgium, Spain, the Netherlands and Italy). The entire European sample showed that the use of antidepressants has increased significantly and approximately 80% of the users of antidepressants had presented a mood disorder, anxiety disorder or alcohol use disorder during their lifetime. Similar results were reported for New Zealand (Roberts and Norris, 2001), for Australia (McManus et al., 2000; Mant et al., 2004) and for Canada (Hemels et al., 2002).

Mojtabai and Olfson (2011) report that a substantial proportion of antidepressant prescriptions are done by non-psychiatrists without a clinical psychiatric diagnosis and these antidepressant visits without a psychiatric diagnosis increased from 59.5% in 1996 to 72.7% percent in 2007. According to their results, patients who are treated with antidepressants without a psychiatric diagnosis have some medical complaints such as fatigue, nonspecific pain, smoking problems, headaches, and have milder forms of common mood and anxiety disorders. However, they argue that antidepressants have little or no therapeutic effect on these milder conditions. Hence, they highlight that the intensity of antidepressant use among people with less severe and poorly defined mental health conditions seems to be increasing in general medical practice and there is need to understand why this is happening. In a more recent study, Olfson and Mojtabai (2014) also find evidence that depressive disorders remain undertreated in the United States despite of the increased use of antidepressants over the years 1999-2010.

A growing literature suggests that stressful life experiences and sustained economic hardship are associated with both physical and mental illnesses (Lynch et al., 1997; Schneiderman et al., 2005). Evidence suggests that low socioeconomic status (SES) is associated with poor health (Adler et al., 1994; Adler and Stewart, 2010; Currie et al., 2012; Hidaka, 2012). A decrease in SES, conventionally measured by income, poverty, education, wealth, and occupation, was associated with increasing mental health problems (Kaplan et al., 1987; Lorant et al., 2003; Lorant et al., 2007; Goodman and Huang, 2001; Ansseau et al., 2008) as much as physical health problems (Lantz, 1998; Duncan et al., 2002). This inverse relationship between SES and health are more common and stronger for children (Reiss, 2013), adolescents (Goodman and Huang, 2001; Torsheim et al., 2004; Elgar et al., 2015), and women (Duncan et al., 2002; Ansseau et al., 2008; Freeman et al., 2016). More recent studies also show that involuntary job loss and financial strain has clear worsening effects on psychological and physical disorders (Zimmerman and Katon, 2005; Catalano et al., 2011; Currie and Tekin, 2015; Caroli and Godard, 2016). Many studies have shown that unemployment lead to depression (Hamilton et al., 1997; Currie et al., 2015). Bradford and Lastrapes (2014) find that the number of mental health drug prescriptions used for the treatment of depression and anxiety rises by about 10% when employment falls by 1% in the U.S. Others found that indebtness has commonly been associated with increased stress, poor health status and this relationship is especially strong for mental health, in particular depression (Jenkins et al., 2008; Bridges and Disney, 2010; Richardson et al., 2013; Sweet et al., 2013; Hojman et al., 2016). For example, Clayton et al. (2015) examine the relationship between indebtness and aggregate health outcomes (life expectancy and premature mortality) in 17 European countries over the period 1995-2012 and show that while short- and medium-term debt has a positive effect on population health, longer-term unsecured and mortgage debt lead to poorer health outcomes.

Only a few studies have examined the relationship between SES and antidepressant prescriptions. Hansen et al. (2004) show that incidence rate of antidepressant prescription was higher in Danish people who are female, less educated, unemployed, and single. By using data from a Danish cross-sectional study for the year 2000, Andersen et al. (2009) find that antidepressant prescriptions revealed statistically significant higher prevalence among females, unemployed and low-income individuals in Denmark. In contrast, Kivimäki et al. (2007) investigate socioeconomic differences measured by education and occupational status in antidepressant prescriptions and mortality associated with depressive disorder over the years 1994-2000 in Finland. Their results show that low SES was associated with fewer antidepressant prescriptions among men, but there is no such relationship among women. However, both women and men with poor SES are at high risk of mortality related to depressive disorders. Von Soest et al. (2012) examine the relationship between SES and antidepressant prescription among Norwegian young adults over a 13-year period. Their results indicate that all indicators of low SES (such as education, income, unemployment benefits, disability benefits and parents' education) were significantly related to higher rates of antidepressant prescription.

In this study, we are interested in antidepressant use in Turkey. There are several motivations for our interest in this country. First, about 80 percent of health expenditures are made by the public sector and share of these expenditures in the government budget increased more than 50 percent between 2002 and 2018 (SağlıkAktüel, 2017). According to the IMSHealth data, antidepressant usage increased by 162 percent in 10 years between 2003 and 2012 (Aydın, et al. 2013). In the same period the increase in population was only 14 percent. The possible explanations for soaring use of antidepressants: (1) changes in our social, economic, physical, and natural environment that worsen our mental health, (2) increasing awareness about mental health and decreasing stigma towards mental problems, (3) over-prescription or mal-prescription. As rising health expenditures place a huge burden on the government budget and the spending on pharmaceuticals is a major component of these expenditures, discussions on the issue have emphasized the need for lowering drug expenditures and/or increasing private (out-of-pocket) contributions to health services (Medimagazin, 2012).

Secondly, a report by Turkish Association for Psychopharmacology on the Psychotropic Drug Usage in Turkey states the over-prescription and mal-prescription sales of antidepressants as a major source of the soar in antidepressant sales in Turkey (Aydin et al., 2013). Findings of the study reveals that family physicians and practitioners have prescribed more antidepressants than psychiatrists and neurologists in 2007-2012 period. Regulations that allow all physicians from any discipline to prescribe an antidepressant has made a major contribution to this fact. Antidepressants are an effective tool in treating depression. However, the fact that inappropriate use of antidepressants may trigger other health problems worries policymakers, health experts and related parties as in other countries (Sabah Gazetesi, 2018). Thirdly, despite these concerns, social and economic aspects of antidepressant use have been rarely examined in Turkey.

Given the wide use and prescription of antidepressants that does not necessarily imply physiological malfunctioning, there is vital need to understand the possible role of economic, social, political, environmental as much as personal factors on its growing use. The aim of the current study is to identify economic and social determinants of antidepressant use in Turkey at province level panel data for the period 2012-2017. Turkey is a developing country and an excellent setting to study the rise in antidepressant use. Antidepressant use has been increasing in high-income economies for several decades. If antidepressant use is function of income, then emerging economies will soon experience the same problem. This work studies Turkish data to develop policies for emerging and developing economies to control antidepressant use before it increased. In the second section of the paper, we present a very simple Solowian model towards identifying the role of some major macro variables in antidepressant use. The model assumes that antidepressant use directly increases welfare but steals resources that could be used for capital accumulation. The model shows that long run determinants of income growth also determines antidepressant use. Our panel data analyses show that most SES variables have a significant effect on antidepressant use in Turkey.

The organization of the paper is as follows. In the second section, we present a heuristic attempt of modeling antidepressant use. In the following section, we present the data, methodology, and results. We show that several social, economic and political variables have significant effect on antidepressant use. The last section concludes the work and makes policy suggestions.

2. Theory

This section develops a very simple model in order to understand long run determinants of antidepressant use by using a modified Solowian framework. There are two reasons why Solowian framework has been preferred. First, it is easy to introduce income growth via exogenous technological change, which would be sufficient for our research purposes. Second, the social planner's version of the model is convenient for introducing unemployment, as it does not require any optimization. The drawback of using Solowian framework is that consumption and hence utility is a residual in the model. In that respect, antidepressant use/ demand is not derived from utility maximization but from an exogenous allocation income between competing uses. Details of the model is as follows. Let us suppose that the representative firm's production function Y_t is defined as $Y_t = K_t^{\alpha}(A_t N_t)^{1-\alpha}$, where K_t is physical capital, $N_t = N_0 \cdot e^{nt}$ is the employed stock of labor force, $A_t = A_0 \cdot e^{xt}$ is the labor-augmenting technological progress, $0 < \alpha < 1$ represents the production elasticity of capital, and subscript t is time. We assume that some labor force L_t are unemployed in the model economy and therefore $N_t < L_t$. Given that the fundamental equation of growth implied by the social planner's solution does not imply an optimization, it is legitimate to make this assumption (the competitive solution version of the model would imply the real wage rate determined exogenously and above the equilibrium implied by downward sloping labor demand and vertical labor supply functions at each instant of time). Given that the model does not aim to investigate unemployment but just the role of unemployment on antidepressant use, we prefer to assume constant unemployment in the model. To this end, we assume that total labor stock dynamics is identical to the dynamics of employed labor force, that is, $L_t = L_0 \cdot e^{nt}$. Hence, the unemployment rate, $u_t = \frac{L_t - N_t}{L_t}$ is constant, that is, $u_t = \bar{u} = \frac{N_0}{L_0}$.[1] The saving-investment identity implies that the fundamental equation of growth in per effective capita would be:

[1] We also assume that total population and total labor force are identical.

$$\dot{\tilde{k}}_t = s_K \tilde{k}_t^{\alpha}(1-\bar{u})^{1-\alpha} - (n+\delta+x)\cdot\tilde{k}_t \tag{1}$$

where a dot on top of a variable indicates time derivative of a variable, $\tilde{y} \equiv \frac{Y}{AL}$, $\tilde{k} \equiv \frac{K}{AL}$, s_K is the saving rate for physical capital accumulation, n is the population growth rate, and x is the rate of technological change. We assume that a share of income is spent on antidepressants, $Z_t = s_Z Y_t$, which increases utility. One should note that we use s_Z for matter of notational convenience; otherwise, s_Z is indeed marginal propensity to consume for antidepressants out of total income. In that respect, antidepressants are solely a specified consumption.

The steady state solution of capital per effective capita and output per effective capita are $\tilde{k}_{ss} = \left(\frac{s_K}{n+\delta+x}\right)^{\frac{1}{1-\alpha}}(1-\bar{u})$ and $\tilde{y}_{ss} = \left(\frac{s_K}{n+\delta+x}\right)^{\frac{\alpha}{1-\alpha}}(1-\bar{u})$, where subscript ss represents the steady state. Subsequently, $\tilde{z}_{ss} = s_Z\left(\frac{s_K}{n+\delta+x}\right)^{\frac{\alpha}{1-\alpha}}(1-\bar{u})$. Note that standard Solowian results (without some resources allocated for antidepressants) would be $\tilde{k}_{ss} = \left(\frac{s}{n+\delta+x}\right)^{\frac{1}{1-\alpha}}(1-\bar{u})$ and $\tilde{y}_{ss} = \left(\frac{s}{n+\delta+x}\right)^{\frac{\alpha}{1-\alpha}}(1-\bar{u})$. What are the major implications of the model? First and foremost, compared to no-antidepressant scenario, total utility is augmented by antidepressant consumption:

$$U(c_t, z_t) = L_0 \int_0^{\infty} e^{-\int_0^t r(s)ds}\cdot(c_t+z_t)\cdot e^{nt}dt \tag{2}$$

where c_t and z_t are per capita consumption and per capita antidepressant use, respectively. Equation (2) however does not necessarily imply that overall consumption is higher as positive marginal propensity to consume for antidepressants implies lower marginal propensity to consumption and/or lower saving for capital accumulation. To see this, substitute $C_t = mpc\cdot Y_t$ and $Z_t = s_Z\cdot Y_t$ in the income-expenditure balance, $Y_t = C_t + I_t + Z_t$, which yields $(1-mpc-s_Z)Y_t = I_t$. As $s_K = 1-mpc-s_Z$, it is obvious that either mpc is lower or s_K or both at some combination. Second, for the reason just expressed, it is highly possible that capital accumulation is lower compared to the case with no antidepressant use. Third, per capita antidepressant use increases by income per capita, which grows due to (exogenous) technological change. Fourth, contrary to a priori expectation, higher unemployment rate decreases antidepressant use. Given that the major determinant of antidepressant use is income, we consider a higher unemployment rate lowering antidepressant use a possibility. We will indeed show below that Turkish data supports this idea. Finally, the long run determinants of antidepressant use are as follows:

$$Ln[z_{ss}] = Ln[A_0] + xt + Ln[s_Z] + Ln[1-\bar{u}] + \left(\frac{\alpha}{1-\alpha}\right) Ln[s_K] - \left(\frac{\alpha}{1-\alpha}\right) Ln[n+\delta+x] \quad (3)$$

According to (3), a higher marginal propensity to use antidepressant and marginal propensity to save increases and a higher unemployment rate decreases antidepressant use in the long run.

3. Empirical Analyses

Data

This study uses province level data from Turkey in years 2012-2017. The antidepressant sales data are obtained from IQVIA (formerly known as IMS Health), via personal communication. Our data on the total number of boxes sold in a province include SSRI antidepressants, as well as SNRI antidepressants, antidepressant herbals, mood stabilizers, and all other antidepressants.

Figure 1 below shows a line graph of monthly antidepressant sales in Turkey from May 2012 to April 2018. The data clearly indicates an upward trend -increasing from about 300 thousand boxes per month to over 400 thousand boxes per month- in antidepressant sales in Turkey, as in many other countries across the world.[2]

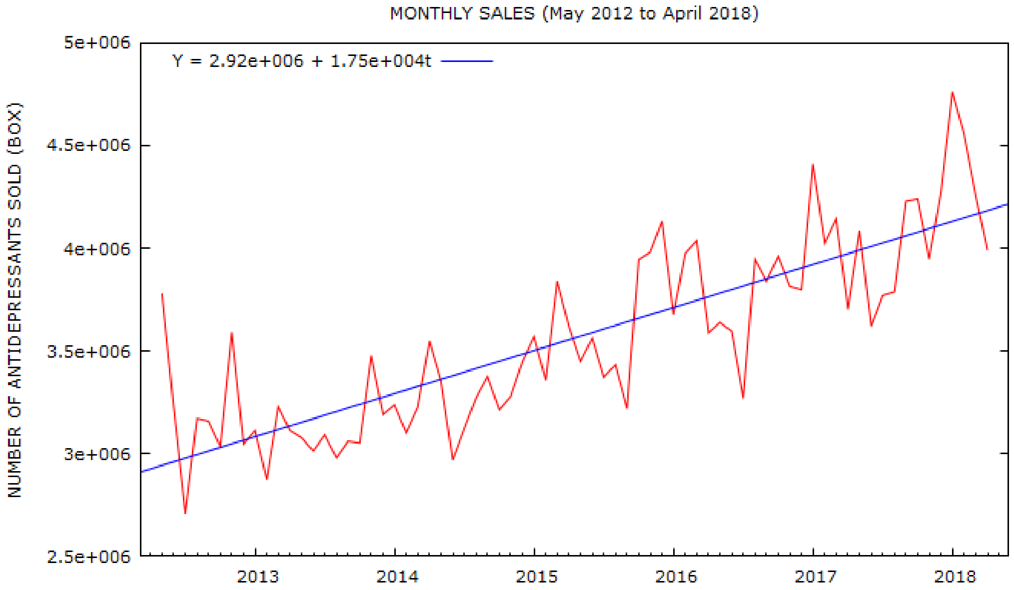

Figure 1: Total antidepressant sales (number of boxes sold) in Turkey

The graph also demonstrates a time trend over the whole range of the dataset in addition to short-term volatility around the trend, which may be related to seasonal factors. Studies in the field of medicine document that mental well-being is influenced by seasons. More specifically, they indicate fewer depression admissions during summer time and fewer antidepressants prescribed in the summer (Gardarsdottir et al., 2010).

Our second data source is the Turkish Statistical Institute (TurkStat) website, from which we obtain data on the economic, social, and demographic characteristics of provinces. These data have annual frequency; therefore, we aggregate monthly drug sales data to calculate annual sales per province. Table 1 lists the variables that are

[2] Consumption of antidepressant drugs has doubled in OECD countries between 2000 and 2015. OECD (2017), *Health at a Glance 2017: OECD Indicators*, OECD Publishing, Paris, https://doi.org/10.1787/health_glance-2017-en.

used in this study. All variables have a yearly frequency and are calculated at the province level.

Table 1: Variable definitions

Variable Name	***Definition***
Boxes	Number of boxes of antidepressants sold per 100 people
Share 65+	Share of the province population in ages 65 and older (%)
Electricity	Total electricity consumption per capita (Kilowatt hours)
Convicted	Number of convicted people per 10 thousand people
Divorced	Number of divorces within the year per 10 thousand people
University	Share of university graduates in the province (%)
Popsqkm	Population per square kilometer
PriceIndex	Price index in the province
Doctors	Number of doctors per 10 thousand people
Migration	Net migration per 1000 people in the province
Unemployed	Number of unemployed people per 10 thousand people
UnivUnempl	Number of unemployed people with a university degree per 10 thousand people
Suicide	Number of suicides per 100 thousand people

Antidepressant sales in a province can be influenced by economic, demographic, and social factors in the province, as well as the availability of health resources (supply related factors) in the province. In other words, the factors that trigger the demand for antidepressants may be related to economic, demographic, health, and social factors. For example, the share of the elderly in the province may be an important determinant, since antidepressants are commonly used to treat depression and the incidence of depression is higher among the elderly.

We would expect the average level of income in the province to have an effect on antidepressant sales. Province-level income data have been estimated by TurkStat, but only up to year 2014. In order not to lose the drug sales data in years after 2014, we turn to an alternative measure of income. We use total electricity consumption per capita as a proxy for average income. We believe that total electricity consumption per capita is a good proxy for income per capita at the province level, since the correlation coefficient between the two variables is 67% (based on 2007-2014 data).

The factors that affect the level of stress are also expected to be correlated with antidepressant sales. Such factors may be the share of the convicted people in the province in a given year or the number of divorces that took place in the province in a given year. The crowdedness of the province or the high cost of living in the province may be other candidates to affect the average stress level in the province. Unemployment may create unhappiness and stress, but it also creates a drop in purchasing power. Migration inflows and outflows may also be related to stress, dissatisfaction with life, and disappointment. Suicide is an outright manifestation of severe depression; therefore, we would like take into account the suicide rate in the provinces in our analyses.

We should mention here that, due to lack of data on unemployment rates (the share of the unemployed in the labor force) by province, our unemployment variable is the share of the unemployed individuals in the population of the province. We can expect the level of average education in the province to be correlated with antidepressant sales. The reason is that better educated people may have higher aspirations and thereby more likely to be disappointed with life. They may also have better information about the availability of drugs. Another reason is that education acts in our framework as a measure of socio-economic status, since we do not have province-level income data for all the years that we study. The supply of health services in the province is another potential factor that can be correlated with antidepressant sales. We use the number of doctors in the province (per 10 thousand people) as an indicator of access to health services.

Table 2 presents the descriptive statistics of the variables in Table 1. All statistics are weighted by province populations.

Table 2. Descriptive Statistics of the Data

Variable	Mean	Std.Dev.	Min	Max
Boxes	53.37	18.97	8.03	123.3
Share 65+	7.64	2.6	2.54	18.16
Electricity	2530.34	1315.09	443.00	8565.00
Convicted	16.64	8.05	1.69	39.12
Divorced	15.77	6.25	0.96	28.12
University	11.46	4.17	2.17	22.41
Popsqkm	599.86	984.53	10	2892
PriceIndex	218.19	54.27	130.13	330.03
Doctors	16.96	6.06	5.95	39.40
Migration	0.04	9.28	-118.97	121.52
Unemployed	0.94	0.91	0.18	10.59
UnivUnempl	0.17	0.18	0.01	2.14
Suicide	4.04	1.24	0.61	16.65

Note: Max., Min. and Std. Dev. denote maximum, minimum and standard deviation, respectively.

As evident from Table 2, there is substantial variation in the data for all variables.

Method

This study uses province level panel data from Turkey for the period 2012-2017 to understand the determinants of antidepressant sales. We estimate the following models:

<u>Model 1</u>: Seasonal trends in antidepressant sales

Figure 1 indicated that there might be a seasonal pattern in the data. For this reason, we first examine seasonal patterns of antidepressant sales in Turkey. We tested the data for stationarity applying the augmented Dickey-Fuller test. In order to distinguish statistically significant changes from random fluctuations, we regressed changes in antidepressant sales (Δy) against seasonal dummies (D) by using the following deterministic model:

$$\Delta y_t = \sum_{i=1}^{12} \beta_i D_{it} + \varepsilon_t, \qquad (4)$$

where β_i are the monthly mean of changes in antidepressant sales and ε_t is a white-noise error term.

Model 2: Panel data estimation

$$y_{it} = \alpha + x_{it}' \beta + \delta_1 C_i + \delta_2 T_t + \varepsilon_{it}, \quad (5)$$

where, y_{it} is the antidepressant consumption per person per year in province i in year t; x_{it} is a vector of the explanatory variables and β is the corresponding vector of coefficients. Table 1 lists the definitions of the variables that we use in the estimation of Model 2. We exclude the suicide rate from the model because of concerns for endogeneity of the variable with antidepressant sales.

In equation (5), C_i and T_t are province-specific and year-specific fixed effects that are used in the model to statistically control for province- and time-specific unobserved variables (Wooldridge, 2002). The explanatory variables in equation (5) are measured in different units. To ease the interpretation of the estimates, we choose to standardize the variables so that the coefficient estimates tell us the effect of a one standard deviation change in an explanatory variable on sales.

Model 3: Dynamic panel data estimation

$$y_{it} = \alpha + \theta y_{i,t-1} + x_{it}' \beta + u_{it}, \quad (6)$$

$$u_{it} = \mu_i + v_{it} \quad (7)$$

$$E(\mu_i) = E(v_{it}) = E(\mu_i v_{it}) = 0 \quad (8)$$

In this model, the lagged dependent variable is in the set of explanatory variables. The error term in equation (6) has two orthogonal components: the province fixed effects, μ_i, and the idiosyncratic shocks, v_{it}. Both the error term, u_{it}, and the lagged dependent variable contain the province fixed effect, μ_i. Therefore, the lagged dependent variable is correlated with the error term; hence, the OLS estimates obtained from equation (6) will be inconsistent. We do not have an instrument for $y_{i,t-1}$ in our dataset. Since the longer lags of the dependent variable contain the fixed effect, they will also be correlated with the error term; therefore, they cannot be used as instruments. To solve the problem, equation (6) can be rewritten as a model of the change in antidepressant sales over time:

$$\Delta y_{it} = y_{it} - y_{i,t-1} = \theta \Delta y_{i,t-1} + \Delta x'_{it} \beta + \Delta v_{it}. \qquad (9)$$

With the transformation, the province fixed effects disappear. In this new model, $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ is correlated with the $v_{i,t-1}$ term in $\Delta v_{it} = v_{it} - v_{i,t-1}$. However, under the assumption of no serial correlation in v_{it}, the longer lags of the explanatory variables are orthogonal to the error term; hence, they are available as instruments.

We estimate the dynamic panel data model (equation (9)) by using the Generalized Method of Moments (GMM), with the help of the 'xtabond2' command in Stata. The command requires the user to specify which variables are exogenous, which are predetermined (and potentially endogenous), and which are endogenous. We assume that Share 65+, Popsqkm, PriceIndex, Electricity, University, and Migration are exogenous explanatory variables. We consider Convicted, Divorced, Doctors, Unemployed, and UnivUnempl as predetermined variables in the regression. We think Suicide is endogenous to antidepressant sales; hence, we treat that variable as such.

Roodman (2006) explains that the estimation of the standard errors of the coefficients in this model assumes that there is no correlation across provinces in the idiosyncratic disturbances. Time dummies make this assumption more likely to hold. We follow his suggestion and add year dummies to the model.

Findings

Given the visible trend in the antidepressant sales data, we first tested the data for stationarity. The augmented Dickey-Fuller test indicated that antidepressant sales data have a non-stationary random walk pattern. The data are then transformed to a stationary process by differencing. Figure 2 below depicts the means of first-order differenced antidepressant sales by month. The figure indicates, on average, a downward change in sales in February, April, June, July and December, and an upward change in the reverse manner in the other months. The figure also shows that the biggest drop in sales appears in June.

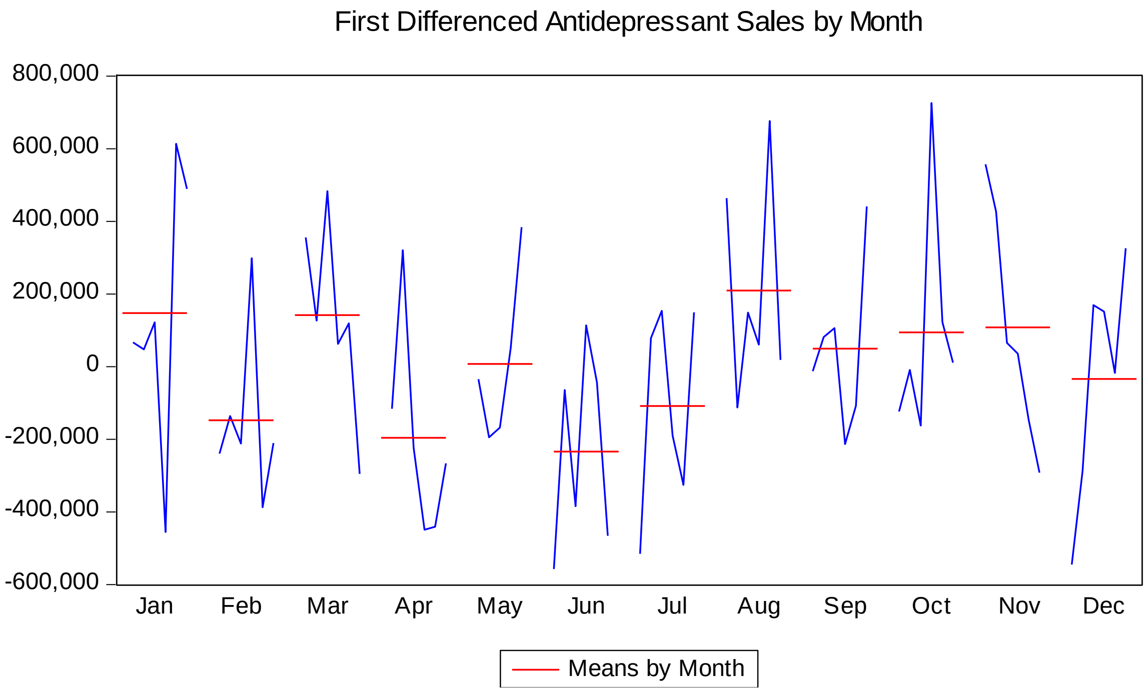

Figure 2: First-differenced antidepressant sales data by month

We estimate Model 1 (equation (4)) and obtain the results that are shown in Table 3. As can be easily seen, the change in antidepressant sales in April[3] and June are negative, while it is positive in August. In particular, the drop in antidepressant sales is obvious in the beginning of the summer. These findings are consistent with the patterns in other parts of the world.

[3] By slightly relaxing level of significance

Table 3: Estimates from Model (1): Seasonal Patterns

Dependent Variable: Change in Antidepressant Sales
Method: Least Squares
Date: 11/21/18 Time: 17:25
Sample (adjusted): 2012M06 2018M04
Included observations: 71 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
January	147005.5	119136.4	1.23	0.22
February	-147783.2	119136.4	-1.24	0.22
March	141800.5	119136.4	1.19	0.24
April	-195918.0	119136.4	-1.64	*0.11
May	7388.400	130507.4	0.06	0.95
June	-233882.3	119136.4	-1.96	***0.05
July	-108289.7	119136.4	-0.91	0.37
August	209048.2	119136.4	1.75	**0.08
September	49086.67	119136.4	0.41	0.68
October	94010.00	119136.4	0.79	0.43
November	107805.3	119136.4	0.90	0.37
December	-33885.00	119136.4	-0.28	0.78

R-squared	0.219880	Mean dependent var	2970.845
Adjusted R-squared	0.074434	S.D. dependent var	303330.8
S.E. of regression	291823.5	Akaike info criterion	28.15857
Sum squared resid	5.02E+12	Schwarz criterion	28.54100
Log likelihood	-987.6293	Hannan-Quinn criter.	28.31065
Durbin-Watson stat	2.740045		

Notes: *, **, ***, and **** denote significance levels at 15%, 10%, 5%, and 1%, respectively.

Table 4 presents the ordinary least squares (OLS) regression results that we obtain from estimating Model 2. The coefficient estimates are beta estimates (i.e. they show us the standard deviation change in antidepressant sales associated with a one standard deviation change in the explanatory variable). The p-values of the estimates are shown in parentheses. Regressions shown in columns (1) and (2) of the table control for our full list of socio-economic, demographic, and health-supply related variables. In the table, we use stars to mark the level of statistical significance at 1%, 5%, 10%, and 15%.

We find that a one-standard deviation (2.6 percentage point) increase in the population share of the elderly is associated with about 0.5 standard deviation (18.97*0.5 = 9.49 percentage point) increase in sales. Electricity consumption per capita is also positively and statistically significantly associated with sales, but with a much smaller magnitude of effect on sales. The other variables with a statistically significant positive effect are convictions, population per area, net migration rate, and the number of doctors. The number of unemployed people has a negative effect on antidepressant sales, as predicted by our theoretical model. Here, we should emphasize that our variable is not the unemployment rate but the share of the unemployed in the population. We test our results by using a different unemployment variable (the number of unemployed people who are university graduates) in column (2), and confirm that the results are basically the same.

Column (3) adds the year fixed effects to show that there is a statistically significant increase in sales in years 2015 and 2016, relative to 2012 (the base year). Column (4) adds province-level fixed effects. Full results are presented in Appendix Table 1. We find that, compared to İstanbul (the business center of the country), almost all provinces (with the exceptions of Trabzon and Urfa) have lower antidepressant sales. A number of province fixed effects (Sırnak, Van, Rize, Samsun, Adana, and Yalova) have low level of statistical significance (at 15%). When province fixed effects are controlled for, the share of the elderly, the number of divorces per capita, the share of university graduates are found to have a positive and statistically significant effect in the regression. Once again, the number of unemployed people have a small and negative effect on antidepressant sales.

Table 4: The Determinants of Antidepressant Use, 2012-2017 (Model 2)

	(1)	(2)	(3)	(4)
Share 65+	0.514****	0.524****	0.503****	1.025****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Electricity	0.140****	0.141****	0.137****	0.026
	(0.0000)	(0.0000)	(0.0000)	(0.6285)
Convicted	0.126***	0.121***	0.179****	0.032
	(0.0104)	(0.0142)	(0.0009)	(0.2652)
Divorced	0.099*	0.115**	0.056	0.131***
	(0.1301)	(0.0772)	(0.4127)	(0.0122)
University	0.158**	0.142**	0.192***	0.253***
	(0.0676)	(0.0992)	(0.0296)	(0.0433)
Popsqkm	0.305****	0.313****	0.327****	-0.447
	(0.0000)	(0.0000)	(0.0000)	(0.2345)
PriceIndex	-0.024	-0.010	-0.343***	0.130
	(0.6177)	(0.8270)	(0.0190)	(0.2951)
Doctors	0.126***	0.142***	0.134***	0.014
	(0.0283)	(0.0128)	(0.0219)	(0.8094)
Migration	0.090***	0.092***	0.093****	0.012
	(0.0115)	(0.0101)	(0.0078)	(0.2806)
Unemployed	-0.099****		-0.109****	-0.080****
	(0.0009)		(0.0002)	(0.0038)
UnivUnempl		-0.085****		
		(0.0044)		
year=2012 (base year)			-	-
year=2013			-0.031	-0.113****
			(0.5438)	(0.0002)
year=2014			0.051	-0.186****
			(0.5558)	(0.0040)
year=2015			0.202*	-0.192**
			(0.1052)	(0.0530)
year=2016			0.296**	-0.230**
			(0.0820)	(0.0922)
Province fixed effects	No	No	No	Yes
Observations	395	395	395	395
Adjusted R-squared	0.739	0.736	0.748	0.987

Notes: Standard errors are in parentheses. *, **, ***, and **** denote significance levels at 15%, 10%, 5%, and 1%, respectively.

With the introduction of province-level fixed effects to the regression (column (4)), we no longer observe an increase in sales over time. Hence, earlier results may be subject to omitted variable bias. The results indicate the importance of province level characteristics in antidepressant sales. Moreover, the results in column (4) point to a decrease in sales in the years after 2012, with respect to the base year of 2012. This finding, which may be contradictory at first sight, and having seen the trend in Figure 1, might be explained by a government decree released in March 2013 that warns pharmacies not to sell antidepressants without a valid prescription (İstanbul Chamber of Pharmacists, 2013). The decree may have had a negative effect on antidepressant sales. News in the press suggest that some pharmacists took the decree rather seriously and applied it even to medications that can be sold without a prescription (Milliyet, 2013). Without any doubt, we have to recognize that the lack of sales data for years prior to 2012 may weaken our explanation.

Table 5 presents the ordinary least squares (OLS) regression results that we obtain from estimating Model 3. The columns of the table present the estimation results for different specifications. Since the model requires the calculation of time differences, the number of observations is inevitably reduced. The lagged dependent variable (Boxes(t-1)) is statistically significant with a coefficient estimate of about 0.4-0.6. The other explanatory variables that are found to have a statistically significant effect are the share of the elderly (ages 65+) population and the share of the university graduates in the population. This result is consistent with the results obtained from Model 2.

Table 5: The Determinants of Antidepressant Use, Dynamic Model, 2012-2017 (Model 3)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Boxes(t-1)	0.401****	0.463****	0.409****	0.443****	0.519****	0.479****	0.642****
	(0.0001)	(0.0011)	(0.0003)	(0.0001)	(0.0000)	(0.0003)	(0.0000)
Share 65+	5.298****	4.931****	4.613***	4.453****	4.105****	5.156****	3.342***
	(0.0021)	(0.0024)	(0.0121)	(0.0068)	(0.0005)	(0.0001)	(0.0163)
Electricity	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.8094)	(0.8639)	(0.9676)	(0.9020)	(0.9457)	(0.9488)	(0.8762)
Convicted	0.044	-0.038	-0.030	-0.137	-0.081	-0.047	-0.015
	(0.7236)	(0.8041)	(0.8684)	(0.4312)	(0.6271)	(0.7495)	(0.9187)
Divorced	0.213	-0.029	-0.085	-0.105	-0.196	0.008	
	(0.4167)	(0.9210)	(0.7579)	(0.7076)	(0.3974)	(0.9699)	
University	2.564****	2.494***	2.548****	2.803***	2.623****	2.898****	3.084****
	(0.0096)	(0.0116)	(0.0039)	(0.0130)	(0.0006)	(0.0017)	(0.0000)
Popsqkm	-0.007	-0.006	-0.008	-0.002			
	(0.6065)	(0.6218)	(0.5648)	(0.8897)			
PriceIndex	0.141	0.184	0.179	0.226	0.168		
	(0.3524)	(0.1945)	(0.4031)	(0.2602)	(0.3076)		
Doctors	0.144	0.171	0.101	-0.043		-0.172	
	(0.7052)	(0.6082)	(0.7947)	(0.8978)		(0.4126)	
Migration	0.024	0.011	0.009		0.015		
	(0.4352)	(0.7098)	(0.7965)		(0.6530)		
Unemployed	-1.228	-0.309					
	(0.2328)	(0.7278)					
Suicide	0.042	0.160	0.205	0.356	0.350	0.236	0.379
	(0.8591)	(0.5169)	(0.5094)	(0.3350)	(0.2813)	(0.4475)	(0.1982)
UnivUnempl	2.105		-2.873				
	(0.5838)		(0.5249)				
Observations	236	236	236	236	243	236	243
# Instruments	192	144	144	119	95	117	69
A-B test for AR(1)	0.026	0.018	0.029	0.023	0.019	0.027	0.016
A-B test for AR(2)	0.153	0.111	0.194	0.162	0.092	0.194	0.075
Hansen test	0.920	0.899	0.901	0.842	0.098	0.920	0.011

Notes: The reported test statistics are for the Arellano-Bond test and the Hansen test for overidentifying restrictions. Standard errors are in parentheses. *, **, ***, and **** denote significance levels at 15%, 10%, 5%, and 1%, respectively.

Table 5 also reports the statistics for some tests. The Arellano-Bond test for autocorrelation in the error term shows that we can reject the null hypothesis that there is no first-order autocorrelation. Since Δv_{it} is mathematically related to

$\Delta v_{i,t-1}$ via the shared $v_{i,t-1}$ term, negative first-order serial correlation is already expected in differences and finding evidence for its existence (for AR(1)) is not interesting. Thus, we check for second-order correlation in differences, on the idea that this will detect correlation between the $v_{i,t-1}$ in Δv_{it} and the $v_{i,t-2}$ in $\Delta v_{i,t-2}$. On the other hand, in most of the regressions, we cannot reject that there is no second-order serial correlation (AR(2)). Therefore, there is no evidence for serial correlation in levels; hence, the assumption of Model 3 is satisfied and the longer lags of the explanatory variables are available as instruments.

The Hansen test statistic for overidentifying restrictions has a high p-value in many regressions, which means that the number of instruments may be large relative to the number of observations. This is not surprising, since our sample is not very large. Based on the Hansen test statistic, we would be more confident with the specifications in columns (5) and (7). Nevertheless, the coefficient estimates do not vary much across columns.

4. Concluding Remarks and Policy Implications

The use of antidepressants has become progressively more common in many countries over the last three decades. Earlier studies have shown that in Turkey, antidepressant use increased by 162 percent in 10 years between 2003 and 2012. For comparison, population increased by only 14 percent in the same period. The possible explanations for soaring use of antidepressants have been identified as: (1) changes in our social, economic, physical, and natural environment that worsen our mental health, (2) increasing awareness about mental health and decreasing stigma towards mental problems, (3) over-prescription or mal-prescription. As rising health expenditures place a huge burden on the government budget and the spending on pharmaceuticals is a major component of these expenditures, discussions on the issue have emphasized the need for lowering drug expenditures and/or increasing private (out-of-pocket) contributions to health services. Important for our study, despite these concerns, social and economic aspects of antidepressant use have been rarely questioned and examined in Turkey.

This paper studies the socio-economic determinants of antidepressant use in Turkey, using province level panel data for the period 2012-2017. We build a simple theoretical model, which implies that total utility is augmented by antidepressant consumption, per capita antidepressant use increases by income per capita, and contrary to a priori expectation, a higher unemployment rate decreases antidepressant use.

The dataset that includes province level antidepressant sales and socio-economic characteristics allows us to test three different models: First, a model that uses monthly sales data to test for seasonality in sales; second, a panel data model on province level annual data; and third, a dynamic panel data model, again on province level annual data.

The first model shows us that there is a fall in antidepressant sales in the spring and summer, followed by an increase at the end of the summer, which indicate a seasonal pattern, similar to the pattern seen in the other parts of the world.

The estimation of the two panel data models shows us that several socio-economic variables are indeed correlated with antidepressant sales in the provinces: The share of the elderly (ages 65+), the number of divorces per capita, the share of university graduates are found to have a positive and statistically significant effect; the number of unemployed people have a small and negative effect on antidepressant sales.

As a final comment, evidence suggests that the government decree, released in March 2013, which warns pharmacies not to sell antidepressants without a valid prescription may have reduced or have controlled the surge in antidepressant sales.

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Appendix:

Appendix Table 1: Full results of Model 2. Standardized beta coefficients. (The specification is the same as that in Table 4, column (4))

Variable:	Coefficient	P-value	Variable:	Coefficient	P-value
Share 65+	1.025****	(0.0000)	Kahramanmaras	-0.226***	(0.0212)
Electricity	0.026	(0.6285)	Osmaniye	-0.113**	(0.0957)
Convicted	0.032	(0.2652)	Kirikkale	-0.195****	(0.0002)
Divorced	0.131***	(0.0122)	Aksaray	-0.205****	(0.0004)
University	0.253***	(0.0433)	Nigde	-0.199****	(0.0003)
Popsqkm	-0.447	(0.2345)	Nevsehir	-0.188****	(0.0002)
PriceIndex	0.130	(0.2951)	Kirsehir	-0.180****	(0.0001)
Doctors	0.014	(0.8094)	Kayseri	-0.330****	(0.0047)
Migration	0.012	(0.2806)	Sivas	-0.272****	(0.0000)
Unemployed	-0.080****	(0.0038)	Yozgat	-0.172****	(0.0000)
year=2012	0.000	(.)	Zonguldak	-0.154***	(0.0236)
year=2013	-0.113****	(0.0002)	Bartin	-0.126****	(0.0009)
year=2014	-0.186****	(0.0040)	Kastamonu	-0.341****	(0.0000)
year=2015	-0.192**	(0.0530)	Çankiri	-0.253****	(0.0000)
year=2016	-0.230**	(0.0922)	Sinop	-0.229****	(0.0000)
Istanbul	0.000	(.)	Samsun	-0.158*	(0.1289)
Tekirdag	-0.166**	(0.0659)	Tokat	-0.305****	(0.0000)
Edirne	-0.173****	(0.0047)	Çorum	-0.368****	(0.0000)
Kirklareli	-0.181****	(0.0010)	Amasya	-0.261****	(0.0000)
Balikesir	-0.366****	(0.0002)	Trabzon	-0.025	(0.7635)
Çanakkale	-0.278****	(0.0001)	Ordu	-0.254****	(0.0006)
Izmir	-0.435***	(0.0207)	Giresun	-0.174****	(0.0033)
Aydin	-0.306****	(0.0011)	Rize	-0.081*	(0.1314)
Denizli	-0.278****	(0.0032)	Artvin	-0.194****	(0.0000)
Mugla	-0.265****	(0.0045)	Gümüshane	-0.155****	(0.0000)
Manisa	-0.289****	(0.0057)	Erzurum	-0.302****	(0.0009)
Afyonkarahisar	-0.298****	(0.0001)	Erzincan	-0.210****	(0.0000)
Kütahya	-0.302****	(0.0000)	Bayburt	-0.112****	(0.0001)
Usak	-0.209****	(0.0001)	Agri	-0.157***	(0.0389)
Bursa	-0.281**	(0.0606)	Kars	-0.192****	(0.0005)
Eskisehir	-0.219***	(0.0209)	Igdir	-0.113***	(0.0112)
Bilecik	-0.145****	(0.0011)	Ardahan	-0.166****	(0.0000)
Kocaeli	-0.230***	(0.0496)	Malatya	-0.313****	(0.0004)
Sakarya	-0.192***	(0.0268)	Elazig	-0.220****	(0.0037)
Düzce	-0.158****	(0.0049)	Bingöl	-0.157****	(0.0027)
Bolu	-0.212****	(0.0001)	Tunceli	-0.157****	(0.0000)
Yalova	-0.068*	(0.1280)	Van	-0.173*	(0.1104)
Ankara	-0.550***	(0.0356)	Mus	-0.145***	(0.0267)
Konya	-0.427****	(0.0024)	Bitlis	-0.140***	(0.0210)
Karaman	-0.141****	(0.0025)	Hakkari	-0.095**	(0.0947)
Antalya	-0.299**	(0.0518)	Gaziantep	-0.210**	(0.0924)
Isparta	-0.175****	(0.0076)	Adiyaman	-0.223****	(0.0030)
Burdur	-0.191****	(0.0001)	Kilis	-0.083***	(0.0194)
Adana	-0.227*	(0.1162)	Sanliurfa	-0.185	(0.1711)
Mersin	-0.262***	(0.0403)	Diyarbakir	-0.288***	(0.0279)

Hatay	-0.236***	(0.0322)	Mardin	-0.190***	(0.0267)
			Batman	-0.136**	(0.0720)
			Sirnak	-0.111*	(0.1201)
			Siirt	-0.113**	(0.0511)
			Observations	395	
			Adjusted R2	0.987	

Notes: Standard errors are in parentheses. *, **, ***, and **** denote significance levels at 15%, 10%, 5%, and 1%, respectively.