Mental Health Stigma *

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Abstract

Comparing self-reports to administrative data records on diagnosis and prescription drug use, we find that survey respondents under-report mental health conditions 36% of the time when asked about diagnosis and about 20% of the time when asked about prescription drug use. Survey respondents are significantly less likely to under-report other conditions such as diabetes or hypertension. This behavior is consistent with a model in which mental health illnesses are stigmatized and agents have incentives to hide such traits from others. We show that differential under-reporting of depression is correlated with age, gender, and ethnicity and that these characteristics also predict a lower probability of mental health treatment, suggesting that stigma can play an important role in determining health-seeking behavior.

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1 Introduction

The fear of being stigmatized or socially sanctioned and disgraced governs many aspects of human behavior. In many cases, the fear of stigma does not result in actual behavior change but rather leads individuals to simply hide certain behaviors or actions (for example, smoking in secrecy). This is in line with the definition of stigma in the seminal work on the topic by Goffman (1963): i.e., that stigma results in a "spoiled identity," which is the result of a deviance from social norms, and therefore leads an individual to be discredited by society. In this instance, "the social label of deviance compels stigmatized individuals to view themselves and others to view the stigmatized as discredited or undesirable" (Mahajan, Sayles, Patel, Remien, Ortiz, Szekeres, and Coates, 2008). Because fear of stigma leads individuals to hide their behaviors or characteristics, empirically quantifying the existence of stigma poses a challenge. Despite the centrality and importance of stigma in influencing human behavior, formal treatments of it in economics have been limited.[1] However, it is commonly agreed that stigma exists and influences behavior in many spheres.

We show the existence and consequences of stigma in an important area of public health concern: mental health. In 2012, 18.6 percent of all U.S. adults had a recent mental illness;[2] the prevalence of mental illness is similar in other developed countries. Studies show that public knowledge about mental health illnesses has recently increased, but considerable stigmatization of individuals with mental health illnesses remains; for example, mental illness is ranked near the bottom of other illnesses in terms of public acceptance (Hinshaw, 2007). As a result, the negative effects of stigma have been hypothesized to be as harmful as the direct effect of mental disorder (Hinshaw, 2007). According to the U.S. Surgeon General report, stigma is the main barrier to mental health care: "It deters the public from seeking, and wanting to pay for, care" (U.S. Department of Health and Human Services, 1999). Hence, stigma could prevent individuals from seeking care, leading to more intense (and perhaps less successful) and expensive treatment options later (Kupfer, Frank, and Perel, 1989).

[1] The papers that do examine stigma have largely concentrated on explaining low program take-up in cases where there are obvious benefits to individuals like welfare and food stamps (Moffitt, 1983; Besley and Coate, 1992; Blumkin, Margalioth, and Sadka, 2014). Despite the large literature in this area, it is difficult to formally test the stigma hypothesis as there are competing explanations for low program take-up, such as transaction costs or information constraints (see Currie (2004) for an excellent review). A small theoretical literature has examined the role of stigma in shaping individual behavior in issues such as crime and divorce (Furuya, 2002; Blume, 2002; Ishida, 2003).

[2] http://www.nimh.nih.gov/health/statistics/prevalence/ any-mental-illness-ami-among-adults.shtml

In line with Goffman's definition of stigma, we build a simple model in which agents that have traits that are stigmatized by society want to hide these traits from others.[3] In particular, agents face costs if traits that are stigmatized are revealed publicly, but they also face costs for not reporting truthfully. However, in each situation where the agent is asked about whether she has a certain stigmatized condition (an example is a survey), she is unable to determine whether her answer will be made public (i.e., privacy concerns). Hence, coarse perception regarding the cost of truthful reporting can generate relatively greater misreporting for traits that are stigmatized, even on surveys where anonymity is assured.[4] We show evidence of this "hiding" behavior for mental health problems by comparing survey self-reports on diagnoses and mental health drug use to administrative data on prescription drug use. While there could be various drivers for the differences between survey self-reports and administrative data, our leading explanation is that if mental illnesses were not stigmatized, the difference between self-reported survey responses and objective administrative records should be statistically similar to other diseases. Our operational definition of stigma is quite broad, and aggregates causes such as shame, guilt, self image, and concerns for social discrimination, but we are able to specifically separate out labor market discrimination concerns.

We find that approximately 36% of individuals whom we observe with a diagnosis of depression self-report as not having a mental disorder. The degree of misreporting is lower when individuals self-report prescription drug use for depression (20%). In contrast, people under-report other diagnoses, such as cardiovascular diseases and diabetes, about 17% of the time (14% in the case of self-reported prescription drug use). These differences are statistically significant. Our sample is unique in that about 25% of the population are migrants to Australia. When examining the degree of under-reporting by country of origin, our results suggest that individuals from Asia and the Middle East are more likely to under-report relative to individuals from Northern Europe or the Americas. There is also a steep age gradient in misreporting, with older people more likely to misreport than younger people. Males are more likely to misreport compared to females.

[3] Our model is adapted to the survey setting, but is comparable to the public good contribution model of Benabou and Tirole (2011).

[4] Our results are also evidence of stigma if we alternatively assume that agents are fully aware of the costless nature of the survey (that no one will ever re-identify the agent's responses to the survey). In this case, misreporting on a survey is driven by self-image issues, which ultimately are generated by a notion of stigma (see, for example, Bénabou and Tirole (2011) on self-signaling and self-image). Under this assumption, we are unable to distinguish between self-image and stigma because our data does not allow us to assess individual perceptions over the costliness of the surveys. We develop this idea more formally in Section 2.

We provide suggestive evidence that stigma is likely to play a role in the decision to seek treatment by examining the characteristics of people who self-report as having mental health issues according to a commonly used measure (the Kessler Psychological Distress scale), but do not seek mental health treatment in the subsequent 12 months. The overlap of socioeconomic and demographic characteristics that predict both under-reporting conditional on seeking care and not seeking care conditional on a high probability of having mental health problems, is suggestive of the role that stigma plays in preventing health care seeking.

We recognize that not all forms of hiding behavior or trait concealment are the result of stigma. For example, individuals might lie on a survey given by an employer by showing extra years of experience or misreporting other information, including mental health history, to get a higher wage or a promotion. This sort of strategic reporting could be motivated by an individual's concern of stigma as well as labor market discrimination (if persons with a mental health disorder are indeed less productive on the job). Our results are interpretable as evidence of stigma in mental health if we assume that the labor market discrimination motive in misreporting is similar across various diseases, such as diabetes or hypertension; hence, the *relative* excess misreporting in mental health is evidence of stigma. Importantly, our sample consists of a large number of nonemployed individuals, mainly retirees, for whom we can plausibly claim that the labor market discrimination motive is weak; hence, for this subsample, our reliance on the homogeneity of the labor market discrimination motive is mitigated.

There could also be a general concern about survey reporting error that is driven by inattention, recall, lack of clear communication between doctors and patients etc. (see Bound, Brown, and Mathiowetz (2001) for a comprehensive list). Such general explanations for differences in survey and administrative data records leads us to test a few observations. First, these general explanations might result in *all* diseases and conditions being under-reported to a similar extent. This is contradicted by the data. Second, differential misreporting remains when we change the recall window over which we compare survey reports to administrative data, suggesting that simple recall issues are not driving our results. Third, our results are robust to analysis that is akin to a fixed-effect model: an individual who is treated for *both* cardiovascular disease and depression, for example, is much more likely to under-report his mental health condition relative to his heart condition. Fourth, doctor fixed effects regressions leave the results largely unchanged; hence, doctor-specific communication strategies are not driving our results. Finally, while some anti-depressants might be used for conditions other than depression, institutional insurance reasons and other robustness tests that we pursue suggest that this is extremely unlikely to be driving our results.

Our work complements a recent set of papers in economics that focus on stigma in the case of Human Immunodeficiency Virus (HIV) (Thornton, 2008; Derksen, Muula, and van Oosterhout, 2014; Hoffmann, Fooks, and Messer, 2014; Ngatia, 2011).[5] Using randomized control trials, these papers highlight the role of incentives, information, and social networks in understanding and mitigating the negative consequences of HIV-related stigma. We add to the economic literature on health-related stigma by showing the existence of stigma in mental health using administrative data and by directly showing "hiding" behavior, which is one of the consequences of stigmatized traits. Our results on heterogeneity in hiding (under-reporting) and how stigma might affect health-seeking behavior are additional contributions in this space.

Our paper is also related to other papers that match self-reported health measures to administrative health records. An excellent example of such work is Baker, Stabile, and Deri (2004) where self-reports of specific ailments are compared to administrative medical records in Canada to better understand the use of self-reported "global wellbeing" measures. However, the data they use does not contain information on mental health, nor do they have self-reported data on prescription drug use, both of which are central to our analysis. More recently, work by Johnston, Propper, and Shields (2009) shows misreporting in hypertension using data from England. However, it is unclear in their study whether there is any strategic or stigma-driven misreporting; because the objective measures of hypertension are gathered *after* self-reports of hypertension have been collected, individuals may not be aware of hypertension, as it is often asymptomatic (Johnston, Propper, and Shields, 2009). In a review of papers comparing self-reports to medical data, Harlow and Linet (1989) find that most papers focus on reproductive health; no examples of such comparisons in the mental health space are cited.

Finally, our paper is also related to the literature examining the degree of misreporting in other government programs and in surveys in general.[6] In a general review of measurement error in surveys, Bound, Brown, and Mathiowetz (2001) discuss the possibility of "social desirability" influencing how data could be misreported. Thus, our paper adds evidence to this literature on measurement error in surveys by providing evidence on misreporting along an important variable of public health concern; by contrasting with other diseases, we

[5] There is certainly a broader, multidisciplinary set of papers on the issue of stigma in HIV. See Mahajan, Sayles, Patel, Remien, Ortiz, Szekeres, and Coates (2008) for an excellent review.

[6] Almada, McCarthy, and Tchernis (2015) provide some excellent examples of such work in the case of the Supplemental Nutrition Assistance Program (SNAP). For example, Marquis and Moore (2010) show the extent of under-reporting of SNAP receipt in the Survey of Income and Program Participation (SIPP) by comparing self-reports to administrative records. See also Meyer, Mok, and Sullivan (2009) for measures of under-reports in other transfer programs in the United States.

also posit a possible mechanism (stigma) for systematic excess under-reporting for socially undesirable traits. In that sense, this paper is related to the literature seeking to document and understand social desirability bias using other methods in different settings (Coffman, Coffman, and Ericson, 2013).

2 Misreporting due to stigma

We construct a simple model of stigma and choices in the face of stigma. Each individual i *privately* observes whether he has a designated condition. We denote $b_i = 0$ if individual i does not have the condition, and $b_i = 1$ if he has the condition.

The individual is faced with one of multiple situations (surveys) in which he is queried about his status with respect to this condition. We denote the set of possible situations by S, and a specific situation by s_j. The cardinality of S, denoted $|S|$, is at least 2. We assume that any one of these situations is equally likely—i.e., each of these situations occurs with probability $\frac{1}{|S|}$.[7]

The individual is free to misreport his status. Denote the response of the individual by $\hat{b}_i$. This response may either be publicly revealed, or not. If the individual is in situation s_j, his response $\hat{b}_i$ is publicly revealed if a variable r_j that he does not observe equals 1, and is not revealed if this variable equals 0. There is a true probability $\pi_j \in [0, 1]$ that $r_j = 1$. This probability is a composite assessment of the probability of several possibilities that the individual must consider: the probability that the report in the situation is explicitly made public (for example, an answer to a question in a public forum is overheard), the possibility that even an anonymous response is later re-identified, etc.[8]

The individual's ex-post payoff is a function of his private type b_i, his reported type $\hat{b}_i$, and whether his report is revealed; i.e., r_j—formally, we denote his ex-post payoff by $u_i(\hat{b}_i, b_i, r_j)$. Because the individual does know the realization of r_j at the time he makes his report, and instead only knows the situation he is in, we denote by $U_i(\hat{b}_i, b_i, s_j)$ his assessment of his options in situation s_j, given the fact that his true status is b_i.

We make three assumptions about the agent's payoffs. The first two assumptions structure how the agent evaluates ex-post outcomes (u_i), while the final assumption concerns how he aggregates these ex-ante (U_i).

[7] It is straightforward to generalize this to cover other distributions.

[8] See the survey by Heffetz and Ligett (2014) for several famous instances of the latter.

Firstly, we assume that having the condition is "stigmatic." In other words, we assume that if the individual reports having the condition ($\hat{b}_i = 1$) and this report is revealed publicly ($r_j = 1$), then the individual suffers some cost $c_i > 0$. This cost is a reduced form assessment of the individual's perception of harm that he will suffer if his report of having this condition is revealed.

We posit two sources of cost—the first, c_i^d, is his assessment of the cost of labor market discrimination he would suffer—e.g., reduced/lost wages, forgone employment opportunities etc. The second, c_i^s, is stigma—e.g., psychological cost (embarrassment, lost prestige, etc.) or social (the fact that the individual suffers this condition becomes a part of his identity, causing losses during interactions with other individuals, as outlined in Akerlof and Kranton (2000)). To this end we can decompose

$$c_i = c_i^d + c_i^s. \tag{1}$$

Secondly, we assume that lying is costly to the individual. In other words, if the individual reports $\hat{b}_i \neq b_i$, he suffers a cost d_i. This cost in turn can be interpreted in two ways. The first is that this cost is purely psychological—i.e., it is a cost of the cognitive dissonance that results from misreporting one's true status.[9] The second is akin to c_i—i.e., just as c_i is the individual's assessment of the cost when he has the condition, d_i is the social cost that will accrue to him were it revealed that he had misreported his condition status. We are agnostic here as to the source of this cost—though, as we show below, it is important for our interpretation that $d_i > 0$.

Note that these two assumptions amount to

$$u_i(\hat{b}_i, b_i, r_j) = -c_i \chi_{\{\hat{b}_i = r_j = 1\}} - d_i \chi_{\{\hat{b}_i \neq b_i\}},$$

Finally, we assume that the agent is an expected utility maximizer. However, we assume that assessing the probability of the information being revealed in any individual situation is not possible for this agent. Instead, we assume that he uses a composite probability of revelation, $\bar{\pi}$ in his assessments:

$$\bar{\pi} = \frac{1}{|S|} \sum_{s_j \in S} \pi_j.$$

[9] For a classic reference see Festinger and Carlsmith (1959).

In other words, the individual averages out the probability of disclosure across situations. We posit this is an artifact of the individual's inability to assess the exact probability of disclosure that he is facing in his specific situation. This may be a result of insufficient data known to the agent about past disclosures in each of these situations, which causes him to "coarsen" and use the aggregate probability as a more reliable summary statistic (Al-Najjar and Pai, 2014). Alternately, it may be a result of cognitive shortcomings (Mullainathan (2002), Mullainathan, Schwartzstein, and Shleifer (2008), Schwartzstein (2014)) that cause him to be unable to discern the exact situation he is in and to therefore average over some class of situations.

This assumption implies that:

$$U_i(\hat{b}_i, b_i, s_j) = \mathbb{E}_{\bar{\pi}}[u_i(\hat{b}_i, b_i, s_j)].$$

Given our assumptions on the payoff of the individual, some simple observations follow:
Observation 1. Any individual i who does not have the condition (i.e., $b_i = 0$) reports his status truthfully, regardless of the situation he is in ($\hat{b}_i = 0$).

This is straightforward: note that lying comes at a cost (d_i), but if the agent does not have the condition, then lying confers no benefit. However, while someone without the condition always reports his status truthfully, someone with the condition may choose to hide his condition.
Observation 2. An individual i with the condition (i.e. $b_i = 1$) misreports his status ($\hat{b}_i = 0$) whenever

$$c_i \bar{\pi} > d_i, \tag{2}$$

i.e., only if the (dissonance) cost of lying (d_i) is less than the expected loss from revealing the condition.

A couple of comparative statics drop out fairly immediately from (2). First, the magnitude of misreporting costs d_i matters—in the absence of any misreporting costs, individuals *always* misreport their condition status, even if the cost c_i or probability of disclosure is infinitesimally small. Second, the coarse perception of the agent may cause misreporting in situations that have a "low" probability of disclosure.

Observation 3. Suppose an individual i is faced with a situation s_j such that the $\pi_j < \pi_{j'}$ for any $s_{j'} \in S$. Then, for an appropriate level of dissonance cost d_i, it can be the case that:

$$c_i\bar{\pi} > d_i > c_i\pi_j.$$

In other words, there are settings where (counterfactually) an agent who is able to discern the situation he is in would not choose to hide his conditions, as he assesses the probability of disclosure as too low to be worth the dissonance cost. However, his coarse perception causes him to overestimate the probability of disclosure and hence misreport his condition.

Finally, note that an agent with higher costs c_i will misreport whenever an agent with lower costs does, *ceteris paribus*. For example, fixing the cost from labor market discrimination, c_i^d, and increasing the stigma c_i^s will result in more misreporting. To see this, combine (1) and (2) to observe that an agent with the condition misreports whenever

$$(c_i^d + c_i^s)\bar{\pi} > d_i.$$

To summarize, this theory provides simple predictions about the nature of reporting in the face of stigma that are borne out in our data: Firstly, coarse perception of the risk of disclosure leads individuals to misreport their status even in anonymous surveys where the risk is "low." Secondly, while individuals who have the condition may choose to hide it (i.e., under-report), agents who do not have the condition will not choose to misreport that they suffer from the condition (i.e., they will not over-report). Finally, fixing the labor market discrimination cost faced by an individual, higher stigma costs lead to more misreporting.

3 Data and methods

For the empirical analysis, we use a unique data set from Australia constructed by linking the Sax Institute's 45 and Up Study data to the individual medical records. The 45 and Up Study is a survey of more than 250,000 individuals 45 years of age or older residing in New South Wales (NSW), the most populous state of Australia. The sample is drawn from the database of Australia's public health insurance program, Medicare, which covers all citizens and permanent residents of Australia. People 80 years of age or older and residents of rural and remote areas are oversampled. Information from the 45 and Up Study participants was collected via mail questionnaires in stages from 2006 to 2009. Most of the questionnaires (78%) were completed in 2008. Close to 18% of the sent-out questionnaires were returned,

resulting in the sample of 267,153 individuals (about 11% of the NSW population aged 45 years and over). The 45 and Up sample is broadly representative of the populations of NSW and Australia in terms of most demographic and socioeconomic characteristics (age, gender, marital status, and employment), but there is positive selection on household income (Johar, Jones, and Savage, 2012).

For the analysis, we use the data covering the period of 2007-2010 (233,081 observations), because the questions on mental health were not asked in 2006. After excluding a small number of invalid observations (volunteers and individuals younger than 45) and observations with missing values of key variables, the sample contains 215,618 individuals. Panel A of Table 1 presents the descriptive statistics of demographic and socioeconomic variables in our analysis sample. The sample individuals are on average 63 years old. Males constitute 46% of the sample. Almost three quarters of the sample have European ancestry, and only half identify themselves as Australians. Close to 25% of the individuals have a university degree. Because our sample is older, a large proportion of the sample (38%) are retired. The sample individuals live in relatively well-off areas, as measured by the SEIFA Index of Relative Socioeconomic Advantage and Disadvantage (SEIFA): close to 30% of observations are in the top SEIFA quintile, and less than 10% are in the bottom SEIFA quintile.

The 45 and Up Study, with the consent of all the participants, is linked to the individuals' administrative health records, including the Pharmaceutical Benefits Scheme (PBS) and the Medicare Benefits Schedule (MBS) databases. At least five years of administrative records are available for all individuals in the sample, starting September 2005 and ending August 2010. For the analysis of misreporting of mental health, we mainly use the linkage of the 45 and Up Study to the PBS database.

The PBS database includes all filled drug prescriptions covered by Medicare, with an exception of the drugs that cost less than the co-payment paid by the patient. For the general public, the co-payment varies from A$30.70 to A$32.90 during our analysis period. For the individuals who hold a health care concession card, the co-payment is substantially lower (from A$4.90 to A$5.20). Once the total amount spent on prescription drugs reaches a set amount (Safety Net threshold[10]), individuals without a concession card are also eligible for the lower co-payment for the rest of the calendar year. Most of the drug purchases recorded in the PBS data are made using a health care concession card (83% of all drugs and 77% of mental health drugs). The eligibility for a health care concession card is linked to welfare benefit receipt, veteran status, low income, and/or senior age. Thus, if there is hetero-

[10]The Safety Net threshold varies from A$1,059 to A$1,265 during the analysis period.

geneity in stigma-related misreporting of mental illness, our results are more informative of misreporting in the sub-population that is older and less advantaged.

3.1 Measuring under-reporting

In the first part of our analysis, we investigate the extent of under-reporting of mental illness by matching self-reported mental health information in the 45 and Up Study to the administrative records of filled prescriptions for mental health disorders. We use two types of self-reported measures of mental health from the 45 and Up study.

First, individuals are asked whether a doctor has ever told them that they have a list of health conditions, including mental disorders (see Appendix Figure B.1). In the administrative records, we can observe whether an individual has filled any prescriptions for depression drugs from the start date of the administrative records until the survey date. The drugs for depression are identified using the Anatomical Therapeutic Chemical (ATC) codes, listed in Appendix A.1. To evaluate the extent of under-reporting of mental illness, we calculate the proportion of individuals whom we observe filling prescriptions for depression drugs *do not* report that they have been diagnosed with depression or anxiety.[11] We also compute the under-reporting rates of other health conditions: cardiovascular diseases (hypertension, heart disease, and stroke) and diabetes (Appendix A.1 lists ATC codes used to identify these conditions in the administrative data).

Second, in the 45 and Up Study, individuals are asked about their use of selected prescription drugs in the past four weeks (see Appendix Figure B.2 for the precise survey questions). The survey question includes three drugs most commonly used for the treatment of depression.[12] These drugs account for more than half of the total depression drug sales in Australia (Mant, Rendle, Hall, Mitchell, Montgomery, McManus, and Hickie, 2004). Almost half of all prescriptions for depression drugs in the PBS data were for one of these drugs. We create an indicator variable that takes the value one if an individual reports taking any of the three depression drugs in the past four weeks and the value zero otherwise. We use the administrative records to determine whether an individual filled a prescription for any of the three depression drugs in the past month. The drugs are identified in the administrative records using a drug-specific ATC code (more details provided in Appendix A.1). We then calculate the under-reporting rate of depression drugs as a proportion of the individuals observed fill-

[11] Anxiety disorders are often treated with depression drugs (AMH, 2015).
[12] Zoloft (sertaline), Cipramil (citaloprim), and Efexor (venlafaxine).

ing a prescription for any of the three depression drugs who *do not* report using any of these drugs in the survey.

We also estimate the under-reporting rates of drugs used for treatment of the following other conditions: cardiovascular and blood diseases (hypertension, congestive heart failure, high blood cholesterol, and thrombosis), diabetes, and other diseases (heartburn, gout, and thyroid disease). As in the case of depression drugs, the other drugs included in the survey question are the drugs that are commonly used to treat these conditions. For example, around half of all prescriptions for hypertension and diabetes drugs were for the drugs included in the survey question. This proportion was higher for cholesterol (81%), heartburn (73%), gout(85%), and thyroid (94%) drugs. The higher "market share" of the latter drugs compared to depression drugs may raise a concern that individuals may be more familiar with these drugs and therefore report their use more accurately. To address this concern, we have re-estimated the average under-reporting rate of the other drugs, excluding cholesterol, heartburn, gout, and thyroid drugs, and found consistent results.

Comparing the two self-reported measures of mental health, we expect individuals to be more likely to under-report mental illness diagnosis, because the survey questions directly asks whether they have been diagnosed with a mental disorder. Individuals may be less likely to under-report depression drug use because the question on prescription drug use does not specify that these are depression drugs. Another reason why the under-reporting rate of depression drug use may be lower is that the question about prescription drug use is more specific than the question about diagnoses.

4 Results

Table 2 presents the estimated under-reporting rates of mental disorders and other conditions. Panel A of Table 2 shows that 36.5% of people observed using depression drugs in the administrative data do not report that they have been diagnosed with either depression or anxiety. The average under-reporting rate of all other diagnoses is substantially lower at 17%. Diabetes has the lowest under-reporting rate (11%). Panel B of Table 2 reports the under-reporting rates of prescription drugs. The under-reporting rate of depression drugs is equal to 20%. The under-reporting rates of the other drugs are lower (13%-14%) and significantly different from the under-reporting rate of depression drugs at the 1% significance level. Overall, the results presented in Table 2 suggest that the stigma of mental illness can lead to substantial under-reporting of mental disorders in the survey data.

Table 2 shows that for both mental illness and other conditions, under-reporting is lower when individuals are asked about their drug use rather than about their diagnoses. The under-reporting rate of mental health drugs is lower by almost a half compared to the under-reporting rate of mental illness diagnosis. For the other conditions, the differences are smaller than for mental illness. A likely explanation for the lower degree of misreporting of drugs compared to diagnoses is the substantially shorter time frame (past four weeks versus lifetime). Moreover, the specificity of the question about prescription drug use might prompt some survey responders to examine their drug purchases/receipts rather than rely solely on memory. In the case of mental illness, the differences in the wording of the questions may matter as well, as discussed in Subsection 3.1. These findings suggest that the framing of survey questions may affect truthful reporting of mental illness and other conditions.

Table 3 examines under-reporting for a subset of people who use multiple drugs. This analysis is akin to an individual fixed-effects model. For example, we take an individual observed as taking drugs for both depression and diabetes, and examine the relative excess under-reporting of mental illness for the same individual.[13] Column 2 in Table 3 shows that among people who take both drugs, mental illness diagnosis and drug use is under-reported 45% and 22% of the time, respectively, whereas diabetes diagnosis or drug use is under-reported only 14% of the time. Hence, the *excess* under-reporting of mental illnesses remains and is robust to such individual comparisons. The results are similar for individuals who take depression, hypertension, *and* diabetes drugs (Column 3).

4.1 Sensitivity analysis

In this subsection, we explore alternative explanations besides stigma for our results. First, individuals may not recall that they have been diagnosed with a mental illness; this is unlikely in our setting as we only focus on recent treatments for depression. If we only use the data on the prescription drug use in the past 12 months, the under-reporting rate of depression is 32% and the under-reporting rate of other conditions is 15%.

Second, we investigate how the estimated under-reporting rates of mental illness and other diagnoses vary with treatment intensity. Individuals who use prescription drugs for a given condition rarely or irregularly may be more likely to forget about their diagnosis. Additionally, such individuals may not have been told about their condition by their doctor. The results are presented in Figure 1. In Graph A, treatment intensity is measured by the number

[13] Note that prescription drug frequencies are the same for all conditions in the data; all drugs have to be taken daily.

of prescriptions filled from the start date of the administrative records to the survey date, and in Graph B, it is measured by the duration of the longest treatment spell (in months). For both measures of treatment intensity, we find that under-reporting of mental illnesses indeed decreases with higher treatment intensity, but so does under-reporting of other conditions. Among individuals who have been treated for depression for short periods of time, the under-reporting rate of mental illness diagnosis is higher than 50%. Among those who have been treated for depression for relatively long periods of time, the under-reporting rate of mental illnesses is close to 20%. Importantly, individuals are more likely to under-report mental illness compared to other conditions, irrespective of treatment intensity.

Third, we address the possibility that our results are driven by doctor, rather than patient, behavior. We might be concerned that a doctor may withhold mental illness diagnosis from a patient for various reasons–for example, to not distress the patient. However, according to the "Australian Guidelines for Medical Practitioners on Providing Information to Patients", a doctor can withhold information from the patient only under exceptional circumstances (National Health and Medical Research Council, 2004). Doctors treating depression patients are recommended to take patient preferences into account when prescribing antidepressant treatment (Ellis and Smith, 2002). Still, some doctors might be unclear at communicating the specifics of illnesses to their patients. Under the assumption that doctors are equally unclear at communicating all types of illnesses to their patients, Table 4 presents the results of a doctor fixed-effects specification (we can uniquely identify the prescribing doctor in the administrative data). The main takeaway from this table is that for both, diagnosis and prescription drug use, doctor fixed-effects do little to alter the results. Hence, doctor specific communication issues are not likely to drive the main results.

A more nuanced issue with regards to communication between doctors and patients is that doctors might be particularly unwilling to "label" their patients as being "depressed." The doctor fixed effects specification does not solve this issue. To deal with this possibility, we present an important stylized fact from our data in Figure 2. If doctors either label or do not label their patients as "depressed," under the null that there is no mental health stigma, the *doctor-specific* under-reporting rate of mental illness should be bi-modal—for a given doctor, either all patients under-report, or all patients truthfully report. However, Figure 2 shows that there is a full distribution of under-reporting responses by patients that see the *same* doctor.

A fourth concern is that some patients may be treated with multiple depression drugs before an effective drug is found. This might lead mental health patients to be more uncertain of the exact type of drugs they are currently taking and more likely to misreport in the survey.

We address this concern in Table 5 by examining under-reporting rates for patients who do not switch drugs in the 6 months prior to the survey to patients who switch. Our headline results from Table 2 are largely replicated in Column 1 of this table, showing that drug switching is not driving our results. While the misreporting for switchers is higher (Column 4), the sheer number of switchers are small relative to the overall sample.

Fifth, we tackle the issue of multiple uses for depression-related drugs. Depression drugs may be prescribed for the treatment of other conditions besides depression or anxiety. Depression drugs can be used to treat depressive episodes of bipolar disorder (AMH, 2015). A patient prescribed a depression-related medication, might be taking it for conditions related to physical pain. For example, diabetic neuropathy is one such condition (Goodnick, Jimenez, and Kumar (1997) and Sindrup, Grodum, Gram, and Beck-Nielsen (1991)). We show that this is not a major concern for us for four principle reasons. First, while this would be a relevant worry if we only compared questions about self-reported *diagnosis* to prescription drug use, it is not a concern when we compare self-reported *prescription drug use* to administrative reports on drug use. Second, Australian insurance rules regarding reimbursement are quite strict—most common antidepressants are only covered by insurance if they are prescribed for depression.[14] Third, in Table 6 we show that our results are not affected by excluding patients who take antipsychotic drugs, which are used to treat bipolar disorder. Fourth, in Table 6, we also show our results are robust to the removal of any antidepressant prescribed by a neurologist who typically handles cases related to neuropathic pain. Finally, the most dominant form of antidepressants that are prescribed for chronic pain are tricyclic antidepressants (McQuay, Tramer, Nye, Carroll, Wiffen, and Moore, 1996). The under-reporting rate of mental illnesses decreases from 36% to 27% when we exclude patients taking tricyclic antidepressants, but it still is substantially higher than the under-reporting rate of the other conditions. Note that this may be a conservative estimate, because tricyclic antidepressants have worse side effects than other antidepressants and are prescribed for severe depression when other drugs do not work (AMH, 2015); thus, they may be most under-reported.

A few minor concerns remain. We show that the results are robust to alternative ways to calculate under-reporting rates. Specifically, we had to decide how to treat individuals who leave the question about diagnoses blank—that is, they do not report that they have been diagnosed with any of the conditions listed in the survey question, but they also do not select the option "none." In Table 2, we count them as non-reporting any of the conditions; thus, these individuals contribute to the estimated under-reporting rates of diagnoses. In Appendix

[14]For example, sertraline (Zoloft): http://www.pbs.gov.au/medicine/item/2236Q-2237R-8837D-8836C, page accessed on April 14th, 2015

Table B.1, we present the under-reporting rates of diagnoses when these individuals are, instead, omitted from the sample. The re-estimated under-reporting rate of mental illness diagnosis decreases, but only slightly so (to 34%), as do the under-reporting rates of other diagnoses.

Another is related to "over-reporting." We cannot examine over-reporting of diagnoses, as not all diagnoses result in medication being prescribed (whereas all prescription medications require diagnosis), but we can examine over-reporting of prescription drugs. We define over-reporting rate as the proportion of individuals who report taking a particular drug in the survey who are not observed purchasing this drug in the administrative data. Stigma in mental health should not lead to any over-reporting; instead, we hypothesize that any over-reporting is likely due to survey inattention, lack of doctor-patient communication, recall biases, etc. Given that these potential reasons for over-reporting are not unique to mental illness, we also hypothesize that over-reporting should not be *systematically higher or lower* for mental illness compared to other conditions. In Appendix Table B.2, we examine over-reporting of prescription drug use and find that depression drugs do get over-reported, but at nearly the same rate as other drugs. Hence, over-reporting of depression drug use is likely due to general survey errors. Finally, it might be the case that mental health drugs have more generic options than other drugs, and hence cause issues with remembering exact drug types. We discuss this in detail in section A.1.2 in the Appendix, and conclude that this is not an issue in this context since mental health drugs and other drugs have similar shares of generic options. As Appendix Figure A.1.2 in the Appendix shows, the *ordering* of the prescription drug question on the survey questionnaire places it at the very end of the question box. While this might cause these variables to be under-reported due to survey fatigue, we note that this question is one of the first questions in the survey on medical history of the patient; moreover, the drug question on diabetes is the question just prior to the ones on depression.

4.2 Heterogeneity and Mental Health Care Seeking Behavior

4.2.1 Heterogeneity

In this subsection, we first analyze whether under-reporting of depression drug use varies by the dose of a drug. The treatment of depression usually starts with a lower dose of a drug. If the low-dose treatment is not effective, the dose is increased.[15] Therefore, individuals who

[15] http://www.nhs.uk/conditions/Antidepressant-drugs/pages/introduction.aspx

take a lower dose of a drug are likely to be more recently diagnosed with depression and/or have less severe depression. Recently diagnosed patients may be more likely to hide their mental illness than patients with a longer history of depression, some of whom adapt to their illness and feel less self-stigma. On the other hand, the relationship between disease severity and under-reporting of mental illness can go both ways. On the one hand more severe patients may be more likely to under-report mental illness, because they feel more stigmatized (Hinshaw, 2007). On the other hand, if more severe patients face higher costs of hiding their mental illness, they will be less likely to under-report.

We test these hypotheses in Table 7, in which we present under-reporting rates of depression drugs by the dose of a drug. Appendix A.2 explains how we define "low" and "high" dose.[16] The results show that low-dose depression drugs are under-reported at a higher rate than high-dose depression drugs. This finding is unlikely to be driven by the variation in recall by dose, because we do not find the same pattern for the other drugs. To get further insights in the results, we divide depression patients into two groups by the length of treatment (12 months or less (25%) versus more than 12 months (75%)).[17] Table 7 shows the following: (1) for both groups of patients, under-reporting of high dose drugs is lower; (2) under-reporting of both low- and high-dose drugs decreases with the length of treatment. Taken together, these findings suggest that (1) more severe depression patients may indeed find it more costly to hide their illness, and (2) more recent mental health patients may feel more stigma.

Our data also allows us to examine heterogeneity in under-reporting by demographic characteristics. A recent meta analysis of internalized stigma finds that stigma of mental illness does not seem to systematically (and in a statistically significant way) vary by gender, age, education, employment, and ethnicity (Livingston and Boyd, 2010). For example, results on heterogeneity by gender are mixed, with some studies finding that men feel more stigmatized than women and other studies finding the opposite. Most studies find that the perception of stigma decreases with age, although there are studies with contrary findings. All studies that find a significant relationship between employment and perceived stigma report that more educated and employed individuals are less likely to feel stigmatized than less educated and nonemployed individuals. Finally, there is evidence that non-Caucasian individuals are more likely to feel stigmatized than Caucasian individuals (Livingston and Boyd, 2010). We investigate whether there is variation in under-reporting of mental illness by these charac-

[16] Out of 5,810 individuals who take depression drugs, close to 50% take a low dose of a drug, 35% take a high dose of a drug, and for the rest we cannot determine the dose.

[17] Consistent with treatment guidelines, a smaller proportion of new depression patients (25%) take high-dose depression drugs compared to patients who have been treated for depression for longer (50%).

teristics and also whether these characteristics in general correlate with under-reporting of other conditions.

Figure 3 shows that in our data, under-reporting of mental illness diagnosis increases sharply from age 55 to 75 and then levels off, while the under-reporting rate of depression drug use does not vary with age until 65 and then starts increasing. In Figure 4, we compare under-reporting of mental illness by gender and education. Males are more likely to under-report mental illness than females, irrespective of education level. Under-reporting of mental illness is lower among university graduates. Figure 5 presents the under-reporting rates of mental illness by individuals' employment status and local area SES. The employed are somewhat less likely to under-report mental illness than the nonemployed. On the other hand, the differences in under-reporting of mental illness by local area SES are small.

In Table 8, we analyze the differences observed in the raw data more formally by regressing the indicator for *not reporting* a mental health condition (Column 1) or drug use (Column 2) on gender, age, SES, and ancestry, conditional on taking depression drugs any time before the survey (Column 1) or in the past 4 weeks (Column 2). The results of the regressions are consistent with Figures 3 and 4. We find that under-reporting of mental illness increases with age. Males and individuals without university degrees are found to be significantly more likely to under-report mental illness. Controlling for other characteristics, we no longer observe significant differences in under-reporting of mental illness by employment (except for the unemployed being more likely to under-report depression drug use). However, there is a negative local area SES gradient in under-reporting of mental illness. We find some interesting results on ethnicity. Individuals from Asian, African, or Middle Eastern ethnic backgrounds are significantly more likely to under-report mental illness, especially mental illness diagnosis, whereas having European ancestry decreases the probability of under-reporting mental illness. We wish to highlight that the heterogeneity results are specific to mental illness and that these characteristics are not correlated with under-reporting of all conditions (see Appendix Table B.3).

4.2.2 Health care seeking behavior

We next examine whether characteristics associated with mental illness under-reporting also predict health-seeking behavior.[18] To examine this question, we use information on both mental health drug use and visits to a mental health professional. The information on the visits to a mental health professional comes from the MBS data. All medical services covered

[18]To perform this analysis, we need to make some sample restrictions, described in Appendix A.3.

by Medicare are recorded in the MBS data, including general practitioner (GP) and specialist visits. Medicare does not cover psychologist visits for the general population, but patients with a diagnosed mental disorder are eligible to receive compensation for a limited number of psychologist visits (starting 1 November 2006). Close to 3% of all individuals in our sample have visited a mental health professional in the past 12 months.

We first identify individuals who are deemed to be in "need" of mental health treatment according to the Kessler Psychological Distress Scale (K10), as explained in Appendix A.3 (n = 1,620). We use the results from Table 8 to predict the probabilities of under-reporting mental illness diagnosis and mental health drug use for these individuals. We then examine whether these predicted probabilities are correlated with treatment-seeking behavior in the *subsequent* 12 months. The underlying hypothesis is that characteristics that correlate with under-reporting conditional on seeking treatment should also predict lower probability of seeking treatment. On average, about 18% of this selected sample receive treatment for mental health in the subsequent 12 months (i.e., we observe that they use depression or anxiety drugs or visit a mental health professional). Importantly, we account for concerns about general "access" to health professionals by controlling for the number of GP visits in the past 12 months and presenting results on GP visits as well.

Table 9 presents the results. Consistent with our initial hypothesis that stigma might play a role in preventing health care seeking, we find that individuals with a higher predicted probability of under-reporting are also less likely to seek mental health care (even though they are more likely to seek care from a GP). A 10% increase in the probability of misreporting on the diagnosis question reduces the probability of seeking mental health care by 11% (the corresponding number for under-reporting on the prescription question is even larger at nearly 23%). In Table B.4, we further examine which particular characteristics are driving the results presented in Table 9. Consistent with the heterogeneity results on under-reporting of mental illness, we find that the probability of seeking mental health treatment decreases with age, although older people have more GP visits overall. Similarly, Asian, African, or Middle Eastern individuals are less likely to receive mental health treatment, although they visit a GP more often. We also find that men are less likely to receive mental health treatment than women, but men also have fewer GP visits than women. Overall, the results are suggestive that the stigma of mental illness may affect not only reporting of mental illness but also seeking mental health treatment.

5 Conclusion

Conditional on taking prescription medication, we find that individuals are much more likely to under-report diagnosis and prescription drug use regarding mental health ailments, compared to other conditions. We interpret the additional misreporting in mental health as evidence of the stigma of mental health issues. Our simple model posits that if mental health concerns are seen as an undesirable trait in society, people are more likely to hide them, even when the costs of truthfully reporting are quite low.

Our interpretation of misreporting as evidence of stigma is based on a broad definition of stigma. It is perhaps natural to think of stigma as taste-based discrimination (people dislike others with depression), with the resulting costs. Since we only observe individual agents' reporting choices, we are unable to separate misreporting directly due to stigma concerns from misreporting due to the agent's intrinsic motivations such as guilt, shame, self-image issues, etc. In our context, therefore, stigma is an amalgam of these forces. We posit that these intrinsic motivations also arise indirectly from the same basic force—in the absence of discrimination concerns, there is nothing to feel shameful/guilty about.

We do, however, attempt to separate this notion of stigma from concerns about labor market discrimination—since a large portion of our sample is retired, we can assume that for this sub sample there is no *labor market based* statistical discrimination motive in their responses. In future work, we hope to shed light on the more nuanced differences between discrimination concerns and the related intrinsic motivations mentioned above.

The most important facet of stigma that pertains to public health policy is the extent to which it might prevent individuals from seeking appropriate care. Our results show that stigma concerns play a significant role in determining health care seeking behavior in the case of mental health. To the extent that policy or broader market forces can reduce stigma in mental health, our conclusions suggest that this will lead to more individuals seeking and obtaining treatment, and eventually lessening the burden of the disease.

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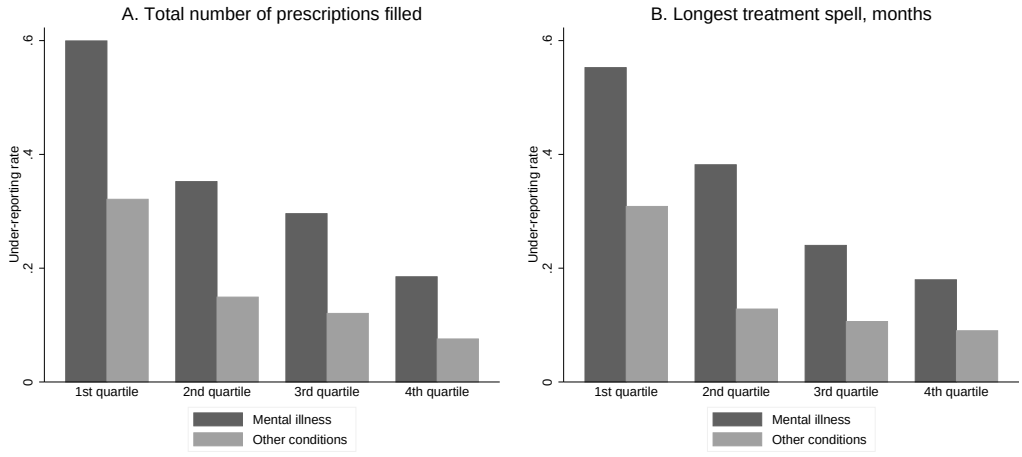
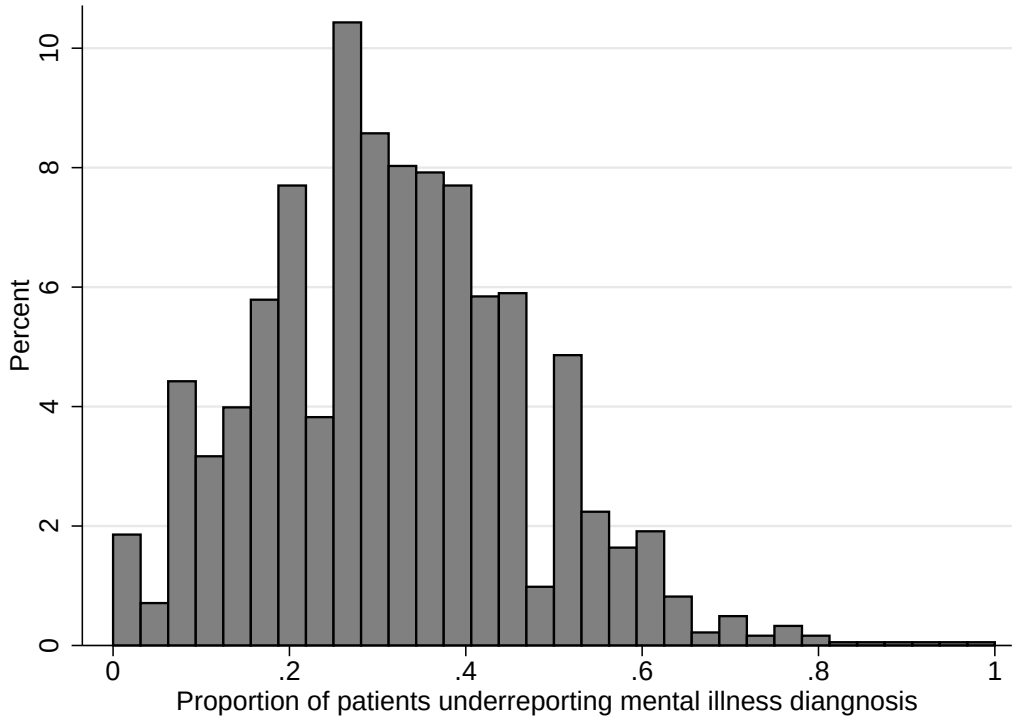
FIGURE 1: Variation in under-reporting rates of mental illness and other diagnoses by treatment intensity.



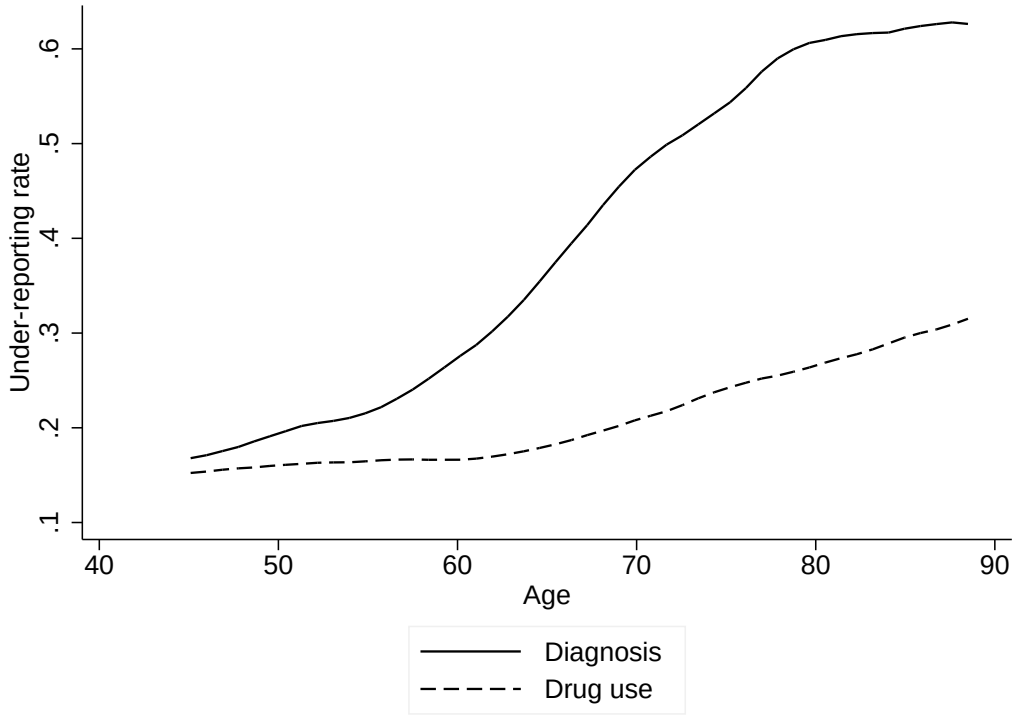
Notes: The under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report this condition in the survey. In Graph A, treatment intensity is measured by the total number of prescriptions filled, and in Graph B, it is measured by the duration of the longest treatment spell (in months).

FIGURE 2: Doctor-specific under-reporting rates of mental illness diagnosis



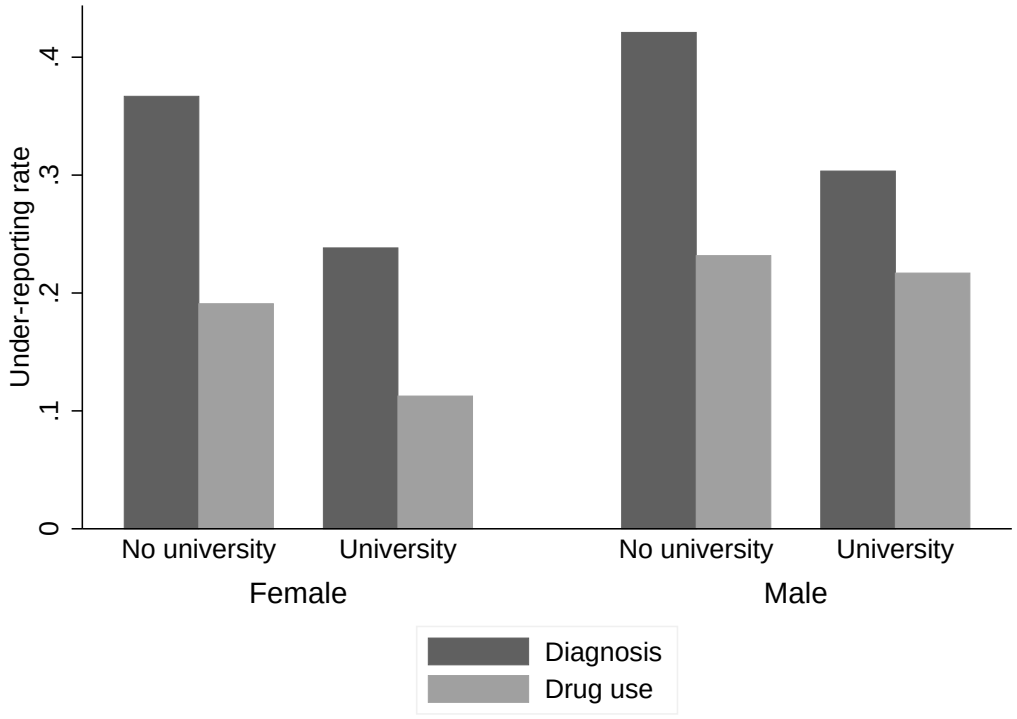
Notes: The under-reporting rate for each doctor is estimated as the proportion of his/her patients observed purchasing drugs for depression who do not report mental illness diagnosis in the survey.

FIGURE 3: Variation in under-reporting rate of mental illness by age



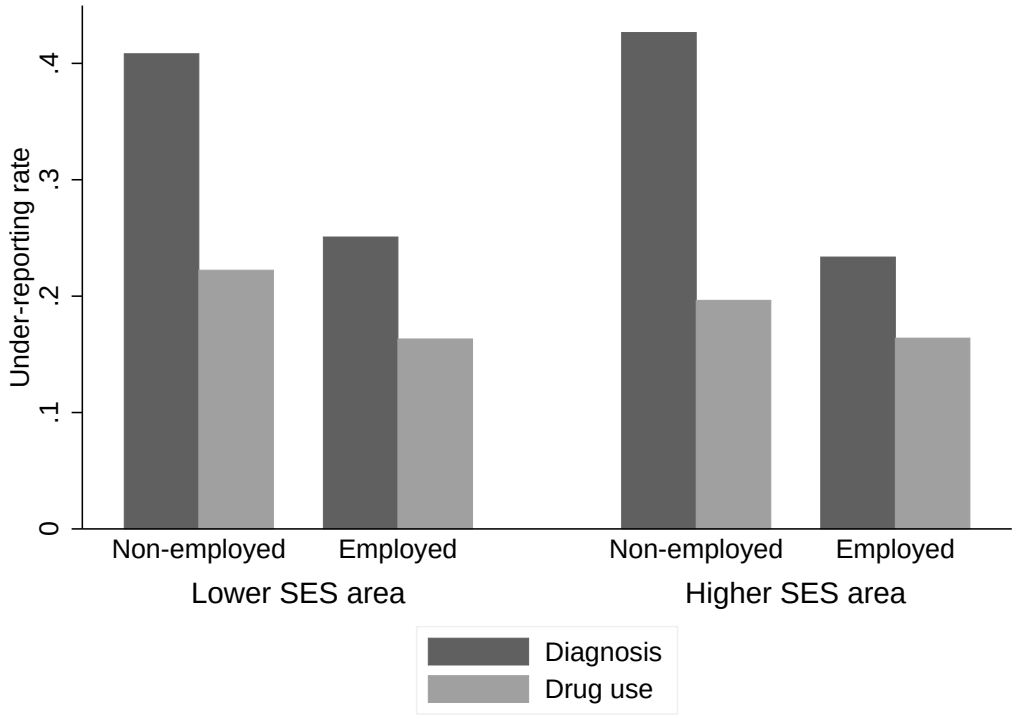
Notes: The under-reporting rate of mental illness diagnosis is estimated as the proportion of individuals observed purchasing drugs for depression drugs who do not report mental illness diagnosis in the survey. The under-reporting rate of mental health drug use is estimated as the proportion of individuals observed purchasing drugs for depression who do not report using depression drugs in the survey. The lines in the graph represent the estimates of Epanechnikov kernel-weighted local polynomial regression estimates. Top 1% of the age distribution are excluded from estimations.

FIGURE 4: Variation in under-reporting rate of mental illness by sex and education



Notes: The under-reporting rate of mental illness diagnosis is estimated as the proportion of individuals observed purchasing drugs for depression who do not report mental illness diagnosis in the survey. The under-reporting rate of mental health drug use is estimated as the proportion of individuals purchasing drugs for depression who do not report depression drug use in the survey.

FIGURE 5: Variation in under-reporting rates of mental illness by employment status and local area socioeconomic status.



Notes: The under-reporting rate of mental illness diagnosis is estimated as the proportion of individuals observed purchasing drugs for depression who do not report mental illness diagnosis in the survey. The under-reporting rate of mental health drug use is estimated as the proportion of individuals observed purchasing drugs for depression who do not report depression drug use in the survey. A "lower" ("higher") socioeconomic status area is as an area with lower (greater) than median SEIFA index.

TABLE 1: Descriptive statistics of key variables

	Mean (sd)
A.Demographic and socioeconomic characteristics	
Age	62.59(11.05)
Male	0.46
Ancestry[a]:	
Australian/New Zealand	0.53
European	0.71
Asian	0.04
African/Middle Eastern	0.01
American	0.01
University degree	0.24
Employment status:	
Self-employed	0.13
Employed for wages	0.35
Unemployed	0.02
Retired	0.38
Other	0.12
Local area SES (SEIFA Index):	
1st quintile	0.10
2nd quintile	0.17
3rd quintile	0.24
4th quintile	0.21
5th quintile	0.28
B. Self-reported lifetime diagnoses	
Depression/Anxiety	0.19
Cardiovascular disease[b]	0.42
Diabetes	0.09
C. Self-reported prescription drug use in past 4 weeks	
Depression	0.04
Cardiovascular disease[c]	0.38
Diabetes	0.05
Other condition[d]	0.26
Observations	215,618

Notes: [a] Ancestry categories are not mutually exclusive, because respondents can select more than one ancestry. [b] Hypertension, heart disease, or stroke. [c] Hypertension, congestive high failure, high blood cholesterol, or thrombosis. [d] heartburn, gout, or thyroid problems.

TABLE 2: The under-reporting rates of mental illness and other conditions

	Under-reporting rate		Difference from MI		
	Estimate	S.E.	Estimate	S.E.	Observations[a]
A. Self-reported diagnoses					
Mental illness	0.365	(0.003)	-	-	31,199
Other conditions:	0.169	(0.001)	-0.196^{***}	(0.003)	94,188
Cardiovascular diseases[b]	0.178	(0.001)	-0.187^{***}	(0.003)	80,344
Diabetes	0.113	(0.003)	-0.252^{***}	(0.004)	13,844
B. Self-reported prescription drug use					
Mental illness	0.196	(0.005)	-	-	5,810
Other conditions:	0.136	(0.001)	-0.059^{***}	(0.005)	108,045
Cardiovascular diseases[c]	0.139	(0.001)	-0.057^{***}	(0.005)	77,711
Diabetes	0.129	(0.005)	-0.067^{***}	(0.007)	5,026
Other diseases[d]	0.130	(0.002)	-0.066^{***}	(0.006)	25,308

Notes: In panel A, under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report this condition in the survey. In panel B, under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report using these drugs in the survey. Standard errors (clustered at the individual level) in parentheses. [a]Unit of observation is individual-condition. [b]Hypertension, heart disease, or stroke. [c]Hypertension, congestive high failure, high blood cholesterol, or thrombosis. [d]heartburn, gout, or thyroid problems. *** indicates that the under-reporting rate of the condition is different from the under-reporting rate of mental illness at the 1% significance level.

TABLE 3: Within-individual differences in the under-reporting rates of mental illnesses and other conditions

	MI+CVD	MI+Diabetes	MI+CVD+Diabetes
	(1)	(2)	(3)
A. Self-reported diagnoses			
Mental illness	0.441	0.446	0.462
	(0.004)	(0.008)	(0.009)
Cardiovascular diseases[a]	0.213	-	0.202
	(0.003)	-	(0.007)
	$[-0.227]^{***}$	-	$[-0.260]^{***}$
Diabetes	-	0.140	0.133
	-	(0.006)	(0.006)
	-	$[-0.307]^{***}$	$[-0.329]^{***}$
Observations	17,521	3,523	3,098
B. Self-reported prescription drug use			
Mental illness	0.221	0.224	0.250
	(0.010)	(0.023)	(0.030)
Cardiovascular diseases[b]	0.144	-	0.149
	(0.009)	-	(0.025)
	$[-0.077]^{***}$	-	$[-0.101]^{***}$
Diabetes	-	0.142	0.144
	-	(0.019)	(0.024)
	-	$[-0.081]^{***}$	$[-0.106]^{***}$
Observations	1,636	344	208

Notes: The sample consists of individuals who take drugs for mental illness as well as cardiovascular disease and/or diabetes. MI stands for mental illness, and CVD for cardiovascular disease. In Panel A, under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report this condition in the survey. In Panel B, under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report using these drugs in the survey. Standard errors in parentheses. The differences between the under-reporting rates of other conditions and mental illnesses in square brackets. [a]Hypertension or heart disease; [b]Hypertension. *** indicates that the under-reporting rate of the condition is different from the under-reporting rate of mental illness at the 1% significance level.

TABLE 4: Within-doctor differences in the under-reporting rates of mental illness and other conditions

	Difference from MI	
	Estimate	S.E.
A. Self-reported diagnoses		
Cardiovascular diseases[a]	-0.169^{***}	(0.002)
Diabetes	-0.239^{***}	(0.003)
Observations[b]	263,326	
Doctors	17,955	
B. Self-reported prescription drug use		
Cardiovascular diseases[c]	-0.060^{***}	(0.005)
Diabetes	-0.079^{***}	(0.007)
Other diseases[d]	-0.070^{***}	(0.005)
Observations[b]	116,573	
Doctors	9,495	

Notes: In Panel A, under-reporting is defined as not reporting a given condition in the survey conditional on purchasing drugs for this condition. In Panel B, under-reporting is defined as not reporting drug use for a given condition in the survey conditional on purchasing these drugs. Presented figures are estimates of prescribing doctor fixed-effects regressions. Standard errors (clustered at the individual level) in parentheses. [a]Hypertension, heart disease, or stroke. [b]Unit of observation is individual-doctor-condition. [c]Hypertension, congestive high failure, high blood cholesterol, or thrombosis. [d]Heartburn, gout, or thyroid problems. *** indicates that the under-reporting rate of a condition is different from the under-reporting rate of mental illness at the 1% significance level.

TABLE 5: Variation in the under-reporting rates of prescription drugs by the number of condition-specific drugs taken in the past 6 months

	One drug			More than one drug		
	Mean	Diff. from MI	n^a	Mean	Diff. from MI	n^a
	(1)	(2)	(3)	(4)	(5)	(6)
Mental illness (MI)	0.187	-		0.283	-	
	(0.005)	-	5,280	(0.020)	-	530
Other conditions:	0.134	0.053***		0.143	0.140***	
	(0.001)	(0.006)	77,478	(0.002)	(0.020)	30,567
Cardiovascular diseases	0.136	0.051***		0.145	0.148***	
	(0.002)	(0.006)	52,298	(0.002)	(0.020)	25,413
Diabetes	0.145	0.042***		0.117	0.166***	
	(0.008)	(0.009)	2,143	(0.006)	(0.020)	2,883
Other diseases	0.128	0.059***		0.156	0.127***	
	(0.002)	(0.006)	23,037	(0.008)	(0.021)	2,271

Notes: The under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report using these drugs in the survey. Standard errors (clustered at the individual level) in parentheses. [a]Unit of observation is individual-condition.

TABLE 6: Sensitivity of results to taking into account alternative uses of antidepressants: under-reporting rate of mental illness diagnosis

	Estimate	S.E.	Observations
Excluded observations:			
Patients treated for bipolar disorder	0.375	(0.003)	29,548
Antidepressants prescribed by neurologist	0.359	(0.003)	29,967
Tricyclic antidepressants	0.271	(0.003)	23,240
All of the above	0.275	(0.003)	21,292

Notes: Under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for depression who do not report mental illness diagnosis in the survey. Standard errors in parentheses.

TABLE 7: Variation in the under-reporting rates of prescription drugs by dose

	Low dose		High dose	
	Estimate	S.E.	Estimate	S.E.
Mental illness:				
All patients	0.237	(0.008)	0.145	(0.008)
Treated for $\leq$ 12 months	0.354	(0.017)	0.220	(0.028)
Treated for $>$ 12 months	0.192	(0.009)	0.136	(0.008)
Other conditions:				
All patients	0.135	(0.002)	0.144	(0.002)

Notes: The under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report using these drugs in the survey. Standard errors (clustered at the individual level) in parentheses.

TABLE 8: Variation in under-reporting rate of mental illness by demographic and socioeconomic characteristics.

	Diagnosis		Prescription drug use	
	Estimate	S.E.	Estimate	S.E.
Age	0.013***	(0.000)	0.004***	(0.001)
Male	0.026***	(0.006)	0.033***	(0.011)
Ancestry:				
Australian/New Zealand	−0.009	(0.006)	−0.003	(0.012)
European	−0.042***	(0.007)	−0.028**	(0.013)
Asian	0.146***	(0.018)	0.082*	(0.046)
African/Middle Eastern	0.094***	(0.021)	0.060	(0.054)
American	0.076**	(0.031)	−0.021	(0.073)
University degree	−0.070***	(0.007)	−0.045***	(0.015)
Employment status:[a]				
Self-employed	0.008	(0.011)	0.011	(0.023)
Employed for wages	0.001	(0.008)	0.013	(0.015)
Unemployed	−0.012	(0.015)	0.056**	(0.026)
Local area SES:				
2nd quintile	−0.007	(0.010)	−0.006	(0.018)
3rd quintile	−0.012	(0.009)	−0.011	(0.017)
4th quintile	−0.016*	(0.009)	−0.023	(0.018)
5th quintile	−0.025***	(0.010)	−0.043**	(0.019)
Mean (dep var)	0.365		0.196	
Observations	31,199		5,810	

Notes: In Column 1, the sample consists of individuals who purchased depression drugs at some time between the start date of the administrative records and the survey date, and the dependent variable takes the value 1 if an individual does not report mental illness diagnosis in the survey and the value 0 otherwise. In Column 2, the sample consists of individuals who purchased selected depression drugs in the past month, and the dependent variable takes the value 1 if an individual does not report using these drugs in the survey and the value 0 otherwise. Presented figures are probit average marginal effects. Regressions control for the time effects. [a] Omitted category is nonemployed. *denotes statistical significance at the 10% level, **denotes statistical significance at the 5% level, and ***denotes statistical significance at the 1% level.

TABLE 9: Variation in health care seeking by predicted probability of under-reporting of mental illness

	GP visits	MH treatment	GP visits	MH treatment
	(1)	(2)	(3)	(4)
$\widehat{Prob}(UR_{diagnosis})$, %	0.041***	−0.002***	-	-
	(0.009)	(0.001)	-	-
$\widehat{Prob}(UR_{drugs})$, %	-	-	0.074***	−0.004***
	-	-	(0.019)	(0.001)
Number of GP visits last year	0.671***	0.004***	0.679***	0.004***
	(0.019)	(0.001)	(0.018)	(0.001)
Mean(dep var)	10.747	0.175	10.747	0.175
Observations	1,618	1,618	1,618	1,618

Notes: See Appendix A.3 for the details on the sample. In Columns (1) and (3), the dependent variable is the number of GP visits in the next 12 months from the survey date and presented figures are OLS coefficients. In Columns (2) and (4), the dependent variable takes the value 1 if an individual took prescription drugs for depression/anxiety or visited a mental health professional in the next 12 months from the survey date and the value 0 otherwise and presented figures are probit average marginal effects. Standard errors are in parentheses. ***denotes statistical significance at the 1% level.

A Data Appendix

A.1 Matching survey data to administrative records

A.1.1 Diagnoses

The drugs for different conditions are identified in the administrative data using the Anatomical Therapeutic Chemical (ATC) Classification System, controlled by the World Health Organization Collaborating Centre for Drug Statistics Methodology (WHOCC)[19]. The following table provides the ATC codes related to the health conditions we analyze.

Disease/Health Condition	ATC codes
Depression	N06A
Cardiovascular disease	All C codes, except for C10[a]
Diabetes	A10

Notes: [a] C10 group of ATC codes consists of cholesterol lowering drugs. Individuals are not asked whether they have been diagnosed with high blood cholesterol in The 45 and Up Study.

A.1.2 Drugs

We match the drugs from the survey question on prescription drug use to the administrative records using a drug-specific ATC code. For example, ATC code for sertraline is N06AB06, ATC code for citaloprim is N06AB04, and ATC code for venlafaxine is N06AX16.

For depression drugs, both drug (active ingredient) name (e.g., sertraline) and brand name (e.g. Zoloft) are mentioned in the survey drugs. Therefore, both patients who use a brand-name drug and patients who use generic versions of the drug should report this in the survey, especially that the names of most generic depression drugs contain the name of the active ingredient. For example, generic sertraline drugs are called APO-Sertraline, Auro-Sertraline 50, Chem mart Sertraline, Eleva 50, GenRx Sertraline, Sertra 50, Sertracor 50, Sertraline AN, Sertraline Actavis, Sertraline Sandoz, Sertraline generic health, Sertraline-DRLA, Setrona, Terry White Chemists Sertraline and Xydep 50. Having said that, we may be somewhat over-estimating the under-reporting of depression drugs because of people who use generic depression drugs that do not contain the active ingredient in their name (like Xydep 50).

[19] http://www.whocc.no/atc_ddd_index/

Although the active ingredient is always listed on the package, people may not pay attention to this information.

For some of the other drugs (most of the hypertension, cholesterol, and heartburn drugs), however, there is only a brand name mentioned in the survey question and the name of the drug (active ingredient) is not specified. Thus, individuals who use a generic version of the drug may answer negatively about their use of these drugs. Consequently, the under-reporting of the other drugs is likely to be over-estimated, more so than the under-reporting of depression drugs, and the true difference between the under-reporting rates of depression and other drugs may be even larger than our estimate.

It is also important to note that the availability of generic alternatives is comparable between the depression drugs and the other most commonly used drugs. For example, there are on average 14 generic versions of the branded depression drugs (15 for Zoloft, 13 for Cipramil, and 14 for Efexor). The hypertension drugs have on average 9, cholesterol drugs 14, and diabetes drugs 11 generic versions of the respective branded drugs. Moreover, it is as common to include the active ingredient in the name of the generic depression drugs (64% of the generic depression drugs on average) as it is for the other drugs. For example, 67% of the generic hypertension drugs have the active ingredient included in the name. The corresponding figures for the generic cholesterol and diabetes drugs are 71% and 82%, respectively.

A.2 Dose

The PBS data have information on the strength of the drug, which we use to classify drugs into low and high dose. We refer to the patient information sheets for each drug to define "low" and "high" dose of a drug. For example, one of the depression drugs, Zoloft (sertraline) comes in 50 mg and 100 mg tablets. According to the patient information sheet, one 50 mg tablet is a usual starting dose, which can be increased gradually up to 200 mg a day if necessary.[20] Thus, we define 50 mg as "low" dose and 100 mg as "high" dose of Zoloft (sertraline).

Our definition of low and high dose relies on an assumption that individuals take one unit (tablet/capsule) of the prescribed drug per day. Some patients may be prescribed low-dose drugs but instructed by their doctor to take more than one unit of a drug per day. In this case, we may misclassify some of the high-dose patients as low-dose patients. To minimize

[20] http://www.betterhealth.vic.gov.au/bhcv2/bhcmed.nsf/pages/pfczolot/$File/pfczolot.pdf

this type of measurement error, we exclude: (1) patients who purchase more than one pack of a low-dose drug at a time, and (2) patients who fill another script for the same low-dose drug within 14 days from the first script (17% of all depression drug users in total). We are do not have enough information to determine whether these patients take a low dose or a high dose of a drug. Additionally, we exclude a small number of patients (n=37) who took both a low dose and a high dose of the drug in the past month.

Another related issue is that patients may be prescribed a combination of multiple low dose drugs for depression. In this case, some of the low-dose depression drug users (as per our definition) may, in fact, take a high combined dose of depression drugs, which again leads to measurement error. To address this issue, we check what proportion of low-dose depression drug users are taking other depression drugs. We find that this proportion is low (3%). Consequently, excluding these individuals does not affect our results.

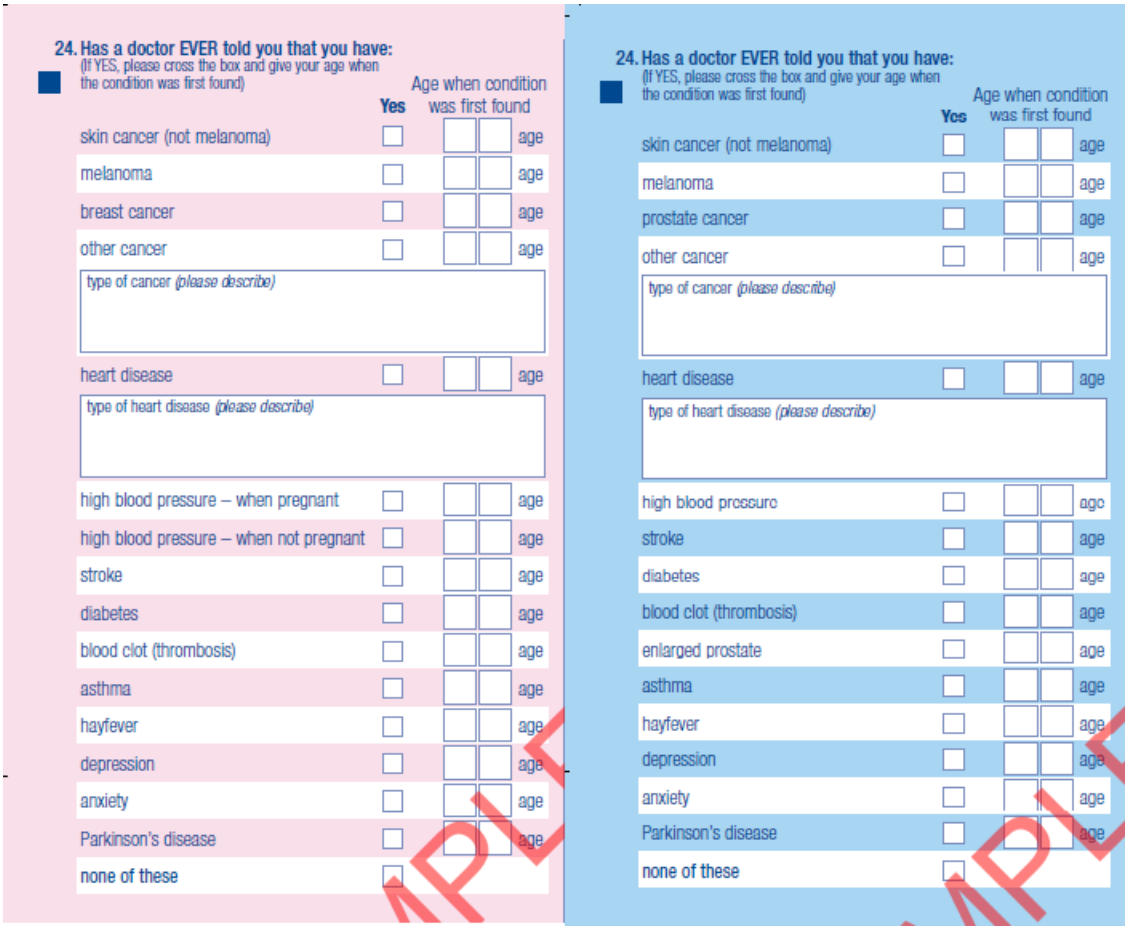
A.3 Analysis of health care seeking: sample selection

In Subsection 4.2.2, an individual is defined as receiving "mental health treatment" if he is prescribed depression/anxiety drugs or is referred to a mental health professional (psychiatrist or psychologist), as per the administrative medical records. Since we can observe the complete history of prescription drug use only for the individuals who hold a health care concession card, we restrict the sample to the concessional individuals in the analysis of health care seeking. More specifically, we limit the sample to the individuals who purchased prescription drugs, other than for depression or anxiety, using a health care card both in the year before and in the year after the survey date (41% of the sample).

To identify individuals in need of treatment, we further restrict the sample to the individuals with a likely moderate or severe mental disorder, according to the Kessler Psychological Distress Scale (K10), which is based on the self-reported depressive and anxiety symptoms. The scores of the Kessler scale vary from 10 (no psychological distress) to 50 (severe psychological distress). A score of 25 or more indicates that an individual is likely to have a moderate or severe mental disorder (Australian Bureau of Statistics, 2012). We exclude individuals who have received mental health treatment in the past 12 months, because we want to focus on "new" mental health patients. Individuals who have died in hospital within 12 months from the survey date and the outliers of GP visits (top 1%) are also excluded from the sample.

B Additional tables and figures

Figure B.1: Survey question on diagnoses.



24. Has a doctor EVER told you that you have:
(If YES, please cross the box and give your age when the condition was first found)

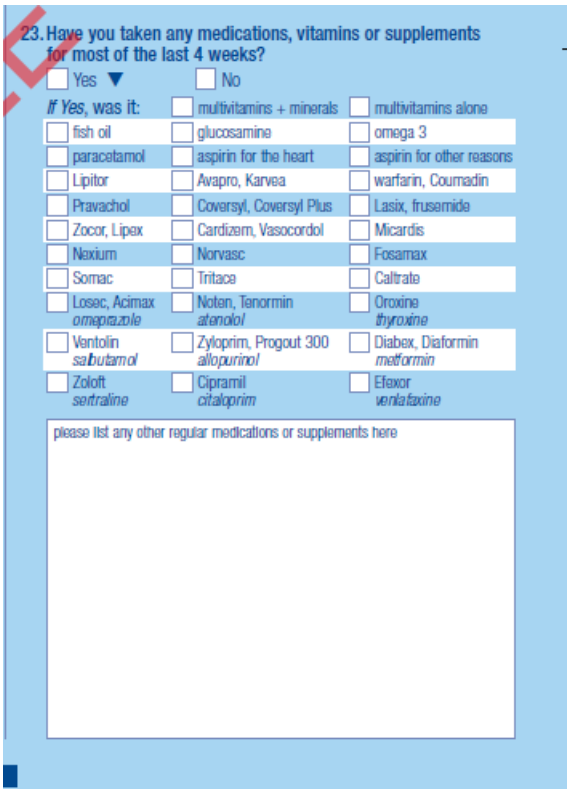
	Yes	Age when condition was first found
skin cancer (not melanoma)	☐	age
melanoma	☐	age
breast cancer	☐	age
other cancer	☐	age
type of cancer *(please describe)*		
heart disease	☐	age
type of heart disease *(please describe)*		
high blood pressure – when pregnant	☐	age
high blood pressure – when not pregnant	☐	age
stroke	☐	age
diabetes	☐	age
blood clot (thrombosis)	☐	age
asthma	☐	age
hayfever	☐	age
depression	☐	age
anxiety	☐	age
Parkinson's disease	☐	age
none of these	☐	

24. Has a doctor EVER told you that you have:
(If YES, please cross the box and give your age when the condition was first found)

	Yes	Age when condition was first found
skin cancer (not melanoma)	☐	age
melanoma	☐	age
prostate cancer	☐	age
other cancer	☐	age
type of cancer *(please describe)*		
heart disease	☐	age
type of heart disease *(please describe)*		
high blood pressure	☐	age
stroke	☐	age
diabetes	☐	age
blood clot (thrombosis)	☐	age
enlarged prostate	☐	age
asthma	☐	age
hayfever	☐	age
depression	☐	age
anxiety	☐	age
Parkinson's disease	☐	age
none of these	☐	

Notes: The left panel presents the question asked to women and the right panel the question asked to men.

FIGURE B.2: Survey question on prescription drug use.



23. Have you taken any medications, vitamins or supplements for most of the last 4 weeks?

☐ Yes ▼ ☐ No

If Yes, was it:

☐ fish oil	☐ multivitamins + minerals	☐ multivitamins alone
☐ paracetamol	☐ glucosamine	☐ omega 3
☐ Lipitor	☐ aspirin for the heart	☐ aspirin for other reasons
☐ Pravachol	☐ Avapro, Karvea	☐ warfarin, Coumadin
☐ Zocor, Lipex	☐ Coversyl, Coversyl Plus	☐ Lasix, frusemide
☐ Nexium	☐ Cardizem, Vasocordol	☐ Micardis
☐ Somac	☐ Norvasc	☐ Fosamax
☐ Losec, Acimax *omeprazole*	☐ Tritace	☐ Caltrate
☐ Ventolin *salbutamol*	☐ Noten, Tenormin *atenolol*	☐ Oroxine *thyroxine*
☐ Zoloft *sertraline*	☐ Zyloprim, Progout 300 *allopurinol*	☐ Diabex, Diaformin *metformin*
	☐ Cipramil *citalopram*	☐ Efexor *venlafaxine*

please list any other regular medications or supplements here

TABLE B.1: Sensitivity of results to alternative variable coding: under-reporting rates of diagnoses

	Under-reporting rate		Difference from MI		
	Estimate	S.E.	Estimate	S.E.	Observations[a]
Mental illness	0.344	(0.003)	-	-	30,191
Other conditions:	0.146	(0.001)	-0.198^{***}	(0.003)	91,718
Cardiovascular diseases[b]	0.155	(0.001)	-0.188^{***}	(0.003)	78,191
Diabetes	0.093	(0.002)	-0.251^{***}	(0.004)	13,527

Notes: In this table, we code individuals who do not report any health conditions in the survey but do not state that they have no health conditions as missing (in Table 2, we code them as non-reporting any conditions). Under-reporting rate is estimated as the proportion of individuals observed purchasing drugs for a given condition who do not report this condition in the survey. Standard errors (clustered at the individual level) in parentheses. [a]Unit of observation is individual-condition. [b] Hypertension, heart disease, or stroke. *** indicates that the under-reporting rate of a condition is different from the under-reporting rate of mental illness at the 1% significance level.

TABLE B.2: The over-reporting rates of prescription drugs for mental illness and other conditions

	Over-reporting rate		Difference from MI		
	Estimate	S.E.	Estimate	S.E.	Observations[a]
Mental illness	0.158	(0.005)	-	-	4,920
Other conditions:	0.148	(0.001)	-0.010^{*}	(0.005)	114,402
Cardiovascular diseases[b]	0.110	(0.001)	-0.048^{***}	(0.005)	75,569
Diabetes	0.176	(0.004)	0.018^{***}	(0.007)	7,265
Other diseases[d]	0.233	(0.002)	0.076^{***}	(0.006)	31,568

Notes: The sample consists of concessional individuals. See Appendix A.3 for the details how concessional individuals are identified. Over-reporting rate is estimated as the proportion of individuals reporting drug use for a given condition in the survey in the past 4 weeks who did not purchase drugs for this condition in the past 3 months. Standard errors (clustered at the individual level) in parentheses. [a]Unit of observation is individual-condition. [b]Hypertension, congestive high failure, high blood cholesterol, or thrombosis. [d]Heartburn, gout, or thyroid problems. * and *** indicate that the over-reporting rate of a condition is different from the over-reporting rate of mental illness at the 10% and 1% significance level, respectively.

TABLE B.3: Variation in under-reporting rates of other conditions by demographic and socioeconomic characteristics.

	Diagnosis		Prescription drug use	
	(1)		(2)	
Age	0.002***	(0.000)	0.001***	(0.000)
Male	−0.053***	(0.003)	0.005**	(0.002)
Ancestry:				
Australian/New Zealand	−0.011***	(0.003)	−0.015***	(0.003)
European	−0.019***	(0.003)	−0.019***	(0.003)
Asian	0.009	(0.008)	0.048***	(0.007)
African/Middle Eastern	0.046***	(0.010)	0.050***	(0.009)
American	0.024	(0.016)	0.016	(0.015)
University degree	−0.023***	(0.004)	−0.026***	(0.004)
Employment status:[b]				
Self-employed	−0.016***	(0.005)	0.003	(0.005)
Employed for wages	−0.034***	(0.004)	−0.004	(0.004)
Unemployed	0.023***	(0.008)	0.054***	(0.008)
Local area SES:				
2nd quintile	0.003	(0.005)	−0.003	(0.004)
3rd quintile	−0.003	(0.004)	−0.008*	(0.004)
4th quintile	−0.009*	(0.005)	−0.011**	(0.004)
5th quintile	−0.013***	(0.005)	−0.024***	(0.004)
Mean (dep var)	0.169		0.136	
Observations[a]	94,188		108,045	

Notes: In Column (1), the sample consists of individuals who purchased drugs for a cardiovascular disease and/or diabetes at some time between the start date of the administrative records and the survey date, and the dependent variable takes the value 1 if an individual does not report this condition in the survey and the value 0 otherwise. In Column (2), the sample consists of individuals who purchased drugs for a cardiovascular disease, diabetes, and/or other conditions in the past month, and the dependent variable takes the value 1 if an individual does not report using these drugs in the survey and the value 0 otherwise. Standard errors (clustered at the individual level) in parentheses. Regressions control for the time effects. [a]Unit of observation is individual-condition. [b]Omitted category is nonemployed. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, and *** denotes statistical significance at the 1% level.

TABLE B.4: Variation in health care seeking by demographic and socioeconomic characteristics.

	GP visits		Mental health treatment	
	(1)		(2)	
Number of GP visits last year	0.663***	(0.019)	0.004***	(0.001)
Age(demeaned)	0.050***	(0.017)	−0.002**	(0.001)
Age(demeaned)^2/100	−0.040	(0.100)	-	-
Male	−0.475	(0.311)	−0.072***	(0.020)
Asian/African/Middle Eastern	1.253***	(0.454)	−0.068**	(0.031)
University degree	−0.402	(0.544)	0.024	(0.034)
Employment status:[a]				
Self-employed	−0.465	(0.744)	−0.065	(0.051)
Employed for wages	−0.120	(0.523)	−0.044	(0.034)
Unemployed	−0.080	(0.545)	−0.006	(0.035)
Local area SES:				
2nd quintile	−0.500	(0.487)	0.064**	(0.032)
3rd quintile	0.451	(0.459)	0.073**	(0.030)
4th quintile	1.192**	(0.490)	0.033	(0.033)
5th quintile	0.646	(0.536)	0.046	(0.035)
Mean(dep var)	10.747		0.175	
Observations	1,618		1,618	

Notes: See Appendix A.3 for the details on the sample. In Column (1), the dependent variable is the number of GP visits in the next 12 months from the survey date. In Column (2), the dependent variable takes the value 1 if an individual took prescription drugs for depression/anxiety or visited a mental health professional in the next 12 months from the survey date and the value 0 otherwise. Standard errors in parentheses. [a]Omitted category is nonemployed. * denotes statistical significance at the 10% level, ** denotes statistical significance at the 5% level, and *** denotes statistical significance at the 1% level.