Marquardt, Kelli

Working Paper

Mis(sed) diagnosis: Physician decision-making and ADHD

Working Paper, No. WP 2022-23

Provided in Cooperation with:
Federal Reserve Bank of Chicago

Suggested Citation: Marquardt, Kelli (2022) : Mis(sed) diagnosis: Physician decision-making and ADHD, Working Paper, No. WP 2022-23, Federal Reserve Bank of Chicago, Chicago, IL, https://doi.org/10.21033/wp-2022-23

This Version is available at:
https://hdl.handle.net/10419/267982

Federal Reserve Bank of Chicago

Mis(sed) Diagnosis: Physician Decision-Making and ADHD

Kelli Marquardt

June 2022

WP 2022-23

https://doi.org/10.21033/wp-2022-23

Mis(sed) Diagnosis: Physician Decision-Making and ADHD

Kelli Marquardt*
Federal Reserve Bank of Chicago†
The University of Arizona

June 2022

Abstract

While the presence of disparities in healthcare is well documented, the mechanisms of such disparities are less understood, particularly in relation to mental health. This paper develops and estimates a structural model of diagnosis for the most prevalent child mental health condition, Attention Deficit Hyperactivity Disorder (ADHD). The model incorporates both patient and physician influences to highlight four key mechanisms of mental health diagnosis: underlying prevalence of ADHD symptoms, mental healthcare utilization, diagnostic uncertainty, and disutility from diagnostic errors. I estimate gender-specific model parameters using novel doctor note data together with machine learning and natural language processing techniques. In raw comparisons, male patients are 2.3 times more likely to be diagnosed with ADHD than female ones. Counterfactual simulations using model estimates show that less than half of this diagnostic disparity can be explained by differences in underlying symptom prevalence by gender. Through this exercise, I find that physicians view *missed diagnosis* to be costlier than *misdiagnosis*, especially for their male patients. Back of the envelope calculations suggest that reducing ADHD diagnostic errors could save $27.6-$52.8 billion dollars nationally.

Keywords: ADHD, Child Mental Health, Diagnostic Disparities, Physician Decision-Making.
JEL classification: I14, D81, C5.

*I am grateful for helpful feedback from my dissertation committee: Gautam Gowrisankaran, Keith Joiner, Ashley Langer, Juan Pantano, and Tiemen Woutersen. I also thank Keith Ericson, Ali Hortacsu, Christoph Kronenberg, Daniel Millimet, Jessamyn Schaller, and conference and seminar participants at various universities and institutions. This paper is based upon work supported by the University of Arizona Graduate and Professional Student Council, Research and Project (ReaP) Grant -2019. Data provided by the University of Arizona Center for Biomedical Informatics & Biostatistics, Department of Biomedical Informatics. Author email: kmarquardt@frbchi.org

†The views here do not represent those of the Federal Reserve Bank of Chicago or the Federal Reserve System.

1 Introduction

Healthcare disparities, traditionally defined as differences in health treatment and outcomes across population groups, are of substantial concern in the United States.[1] While overall health disparities have been declining recently, mental health disparities show the opposite trend (AHRQ, 2019). Within mental health, disparities are particularly salient for Attention Deficit Hyperactivity Disorder (ADHD). Approximately 10% of children are diagnosed with ADHD, and males are diagnosed and treated 2 to 3 times more frequently than females. The psychology literature suggests that this clinical diagnostic difference is larger than what can be explained by true underlying prevalence rates, with evidence showing over-diagnosis of males and under-diagnosis of females on average (Bruchmüller et al., 2012; Hinshaw, 2018). Both *missed* and *mis*-diagnoses are costly, including lower productivity and human capital accumulation for untreated ADHD and harmful side-effects from over-treatment.[2] Ensuring accurate diagnosis for ADHD is essential because its annual economic impact is large, ranging from $168 to $312 billion U.S. dollars (Doshi et al., 2012).[3]

This paper develops and estimates a model of ADHD diagnosis in order to explore the potential causes of differing diagnosis rates across male and female children. I propose and analyze four key mechanisms of ADHD diagnostic disparities: (1) differences in patient preference to seek mental health care, (2) varying rates of diagnostic uncertainty, (3) heterogeneous physician preferences for ADHD diagnosis, and (4) underlying differences in the true prevalence of ADHD symptoms between boys and girls. Importantly, the model also allows me to identify the extent of ADHD diagnostic errors (both *missed* and *mis*-diagnosis) according to national guidelines as well as the potential heterogeneous impact across patients.

[1] U.S. Congress mandates annual *National Healthcare Quality and Disparities Reports* in accordance with the Healthcare Research and Quality Act of 1999. State governments have also enacted legislation in response to healthcare disparities (see: `https://www.ncsl.org/research/health/health-disparities-laws.aspx`).

[2] Diagnosed ADHD is often managed with stimulant medications that fall under the CDC schedule IIN controlled substance category associated with "high potential for abuse which may lead to severe psychological or physical dependence." See: `https://www.deadiversion.usdoj.gov/schedules/`

[3] Inflated to 2019 U.S. dollars using consumer-price-index from the U.S. Bureau of Labor Statistics.

My model has three distinct stages to reflect how the mental health diagnosis decision is made. In the first stage, patients (or rather their parents) decide whether or not to schedule a behavioral assessment with a diagnosing physician. This is a function of underlying unobserved symptom severity in addition to mental healthcare utilization costs. Second, physicians conduct a behavioral assessment for this subset of patients and record/document the patient responses in a clinical doctor note. The physicians use this information to update their belief as to whether the patient matches national guidelines for ADHD diagnosis via a Bayesian learning process. In the final stage, physicians decide whether or not to diagnose the patient with ADHD. They do so if the patient specific posterior belief of ADHD symptom match is above a gender-specific diagnostic threshold. This threshold is set by the physician ex-ante and is a function of the costs they bear from potential diagnostic errors. I allow for both diagnostic uncertainty and diagnostic preferences to vary by patient gender to emphasize how the physician decision-making process contributes to diagnostic disparities.[4]

I empirically analyze the male/female ADHD diagnostic disparity using data derived from electronic health records from 2014 to 2017 provided by a large healthcare system in Arizona. The dataset includes over 136,000 pediatric visits for approximately 30,500 patients. In the raw data, 8% of males and 3% of females are diagnosed with ADHD, implying a male-to-female ADHD diagnostic disparity of 2.26:1. This disparity persists even after controlling for a variety of patient observables, supporting the need for a structural model and estimation approach.

I first construct mental health related variables necessary for model estimation using novel data that includes clinical doctor notes and advanced data analytic techniques including machine learning and natural language processing. Specifically, I determine whether patients receive a behavioral assessment using a machine learning prediction approach based on a

[4]Within the medical community, it remains an open question as to whether the difference in ADHD prevalence stems from biological (sex) or social/cultural (gender) factors. In reference to ADHD prevalence differences in general, Hinshaw (2018) writes: "All-biological or all-cultural perspectives are therefore reductionist and short-sighted." To be consistent within this paper, I refer to differences in male and female model parameters and outcomes as gender-specific differences.

training set of appointments in which this label is readily observed in the electronic health record. For the set of patients that seek mental health care, I also use the information provided in the clinical doctor note to construct an observable proxy for the ADHD match signal that physicians receive during the behavioral assessment. To do this, I use natural language processing techniques and measure how closely the encounter summary provided in the doctor note matches with national diagnostic guidelines for ADHD which are outlined in *The Diagnostic and Statistical Manual of Mental Disorders*, currently in its 5th edition (DSM-V).

I then use the constructed mental health variables and clinical diagnoses to estimate the underlying parameters of the structural model. My first stage presents a selection problem in which the ADHD match signal is only observed if the patient first chooses to schedule a behavioral assessment with a diagnosing physician. While this *diagnosing* physician may be chosen endogenously, I assume that the patients' choice of *original* primary care physician is orthogonal to behavioral symptom development. I show that these base primary care physicians have different referral rates, providing me with an exclusion restriction that allows identification of patient costs from scheduling a behavioral assessment (patient utilization costs). This also allows me obtain selection-adjusted estimates of the population mean ADHD risk for males and females via extrapolations of ADHD match signals on quasi-exogenous behavioral assessment propensity. This exogenous extrapolation approach is similar to the methods proposed by Arnold et al. (2020), who measure racial discrimination in judge bail decisions.

Finally, the outcome for the third stage is the patients' clinical diagnosis, assigned by the physician and observed in the electronic health record. I estimate the components of diagnostic uncertainty and physician preferences by analyzing differences in diagnosis rates by patient gender conditional on the constructed ADHD match signal. The weight that the physician places on this signal identifies varying levels of diagnostic uncertainty, with higher weights corresponding to stronger signal quality. I then show that conditional on diagnostic uncertainty and patient selection, the mean diagnosis rates for each gender is a function of physician prior beliefs and physician disutility from diagnostic errors. I am able to separately

identify these two values using estimates of mean male/female ADHD risk obtained in the initial selection stage.

The model parameter estimates show that less than half of the observed ADHD diagnostic disparity between male and female patients can be attributed to differences in the underlying ADHD risk distribution, with the rest explained by variation in physician decision-making across patient gender. In particular, I find that physicians perceive female ADHD signals to be more informative of true health states and thus place more weight on female patient symptoms when making a diagnosis decision. This is consistent with the vignette study by Bruchmüller et al. (2012) which finds that physicians rely on heuristics rather than official DSM-V criteria when diagnosing males with ADHD. I also find that physicians use significantly lower diagnostic thresholds for male patients, suggesting that physicians bear greater costs of inaccurately diagnosing male patients than female ones.

Using the diagnosis model and parameter estimates, I run counterfactual simulations to examine the extent of over and under diagnosis. I find that physicians view *missed diagnosis* to be more costly than *misdiagnosis* on average, though the cost is much larger for males than females. While this finding may suggest that ADHD is over-diagnosed, simulations that additionally account for patient selection and physician uncertainty show that this condition is slightly underdiagnosed in the sample population. Based on the DSM-V definition of ADHD, I estimate that 1.9% of the adolescent population is over-diagnosed (2.7% of males and 1.2% of females) and 2.5% of the adolescent population is under-diagnosed (2.7% of males and 2.3% females). Importantly, simulations show that the majority of the *missed diagnosis* rate is due to high patient costs of seeking mental health care, suggesting a potential need to increase mental health education and reduce stigma in the sample population.

These results add to the existing literature exploring the potential for ADHD diagnostic errors. For example, in the health economic literature a list of papers show where a child's birth-date falls in relation to the school entry cut-off date is a strong predictor of ADHD diagnosis, implying that teachers are subjectively comparing the younger students in the class to older students and mistaking immaturity for ADHD (e.g., Elder, 2010; Layton et al., 2018; Persson et al., 2021). Understanding ADHD diagnosis is also explored in the medical

and public health literature, including meta analyses on diagnostic differences (e.g., Sciutto and Eisenberg, 2007; AHRQ, 2011; Hinshaw, 2018), physician and patient surveys (e.g., Visser et al., 2015; Chan et al., 2005), and vignette studies exploring variation in ADHD diagnosis decisions by patient groups (e.g., Morley, 2010; Bruchmüller et al., 2012). My paper adds to this literature by presenting new estimates of over/under diagnosis along with a structural model to identify where these errors come from.

My paper also contributes to the vast literature on explaining variation and disparities in healthcare. This includes papers estimating physician practice style (e.g., Epstein and Nicholson, 2009; Currie et al., 2016; Gowrisankaran et al., 2017), structural models of physician decision making under uncertainty (e.g., Abaluck et al., 2016; Currie and MacLeod, 2017; Chan et al., 2021), and identification of physician prejudice (e.g., Balsa et al., 2005; Chandra and Staiger, 2010; Anwar and Fang, 2012). This existing literature typically focuses on physical health applications and thus relies on two assumptions that do not hold in mental health settings. The first is that patient preferences play a small role in explaining variation in health care (Cutler et al., 2019). While this assumption of insignificant demand-side influences might be supported in physical health applications, it is not the case with mental health in which stigma plays a potentially large role in determining mental health-care utilization. My paper develops a novel model of mental health diagnosis taking insights from this literature and adds a patient selection stage in order to explore how both demand-side and supply-side factors can lead to disparities in mental health diagnosis. Second, the extant literature assumes that health states or true diagnoses are observed on some level, which is not the case in mental health applications as diagnosis is based on the presence of behavioral symptoms and cannot be confirmed via traditional medical testing. My paper innovates to deal with this challenge by instead using clinical doctor note data and text analysis techniques to construct a proxy for ADHD symptom match according to national diagnostic guidelines.

Finally, the methods I use in this paper also add to the more recent literature on using text analysis, machine learning, and natural language processing in economic research (see Currie et al., 2020, and citations therein). In this paper, I combine machine learning methods

outlined in Clemens and Rogers (2020) with text analysis methods proposed in Marquardt (2021) to construct key mental health variables which I then use in a structural model to estimate variation in both patient and physician decision-making. While I focus on ADHD in particular, the methods I propose can be used in a variety of settings where researchers have access to clinical doctor notes, especially those focused on mental health in which diagnosis depends on subjective interviews documented via text as opposed to biological testing/ medical imaging.

The remainder of this paper is structured as follows. Section 2 provides medical details on ADHD diagnosis to help motivate the theoretical model, which is then outlined in Section 3. In Section 4, I summarize the electronic health record data with reduced form comparisons and describe the the machine learning/natural language processing techniques used to extract important information from clinical doctor notes. Section 5 presents the empirical strategy, identification discussion, and parameter estimates. In Section 6 I conduct ADHD diagnostic simulations to isolate mechanisms of disparities and quantify diagnostic errors. Finally, Section 7 concludes.

2 Background and Medical Details

I study the physician decision to diagnose Attention Deficit Hyperactivity Disorder in children and young adolescents. ADHD is a chronic mental disorder associated with symptoms of inattention, hyperactivity, and impulsivity. These symptoms are associated with lower educational attainment (Currie and Stabile, 2006) in addition to long term effects on earnings and employment opportunities (Fletcher, 2014; Knapp et al., 2011). Importantly, treatment through stimulant medication and/or behavioral therapy has been shown to reduce the symptoms and associated costs related with this condition (Jensen et al., 2001), making accurate ADHD diagnosis and subsequent treatment essential for human capital development.

While the exact cause of ADHD is unknown, the medical literature agrees there is a strong heritability component. However, genetics alone do not indicate a diagnosis, and there is less

consensus regarding other environmental and structural factors (Hinshaw, 2018).[5] There is no biological or medical test to determine the presence of ADHD in a given patient. Instead, an ADHD diagnosis is defined by a list of behavioral symptoms outlined in *The Diagnostic and Statistical Manual of Mental Disorders*, currently in its fifth edition (DSM-V).[6] There are three possible types or presentations of ADHD: inattentive, hyperactive-impulsive, and combined type. A child (ages 4-17) meets the clinical definition of ADHD if they meet 6 or more behavioral symptoms presented in Table 1. In addition, these symptoms should be present in two or more settings (e.g., home and school) and experienced before age 12.

Table 1: DSM-V Symptoms for ADHD

Type I- Inattention
1. Often fails to give close attention to details or makes careless mistakes.
2. Often has difficulty sustaining attention in tasks or play activities.
3. Often does not seem to listen when spoken to directly.
4. Often does not follow through on instructions.
5. Often has difficulty organizing tasks and activities.
6. Often is reluctant to engage in tasks that require sustained mental effort.
7. Often loses things necessary for tasks or activities.
8. Is often easily distracted by extraneous stimuli.
9. Is often forgetful in daily activities.
Type II- Hyperactive/Impulsive
1. Often fidgets with or taps hands or feet or squirms in seat.
2. Often leaves seat in situations when remaining seated is expected.
3. Often runs about or climbs in situations where it is inappropriate.
4. Often unable to play or engage in leisure activities quietly.
5. Is often "on the go," acting as if "driven by a motor."
6. Often talks excessively.
7. Often blurts out an answer before a question has been completed.
8. Often has difficulty waiting his or her turn.
9. Often interrupts or intrudes on others.

Note: This table reflects abbreviated list of DSM-V symptoms by ADHD type. The full version is published in American Psychiatric Association (2013).

[5]Common risk factors mentioned in the medical literature include: low birth-weight, prenatal toxins, and exposure to lead. A list of more debated causes include: food additives/diet, in-utero cellphone radiation, and excess exposure to television/video games.

[6]The 5th edition of the DSM was released in May 2013; however, guidelines for ADHD in particular did not change significantly from the DSM-IV edition(Epstein and Loren, 2013).

It should be noted that the DSM-V does *not* have different symptom definitions or diagnostic guidelines for males and females. This is important for modeling and counterfactual diagnosis purposes as it explicitly restricts differences in ADHD prevalence to come only from differences in symptom expression between male and female children. Bruchmüller et al. (2012) discuss the medical and epidemiological literature on ADHD presentation and diagnosis, and conclude it is "unlikely that gender differences in the expression of ADHD can fully account for the fact that boys with ADHD receive treatment two to three times more often than girls with ADHD." This motivates the question: what other factors contribute to the large difference in ADHD diagnosis rates between boys and girls? To answer this question I first outline how an ADHD diagnosis is made.

In order to receive a clinical diagnosis, a patient must schedule and receive a behavioral assessment from a diagnosing physician. Scheduling this assessment is not required for all children, but may be encouraged based on feedback from teachers, guidance counselors, or primary care physicians during annual wellness checks.

According to pediatric best-care practices outlined in American Academy of Pediatrics (2011), a behavioral assessment should include an interview with the patient, the parent, and a teacher or alternative care-giver. Physicians may use published ADHD rating-scales along with open-ended questions, but should consult the DSM and document the presence of relevant symptoms. Based on this assessment, the physician should diagnose ADHD if they believe the patient meets the minimum requirements for diagnosis outlined in the DSM-V.

While American Academy of Pediatrics (2011) outlines best-practices for ADHD diagnosis, they also admit that these guidelines are often difficult for pediatricians and primary care physicians to follow in practice "because of the limited payment provided for what requires more time than most of the other conditions they typically address." Due to time, payment, or a variety of other constraints, it is unlikely that physicians are able to strictly follow these best-practice guidelines. In fact, surveys suggest that only about 60% of physicians incorporate these guidelines into their practice (Rushton et al., 2004; Chan et al., 2005). This finding, along with the institutional features of non-mandatory mental health screening, motivates the need for a structural model of ADHD diagnosis that incorporates

these different elements of diagnosis in order to separately identify the different mechanisms leading to diagnostic disparities.

3 Conceptual Framework

In traditional models of decision-making under uncertainty, deciding agents receive a noisy signal of the true state of the world, use the signal to update their prior beliefs, and make a decision to maximize utility. These types of models have been empirically estimated in healthcare settings (e.g., Anwar and Fang, 2012; Chan et al., 2021) in addition to other applications such as the judicial system (e.g., Arnold et al., 2020). What is missing from these models, however, is individual selection, which I show is an important mechanisms to understanding disparities in outcomes across patient groups, specifically in relation to mental health. In what follows, I present a model of ADHD diagnosis that pairs a physician decision-making under uncertainty model with a first-stage selection component that endogenizes the patient decision to seek mental health care (selection). I allow, but do not enforce, key model parameters to vary based on patient gender. I then discuss comparative statics to highlight the four potential mechanisms underlying ADHD diagnostic disparities between boys and girls: symptom prevalence, patient utilization costs, diagnostic uncertainty, and physician preferences.

3.1 Diagnosis Model with Endogenous Selection

The model is composed of three stages: a patient selection stage, a physician learning stage, and a clinical diagnosis stage. In the first stage, patients choose to schedule a behavioral assessment if their ADHD symptoms outweigh any costs associated with mental healthcare utilization. Conditional on selecting into care, the patient enters the second stage of the model in which the physician conducts a behavioral assessment, learns about the relevant symptoms, and develops a posterior probability of ADHD likelihood. In the final stage, the physician will choose a diagnosis decision based on ADHD posterior risk and the costs he bears from making a diagnostic error. The model allows for prevalence rates, patient

scheduling costs, physician costs, and physician learning rates to vary by patient gender as a way to capture the varying components of mental health diagnostic disparities.

ADHD Prevalence

Each child has some unobserved latent ADHD risk, v_i, which measures the extent of ADHD related symptoms. This comes from a continuous distribution $F_\theta(v)$, where θ indicates whether patient gender is male or female: $\theta \in \{m, f\}$. For computational simplicity, I assume $F_\theta(v)$ is a Normal CDF, though this assumption is not essential for identification, further discussed in Section 5.

$$v_i \sim N(\mu_\theta, \sigma_\theta^2) \tag{1}$$

This continuous mental health risk is in line with the medical literature that suggests ADHD symptoms present on a continuum (AHRQ, 2011). Despite this fact, ADHD diagnosis is binary by definition. Following the diagnostic guidelines in defining ADHD, a child has ADHD if and only if they meet all the requirements for diagnosis outlined in the DSM-V. Therefore, letting $S_i \in \{0, 1\}$ denote the true ADHD status, we have $S_i = 1(v_i > \overline{v})$ where $\overline{v}$ is the DSM-V defined minimum requirement for diagnosis, which by definition does not vary by patient gender.[7] Thus, differences in true ADHD prevalence between boys and girls depend only on differences in ADHD risk distribution parameters, with prevalence increasing in population mean risk, μ_θ.

Stage 1: Patient Choice to Schedule Behavioral Assessment

In the first selection stage of the model, the patient/parent must decide whether or not to schedule a behavioral assessment.[8] Parents will schedule a behavioral assessment if the child's

[7] In the 2013 DSM-V release, guidelines were updated to reflect varying levels of symptoms severity. While these are associated with different CPT codes in how a physician is reimbursed, ICD-9 and ICD-10 codes were not adjusted and still reflect binary indicators, validating the assumption to use a single-valued cut-off. In the main estimation section of this paper, I do not assume a $\overline{v}$ value. However, this is necessary in counterfactual simulations which I discuss further in Section 6.

[8] Because I focus on children as patients, I assume the parent and child make joint decisions and thus

behavioral symptoms outweigh any scheduling costs, c_i, which include a gender-specific mean component, c_θ, and an idiosyncratic cost $\varepsilon_i \mid v_i \sim N(0,1)$. Because health insurance typically covers behavioral assessments with little to no out of pocket expenditures, c_i includes non-monetary constraints (or conversely nudges) impacting the decision to schedule a behavioral assessment. This can include parent time constraints, distance to the nearest health center, recommendations from school teachers, or information obtained from primary care physicians during annual wellness visits. In other words, c_i captures everything that impacts the decision to seek mental health care net of child symptom level, v_i. I allow for differences in the gender-specific mean utilization cost, c_θ, but do not enforce a difference empirically.

I assume the patient observes their costs c_i and their symptoms v_i, but does not have enough medical information to know $\overline{v}$, thus motivating them to seek a professional opinion. Denoting Q_i as an indicator for behavioral assessment, I define $Q_i = \mathbb{1}(v_i > c_i)$. Equation (2) defines the gender-specific behavioral assessment rate, which follows from (1) and the assumption that $c_i = c_\theta + \varepsilon_i \perp\!\!\!\perp v_i$.

$$\Pr\left(Q_i = 1 \mid \theta\right) = \Phi\left(\frac{\mu_\theta - c_\theta}{\sqrt{1+\sigma_\theta^2}}\right) \tag{2}$$

Stage 2: Physician Learning via Behavioral Assessment

I assume that the physician knows the gender-specific ADHD risk distribution, but does not know patient specific ADHD risk, v_i, nor the patient specific healthcare utilization costs, c_i. Thus, the physician prior can be defined by (1) and is a function of ADHD risk distribution parameters μ_θ and σ_θ.[9]

If a patient chooses to schedule a behavioral assessment, the physician will learn about the patient specific ADHD risk, v_i. Through this process, the physician receives a noisy signal, x_i, of the true ADHD risk v_i, defined by equation 3. The signal is unbiased and correlated with the true state through $\rho_\theta \in (0,1)$. I allow correlation to vary by patient

simply refer to "patient" throughout the model.

[9]This assumption allows me to interpret the diagnostic threshold parameter τ_θ as physician preferences over diagnostic errors. In Appendix C.2, I discuss the benefits of this assumption and implications if it fails.

gender as a way to capture variation in diagnostic uncertainty coming from signal quality.[10]

$$\begin{pmatrix} v_i \\ x_i \end{pmatrix} \middle| \; \theta \Bigg) \sim N \left(\begin{pmatrix} \mu_\theta \\ \mu_\theta \end{pmatrix}, \begin{pmatrix} \sigma_\theta^2 & \rho_\theta \sigma_\theta^2 \\ \rho_\theta \sigma_\theta^2 & \sigma_\theta^2 \end{pmatrix} \right) \tag{3}$$

The physicians then uses this information to update their belief of ADHD risk via a Bayesian updating process. After observing $x_i = x$ the physicians update their prior, resulting in the posterior ADHD risk distribution defined in (4). Notice that the updated risk posterior mean is a weighted average of patient observed signal, x, and the physician prior risk mean, μ_θ, where the weight placed on the signal depends on the signal quality ρ_θ.

$$v_i \mid x \sim N \left(\left(\rho_\theta x + (1 - \rho_\theta) \, \mu_\theta \right), \sigma_\theta^2 \sqrt{1 - \rho_\theta^2} \right) \tag{4}$$

Stage 3: Physician Diagnosis Decision

Finally, the physician makes a binary diagnosis decision, $D_i \in \{0, 1\}$. I follow the literature in assuming the goal of the physician is to match the diagnosis decision to the true health state, and thus minimize diagnostic errors. This can be modeled as a a risk-threshold decision rule where physicians diagnose ADHD to patients whose posterior risk of ADHD is above a diagnostic threshold, τ_θ.

$$D_i \mid x, \theta = \mathbb{1}(v_i \mid x \geq \tau_\theta) \tag{5}$$

In Appendix C.1, I present a physician utility framework and derive this risk-threshold decision rule to show how τ_θ can be interpreted as physician preferences over diagnostic errors. Intuitively, if physicians view *misdiagnosis* as costly, they are worried about diagnosing children on the margin of ADHD according to risk and will thus apply a higher diagnostic threshold. On the other hand, if physicians view *missed diagnoses* as costly, they would

[10]This health signaling structure is very similar to that defined in Chan et al. (2021), but assumes that signal strength varies across patient types as opposed to physician types.

prefer to diagnose children on the margin of ADHD and will thus apply a lower diagnostic threshold. I allow these thresholds to differ by patient gender to capture potential differences in physician perceived cost of diagnostic errors.[11]

Using the physician posterior in equation 4, the probability a patient is diagnosed, conditional on behavioral assessment and received signal, is:

$$\Pr\left(D_i = 1 \mid Q_i = 1, x_i, \theta\right) = \Phi\left(\frac{1}{\sigma_\theta\sqrt{1-\rho_\theta^2}}\left(\rho_\theta x_i + (1-\rho_\theta)\,\mu_\theta - \tau_\theta\right)\right) \tag{6}$$

3.2 Mechanisms of Diagnosis and Diagnostic Disparities

Combining equations 2 and 6 yields the following gender-specific diagnosis rate:

$$\begin{aligned}\Pr\left(D_i = 1 \mid \theta\right) &= \Pr\left(D_i = 1 \mid Q_i = 1, x_i, \theta\right) \times \Pr\left(Q_i = 1 \mid \theta\right) \\ &= \underbrace{\Phi\left(\frac{1}{\sigma_\theta\sqrt{1-\rho_\theta^2}}\left(\rho_\theta x_i + (1-\rho_\theta)\,\mu_\theta - \tau_\theta\right)\right)}_{\text{Physician Diagnosis Rate}} \times \underbrace{\Phi\left(\frac{\mu_\theta - c_\theta}{\sqrt{1+\sigma_\theta^2}}\right)}_{\text{Patient Assessment Rate}}\end{aligned} \tag{7}$$

Diagnosis rates are a function of underlying prevalence, mental healthcare utilization costs, diagnostic uncertainty, and physician preferences/diagnostic thresholds. My structural model captures each of these elements via μ_θ, c_θ, ρ_θ, and τ_θ, respectively.

The comparative statics of population-group diagnosis rates are quite intuitive. Groups with higher prevalence, captured by mean risk, μ_θ, are associated with higher diagnosis rates.[12] This increase can be attributed to both the patient selection channel ($\frac{\partial Pr(Q_i)}{\partial \mu_\theta} > 0$) and the physician conditional diagnosis channel ($\frac{\partial Pr(D_i|Q_i)}{\partial \mu_\theta} > 0$), where the latter is due

[11] In analogous models coming from the physician bias literature, this threshold is often referred to as taste-based discrimination as it captures the difference in diagnosis rates for identical patients in terms of risk. However, it may be that the cost of diagnosis errors differ by patient gender, in which case the heterogeneous thresholds are justified. I leave this distinction to the medical literature and instead refer to differences in τ_θ as differences in *perceived* cost of errors, remaining agnostic about its medical accuracy.

[12] Prevalence rates are technically defined as $P(S = 1|\theta) = P(v_i > \overline{v}|\theta)$ where $\overline{v}$ is the DSM-V specified cut-off rule. Provided $\overline{v}$ is not too large, it follows from $v_i \sim N(\mu_\theta, \sigma_\theta^2)$ that there is a one-to-one monotonic correspondence between prevalence and mean risk.

to higher physician prior beliefs. On the other hand, high values of patient utilization costs imply lower diagnosis rates because fewer patients choose to seek mental health care ($\frac{\partial Pr(Q_i)}{\partial c_\theta} < 0$). In terms of physician preferences, high diagnostic thresholds, corresponding to large cost of misdiagnosis, are associated with lower diagnosis rates ($\frac{\partial Pr(D_i|Q_i)}{\partial \tau_\theta} < 0$). Finally, groups with lower diagnostic uncertainty (i.e., higher ρ_θ) will have higher population diagnosis rates ($\frac{\partial P(D_i=1|Q_i=1)}{\partial \rho_\theta} > 0$ in the selected sample).[13]

These population-group comparative statics map directly into mechanisms explaining diagnostic disparities between males and females: $\Delta = \frac{P(D|\theta=m)}{P(D|\theta=f)}$. Diagnosis rates increase with population prevalence and signal quality and decrease with utilization costs and diagnostic thresholds. Therefore, the ADHD diagnostic disparity seen between males and females may be attributed to higher male prevalence ($\mu_m > \mu_f$), higher signal strength for male patients ($\rho_m > \rho_f$), lower utilization costs for male children ($c_m < c_f$), or lower diagnostic thresholds applied to male patients ($\tau_m < \tau_f$). From a health care policy standpoint, it is essential to identify which of these mechanisms explain the diagnostic disparity and by how much. The direction and relative contribution of each mechanisms is an empirical question which I explore in the remainder of this paper.

3.3 Empirical Approach Outline

To identify the mechanisms of diagnostic disparities, I separately estimate the model parameters for both male and female patients: $(\mu_\theta, \sigma_\theta, c_\theta, \rho_\theta, \tau_\theta)$ for $\theta \in \{m, f\}$. I use electronic health record data and estimate equation 7 separately for male and female sub-samples.

The variables required to estimate gender-specific diagnosis rates (7) are clinical diagnosis decision, D_i, behavioral assessment indicator, Q_i, ADHD risk signal, x_i, and patient gender,

[13] $\frac{\partial P(D_i=1|Q_i=1)}{\partial \rho} = \phi(\frac{\rho(x-\mu)+\mu-\tau}{\sigma(1-\rho^2)^(1/2)})(\frac{x-\mu+\rho(\mu-\tau)}{\sigma(1-\rho^2)^(3/2)})$. By contradiction, assume this partial derivative is negative. As $\sigma > 0$ and $\rho \in (0,1)$, this implies that $\rho(x-\mu)+(\mu-\tau)$ and $x-\mu+\rho(\mu-\tau)$ have opposite signs. For the selected sample with $Q_i = 1$, symptoms are on average higher than underlying risk implying $x > \mu$. Additionally, assuming physicians would diagnose less than 50% of population, $\tau > \mu$. Therefore, partial derivative is negative if and only if $\rho > \frac{\tau-\mu}{x-\mu}$ and $\rho > \frac{x-\mu}{\tau-\mu}$ which violates the requirement that $\rho \in (0,1)$. Thus, it must be that $\frac{\partial P(D_i=1|Q_i=1)}{\partial \rho_\theta} > 0$ for selected sample.

θ_i. However, the only variables directly observed in the electronic health record are D_i (via associated ICD-10 codes) and patient gender, θ_i. Even though behavioral assessment, Q_i, and patient signals, x_i, are not directly imputed into electronic health record systems, I show how both variables can be recovered from clinical doctor note text.

I then use these observed and constructed variables to estimate the structural model parameters. I break this down into two steps where the first recovers the gender-specific population mean ADHD risk parameter, μ_θ. Because ADHD risk signals are only observed for an endogenously selected sample, I recover this parameter using quasi-exogenous variation in scheduling costs following an approach outlined in Arnold et al. (2020). Once male and female population mean risk are estimated, the remaining parameters are identified and estimated from moments defined by behavioral assessment rates and the conditional diagnosis probit following equation (7). I discuss this process in detail in Section 5.

4 Data and Variable Construction

The data come from de-identified electronic health records provided by a large healthcare center in Arizona. I obtain encounter level data for all pediatric patients (age<18) who had a health appointment with a diagnosing physician at some point during the sample period of January 2014 to September 2017.[14] I first exclude children younger than 5 years old, whose rates of ADHD diagnosis and treatment are very low and whose medical care requires peer-to-peer review and prior authorization (N=11,183). I then drop erroneous encounters, encounters with insufficient documentation, or patients with missing demographic information (N=1784). The remaining data encompass 37,021 unique patient encounters, for 11,397 unique patients. Patient characteristics include: birthdate, gender, race/ethnicity, original primary care physician, and insurance status. Encounter characteristics include: appointment date, physician seen, associated diagnoses (if any), and most importantly, the clinical

[14] A diagnosing physician is identified as one who diagnosed ADHD at least once during the sample period. There are 220 diagnosing physicians in my dataset.

doctor note summarizing the encounter.

As ADHD is a chronic condition, the unit of observation in the model is at the patient level. I label a patient as clinically diagnosed with ADHD ($D_i = 1$) if the patient has an encounter during the sample period in which one of the first three associated diagnosis codes reflect an ADHD diagnosis.[15] Simple summary statistics are available in Appendix Tables A1 and A2.

Of the roughly 11,000 patients seen from 2014 to 2017, 6.24% have a clinical ADHD diagnosis.[16] Males are diagnosed with ADHD significantly more than females. The raw diagnostic disparity is 2.33:1, with 8.68% of males receiving a clinical diagnosis and only 3.72% of females. Table 2 shows that this male-female diagnostic disparity persists even after controlling for readily observable characteristics such as patient age, insurance status, race/ethnicity, and previous health care utilization.

Table 2: Reduced Form ADHD Diagnostic Comparisons

	(1)	(2)	(3)
Male	0.048***	0.048***	0.039***
	(0.004)	(0.004)	(0.004)
Added Patient Observables:			
Demographic Variables	N	Y	Y
Healthcare Utilization Variables	N	N	Y
Adj. R-squared	0.010	0.014	0.072
Observations	11,265	11,265	11,265

Note: This table presents the estimated coefficient on patient gender from a OLS regression of ADHD clinical diagnosis on patient controls. Demographic Variables: patient age, insurance status, and race/ethnicity. Health Care Utilization Variables: # of doctors seen, # of appointments, appointment year fixed effects, and indicators for other mental health diagnosis, wellness visit, visit with psychiatrist. All controls based on average (or max) across patient appointments, with only those prior to ADHD diagnosis appointment for patients with a clinical diagnosis. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[15]The ICD-9 codes include 314.00 and 314.01, and the ICD-10 codes include F90.0, F90.1, F90.2. I group together the different types of ADHD into a single diagnosis category as a way to increase power in the presence of small sample sizes.

[16]The in-sample ADHD diagnosis rate is slightly lower than the national average during this time period. This is likely due to the fact that a large portion of the population is of Hispanic ethnicity, and research suggests a significantly lower diagnosis rate for this group (see Morgan et al., 2013). I discuss the implications of this sample bias in Section 7.

As discussed in Section 3.3, there are two key mental health variables that are unobserved to the econometrician yet play a central role in the physician diagnosis decision. These are (1) Q_i, which is an indicator for whether a patient receives a behavioral assessment, and (2) x_i, which is the patient specific ADHD match signal observed conditional on behavioral assessment. In the next two sections I discuss how both of these variables are defined and constructed using clinical doctor note data combined with machine learning and natural language processing techniques, respectively.

4.1 Behavioral Assessment- Q_i

The electronic health record does not specifically indicate whether a behavioral assessment was conducted during the visit. Therefore, I manually construct this variable from the data by applying machine learning techniques to clinical doctor notes as a way to predict whether a behavioral assessment was conducted during an appointment using the content of the doctor note. I give a general outline of the procedure here and provide additional details in Appendix B.

I first take a subset of appointments in which the behavioral assessment indicator variable is known with almost certainty. For model training purposes, this must include appointments with a positive behavioral assessment label and appointments with a negative behavioral assessment label. I assume that a behavioral assessment was conducted if the encounter is associated with an ADHD diagnosis, a differential mental health diagnosis (e.g., bipolar disorder), or a comorbid condition (e.g., generalized anxiety disorder) as noted by the DSM-V. The negative labeled appointments are those with an associated diagnosis that is never co-diagnosed with a mental health condition. These include conditions such as strep throat, skin rashes, and sinus infections. Table B10 presents the full list of icd9 codes included under each hand label. The remaining appointments are considered 'unlabeled' due to either no associated diagnoses or appointments with ambiguous icd9 codes that could be related to either mental or physical health concerns (e.g., abdominal pain can be associated with anxiety or a virus). The purpose of this machine learning approach is to determine whether

behavioral symptoms were discussed and ADHD diagnosis considered by the physician during these unknown set of appointments.

I first determine a set of model features using information from the clinical doctor notes in the labeled dataset. I consider 41 features, including note length, relative frequency of the top 20 'positive' label words, and relative frequency of the top 20 'negative' label words. Figure 1 provides a visual of these features with a word cloud representation broken up by behavioral assessment label, where $Q_{ij} = 1$ indicates a behavioral assessment was included in notes for appointment j, and $Q_{ij} = 0$ indicates no behavioral symptom discussion. As expected, the positive behavioral assessment label includes words related to behavioral symptoms such as: *school*, *social*, *behavior*, *family*, and *feel*. The negative behavioral assessment label includes words more related to physical rather than mental health concerns. These include words such as: *pain*, *fever*, *cough*, and *rash*.

Figure 1: Behavioral Assessment Indicator Word Clouds

Non-Behavioral Words **Behavioral Words**

Note: Word clouds based on relative frequency of word-stems in labeled appointments used for machine learning model training, shown separately for Non-Behavioral ($Q_{ij} = 0$) and Behavioral ($Q_{ij} = 1$) labeled appointments, respectively. This figure presents full words, whereas actual stems used for prediction are listed in Appendix B.

Finally, I use the labeled data and selected features to train a random forest machine learning algorithm, which I then apply to the unlabeled dataset in order to predict whether behavioral symptoms were discussed during the appointment based on the information in the clinical doctor note. I take the maximum of this prediction across patient encounters to obtain the behavioral assessment indicator Q_i used in model estimation, based on a 0.5 prediction cut-off.

There is an important distinction to be made here between full symptom discussion

(i.e., behavioral assessment) and symptoms mentioned casually during wellness checks. As ADHD diagnosis can only be made following the former, I require $Q_i = 1$ if and only if the patient receives a behavioral assessment during the sample period. This follows naturally by the construction of the labeled set used in training the machine learning model. The machine learning algorithm will only assign a positive prediction label if the words in the doctor note closely align with the words in the set of appointments with a positive label. By construction, these appointments were ones associated with a mental health diagnosis code and thus the notes most likely reflect a full behavioral assessment. Therefore, appointments in which only a few symptoms were mentioned in passing will not be assigned a positive behavioral assessment label by the machine learning prediction. This includes patients who only briefly (or not at all) talk about child behavior when asked during annual wellness checks. Therefore, the only way in which patient i receives a positive label $Q_i = 1$ is if either (i) patient i receives a clinical mental health diagnosis during the sample period and thus falls in the training set with positive label, or (ii) at least one of the doctor notes associated with an appointment for patient i contains enough mental health symptom words to be labeled as a behavioral assessment by the machine learning prediction.

The machine learning algorithm predicts that approximately 17% of children receive a behavioral assessment, with males scheduling these assessments more than females. This average estimate is in line with the *American Academy of Pediatrics* Clinical Guidelines for ADHD which states: "Primary care pediatricians and family physicians recognize behavior problems that may affect academic achievement in 18 percent of the school-aged children seen in their offices and clinics" (Herrerias et al., 2001).

4.2 ADHD match signal- x_i

Recall that v_i is the (unobserved) true health state and represents a measure of ADHD risk based on behavioral symptoms and that x_i is an unbiased yet noisy signal of v_i that physicians observe during patient behavioral assessment. Because ADHD diagnosis is defined by a list of behavioral symptoms (see Table 1), I interpret v_i as a composite measure summa-

rizing number and severity of symptoms *experienced* by patient i. Following this logic, x_i is then a composite measure summarizing number and severity of symptoms *discussed* with a physician during behavioral assessment.

Even detailed electronic health records do not report readily observable patient behavioral symptoms. Instead, this information is collected during an interview and documented in the clinical doctor note. With access to these clinical doctor notes, I construct a proxy for x_i using natural language processing techniques originally proposed in Marquardt (2021). Essentially, I calculate the overlap between symptoms in the DSM-V symptom criteria list (see Table 1) and symptoms in the collective doctor notes for a given patient, making necessary adjustment to account for semantic content. This text-constructed value is a proxy for the signal observed by the physician assuming they follow clinical guidelines in documenting all "relevant behaviors of inattention, hyperactivity, and impulsivity from the DSM" (American Academy of Pediatrics, 2011).[17]

As x_i is defined on the patient level, I first combine patient notes across encounters into a single document. I combine only notes that were labeled as 'positive behavioral assessment' by the machine learning prediction described in the previous section. For patients with an eventual ADHD diagnosis code, I include the note associated with the first appearance of ADHD diagnosis and behavioral notes from earlier encounters. I also include notes that occur within 60 days after the initial diagnosis to account for the fact that behavioral assessments may expand over multiple visits and physicians are not always consistent on when diagnosis codes are assigned during this process.[18]

With the behavioral assessment notes combined into one document per patient, I then calculate ADHD signal match, x_i. I follow the natural language processing algorithm pro-

[17]In Appendix C.2, I discuss the implications of this full documentation assumption. I argue that if the assumption fails, then I under-estimate mean ADHD risk. Given that my ADHD prevalence rates derived from ADHD risk parameters (presented in Table 6) align with what is found in the medical literature, I do not consider this to be a large concern for the main results.

[18]Of the children that are diagnosed with ADHD in my sample, 33% have a behavioral assessment within 30 days of the initial diagnosis and 42% have a behavioral assessment appointment within 60 days of the initial diagnosis. This suggests that physicians may be breaking up behavioral assessments into multiple visits and assigning ADHD diagnosis codes slightly before the assessment is fully complete.

posed in Marquardt (2021), in which patient documents and DSM-V symptom requirements are compared using an Adjusted Bag-of-Words Model.

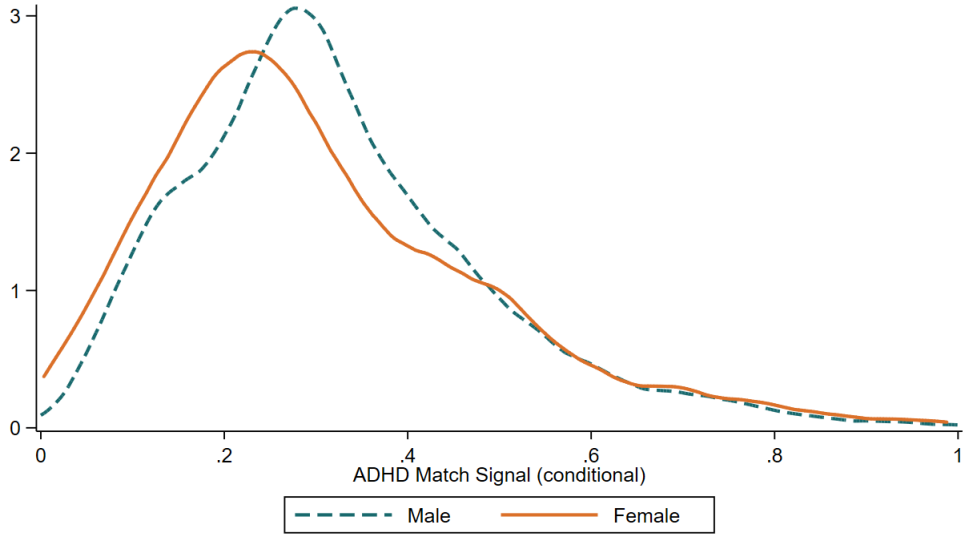
I first pre-process the clinical texts following standard text cleaning procedures (e.g., spell check, abbreviation replacement, and size reductions). I next group words according to contextual meaning which requires part-of-speech tagging and synonym replacement. Each document is then broken into uni-gram and bi-gram tokens, where the latter is included to preserve meaning from negation. Using these tokenized documents, I build the adjusted Bag-of-Words (BOW) matrix where rows (i) represent documents, columns (k) represent bi-grams of word groups, and binary matrix elements indicate the presence of bi-gram k in document i. In this application, I consider N+3 documents. The first N correspond to the patient doctor notes for the N patients that receive behavioral assessments. The latter 3 documents correspond to (1) the list of Inattentive symptoms (Type I in Table 1), (2) the list of Hyperactive/Impulsive symptoms (Type II in Table 1), and (3) the combined list of Type I and Type II symptoms. In the notation of Marquardt (2021), $s = \{1, 2, 3\}$ corresponds the 3 types of ADHD: Inattentive, Hyperactive/Impulsive, and Combined Type. Finally, patient-type specific match values, x_{is} are calculated by taking the cosine similarity measure between the BOW row vector for patient i and the BOW row vector for ADHD Type s. Because I do not distinguish between the different diagnosis types when defining a clinical diagnosis in the data, I construct the patient overall ADHD match signal as the maximum of the patient match value across types. In other words, I calculate $x_i = max\{x_{i1}, x_{i2}, x_{i3}\}$. See Marquardt (2021) for additional algorithm details.

Across both males and females, the average signal match is is 0.314 with a standard deviation of 0.170. For reference, a value of $x_i = 1$ indicates that the note for patient i references *all* symptoms in either the Inattentive list, the Hyperactive/Impulsive List, or the Combined List, and a value of $x_i = 0$ indicates no reference to any symptoms.[19] The

[19]Recall that only a sub-set of symptoms are necessary for appropriate diagnosis, which implies there is some threshold $\overline{x}$ of which $x_i > \overline{x}$ implies ADHD. I remain agnostic about the this threshold value in estimation of the general model, and discuss potential values of this cut-off in Section 6 along with its implications on diagnostic errors.

signal for males is slightly larger than for females; however, the difference is only significant at the 10% level. Figure 2 presents a visual for the ADHD match signal distribution by patient gender. This provides only suggestive evidence of true prevalence differences as the plot represents the match for the (endogenous) set of patients that receive a behavioral assessment. Therefore, in the general population, ADHD risk signal distributions would be shifted to the left, though the magnitude of the shift and change in dispersion depend on mental health utilization costs, which may differ based on patient gender.

Figure 2: Observed ADHD Match Signal by Patient gender



Note: Figure shows gender-specific distribution of constructed ADHD match signals x_i based on NLP techniques described in Section 4.2. This implicitly covers the set of patients with behavioral assessment, $Q_i = 1$, thus shows only a truncated distribution of the true population ADHD risk.

Table 3 presents summary statistics for the key variables needed to estimate the diagnosis model parameters. The top panel of Table 3 presents ADHD diagnosis rates for the full sample and highlights the diagnostic disparity between males and females. While males do receive behavioral assessments significantly more than females, this selection does not explain the entire diagnostic disparity as seen by the lower panel of Table 3. For those that receive a behavioral assessment, 43.3% of males will be diagnosed with ADHD and only 25% of females will be diagnosed. It is also unlikely that differences in symptom presentation fully explain the diagnostic gap as the difference in symptom match is only significant at

the 10% level. This table provides suggestive evidence that the ADHD diagnostic disparity is a function of selection, prevalence, *and* physician decision-making biases. Therefore, a structural estimation approach is needed to separate out the magnitude and direction of these underlying mechanisms.

Table 3: Mental Health Observational Comparisons

	Total	Male	Female	Difference
Full Sample				
ADHD Dx.	0.0624	0.0868	0.0372	0.0495***
	(0.242)	(0.282)	(0.189)	
Behav. Appt. (Q_i)	0.169	0.194	0.143	0.0505***
	(0.375)	(0.395)	(0.350)	
N	11397	5786	5611	
Behavioral Assessment Subsample ($Q_i = 1$)				
ADHD Dx.	0.357	0.433	0.250	0.183***
	(0.479)	(0.496)	(0.433)	
ADHD Match Signal (x_i)	0.314	0.320	0.305	0.0149*
	(0.170)	(0.162)	(0.179)	
N	1923	1120	803	

Note: ADHD Dx. (D_i) based on ICD codes in EHR. Behavioral Assessment rates (Q_i) and ADHD Match Signal measures (x_i) are constructed using machine learning and natural language processing techniques outlined in Sections 4.1 and 4.2, respectively. Differences calculated as female means subtracted from male means, and significance based on two-sample T-test difference in means. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Model Parameter Estimation and Identification

With data on ADHD diagnosis D_i, behavioral assessment Q_i, patient gender θ_i, and conditional ADHD risk signal x_i, I estimate parameters of the structural model: $(\mu_\theta, \sigma_\theta, c_\theta, \rho_\theta, \tau_\theta)$ for $\theta \in \{m, f\}$. As discussed in Section 3.3, the parameter estimation procedure requires two steps where the first recovers gender-specific population mean ADHD risk parameter, μ_θ, and the remaining parameters are obtain via maximum likelihood estimation of behavioral assessment and conditional diagnosis probabilities following equation (7), estimated separately for male and female patient groups.

5.1 First Stage: ADHD Population Risk

The reason for a first stage estimation of population mean ADHD risk μ_θ is shown mathematically in equation (7) but also intuitively following the comparative statics discussion in Section 3.2. Behavioral assessment rates are increasing in mean risk, μ_θ, and decreasing in patient utilization costs, c_θ. At the same time, conditional diagnosis rates are increasing in mean risk, μ_θ, and decreasing in diagnostic thresholds, τ_θ. This makes it difficult to separately identify the three components even with information on Q_i, x_i, and D_i. In an ideal setting in which risk signals are observed for all patients, one could estimate μ_θ using gender-specific sample average risk, $\sum_{i \in N_\theta} x_i$. However, x_i is only observed for the subset of patients that receive a behavioral assessment. Because patients endogenously select into behavioral assessment according to unobserved ADHD risk, the average value of *observed* signals will over-estimate the population risk mean, as shown by equation (8).

$$E[x_i|Q_i = 1] = E[x_i|v_i > c_i] = \mu_\theta + \underbrace{\rho_\theta \sigma_\theta^2 \frac{\phi(\frac{c_i - \mu_\theta}{\sigma_\theta})}{1 - \Phi(\frac{c_i - \mu_\theta}{\sigma_\theta})}}_{\text{upward bias}} \tag{8}$$

I use quasi-exogenous variation in behavioral assessment scheduling costs to recover unbiased estimates of mean population risk for males and females. To build intuition for this approach, consider a set of patients with extremely low behavioral assessment scheduling, c_i. For low enough levels of c_i, the probability of behavioral assessment is approximately 1, so the patient will schedule a behavioral assessment and thus ADHD risk signals, x_i, will be observed. Further, the bias term in (8) for these patients with low c_i goes to 0, and thus sample mean of x_i for patients with low scheduling costs (or conditionally high probability of behavioral assessment) provides an unbiased estimation of population mean risk, μ_θ.

As c_i is unobserved in application, I instead estimate individual propensity to schedule a behavioral assessment using quasi-exogenous "cost-shifters". An individual factor, Z_i, is a valid cost-shifter under the following two conditions:

(a) Z_i is correlated with behavioral assessment propensity through patient scheduling costs, c_i.

(b) Z_i is independent of patient ADHD risk, v_i.

I use primary care physician identifiers as the source of quasi-exogenous behavioral assessment scheduling costs in this application. The electronic health record includes both the *diagnosing physician* as well as the patients' *original primary care physician (PCP)* where the former denotes who the patient meets with during a given appointment, and the latter is the PCP originally seen when the patient first entered the health system. Because diagnosing physicians may be chosen endogenously, I instead focus on the original primary care physician and define Z_i as a vector of size p, where $Z_{ip} = 1$ if child i is a patient of PCP p.[20]

To see how the original PCP identifier is correlated with behavioral assessment scheduling costs, it is relevant to recall Section 2 where I discuss the institutional details of behavioral assessment scheduling. Parents may schedule these appointments independently based on own concerns or suggestions from teachers. However, it is likely that they first bring up these concerns with their child's primary care physician who is trained to ask about patient school performance and behavioral concerns during annual wellness visits (American Academy of Pediatrics, 2011). If warranted by the response, PCPs may encourage the parent to schedule a follow-up appointment (either with themselves, with another pediatrician, or with a psychiatrist) so that a full behavioral assessment can be conducted. This discussion and subsequent recommendation from the child's original primary care physician can reduce the cost of scheduling a full behavioral assessment through increased mental health awareness, help with internal scheduling, comfortability with health system personnel, etc., thus satisfying the relevance condition (a).

Importantly, PCPs have discretion over what to address during routine check-ups and whether or not to suggest the patient seek follow-up mental health care. Some may be more thorough during these wellness checks in regard to questions about child behavior, and thus differ in the rates at which they suggest their patients seek follow-up care and schedule behav-

[20]I use the *original primary care physician* as opposed to the *diagnosing physician* as the latter is likely chosen endogenously. Patients with behavioral concerns may specifically schedule appointments with physicians who specialize in mental health. This would suggest a positive relationship between the diagnosing physician and v_i which violates requirement (b).

ioral assessments (referral rates). Appendix Figure A1 shows the variation in referral rates across primary care physicians. To empirically verify that the PCP identifier meaningfully influences the patient probability of scheduling a behavioral assessment, I regress patient behavioral assessment indicator, Q_i, on patient controls and original PCP fixed effects. I test for and find strong joint significance of PCP fixed-effects, results presented in Appendix Table A3.

Condition (b) is satisfied if original PCPs are chosen or assigned independently of true ADHD risk, v_i. As v_i is unobserved, I cannot test for this directly, though a list of observations and institutional details provide support for its validity. First, primary care physicians are typically selected by patients before age 5, which is the age at which behavioral symptoms may develop. This timing structure means that parents do not chose primary care physicians selectively after observing v_i. Second, there are 600 *original* primary care physicians covering the patients in my sample, but only 24 of these ever diagnose ADHD.[21] So while PCPs may differ in the number of patients they encourage to seek follow-up mental health care, they generally do not diagnose ADHD themselves, suggesting that patients set up behavioral assessments with alternative physicians, again implying no relation between the original PCP and patient v_i. Finally, while patients may not select PCP based on v_i directly, condition (b) would still be violated if PCP selection is based on other factors, W_i, that are correlated with ADHD risk, such as age, race/ethnicity, and income. I test for this by analyzing an ordinary least squares regression of PCP referral rate on various patient demographics. I define PCP referral rate as the leave-one-out average behavioral assessment rate among all other patients of the given PCP. Appendix Table A5 presents the coefficients from this regression, which are not significantly different from zero, providing support for balance across original primary care physicians.[22]

[21] There are 220 diagnosing physicians in my sample. 24 of these are the original primary care physician of the patient they diagnose. The remaining 196 physicians are either pediatricians or psychologists that conduct behavioral assessments for patients referred to them by other PCPs in the system.

[22] There may still be concern that patients choose PCPs based on unobserved factors that are correlated with ADHD risk, leading to biased estimates of μ_θ. However, so long as these unobserved factors are independent of patient gender, the relative difference between male and female ADHD risk is unaffected. I

Under conditions (a) and (b), I can recover population ADHD risk estimates for male and female patients by taking the vertical intercept at one from the fitted relationship between observed ADHD signals and exogenous behavioral assessment propensity. Empirically, I first conduct a probit regression of behavioral assessment Q_i according to equation 9 where W_i includes a set of demeaned patient controls and Z_i denotes original PCP identifiers. Additional details and first stage coefficients are presented in Appendix Table A4.

$$P(Q_i = 1) = \Phi\left(W_i\beta + \delta Male_i + Z_i\gamma\right) \tag{9}$$

Next, I obtain exogenous behavioral assessment propensity, $\widehat{P_\theta(Q_i|Z_i)}$, by predicting behavioral assessment for each patient, holding W_i at sample means. With W_i demeaned, $\widehat{P_\theta(Q_i|Z_i)} = \Phi(\hat{\delta}Male_i + \widehat{\gamma}_{PCP_i})$ and is interpreted as the regression-adjusted exogenous behavioral assessment propensity due to quasi-exogenous variation in scheduling costs coming from original PCP referral rates.

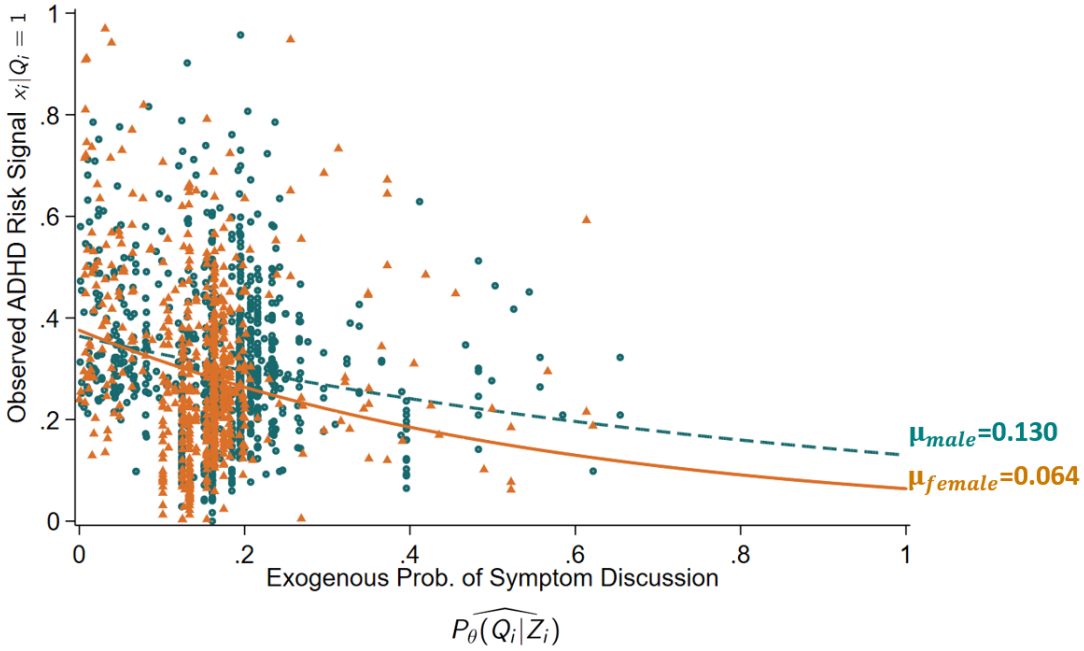
While there is significant variation in selection-adjusted behavioral assessment probability, the maximum value is only 0.65. In the absence of a sufficient number patients with $\widehat{P_\theta(Q_i|Z_i)} \approx 1$, values of μ_θ can be estimated via extrapolations of observed ADHD match signals on exogenous behavioral assessment propensity. Specifically, I fit a model of observed ADHD signals, x_i, on $\widehat{P_\theta(Q_i|Z_i)}$ for both male and female patients, and obtain selection-adjusted values of μ_m and μ_f by evaluating the fitted model at $\widehat{P_\theta(Q_i|Z_i)} = 1$ for $\theta \in \{m, f\}$, respectively. This exogenous extrapolation approach is similar to the methods proposed in Arnold et al. (2020) and in line with the literature on identification in selection models (see Chamberlain, 1986; Heckman, 1990).

Figure 3 provides a visualization of the identification for mean ADHD risk by patient gender. The vertical axis plots patient ADHD match signal, x_i, for the set of patients in which it is observed ($Q_i = 1$), paired with their selection-adjusted behavioral assessment propensity on the horizontal axis.

---

further discuss the implications of this assumption in Appendix C.2.

Figure 3: Behavioral Assessment Rates and Observed ADHD Risk



Note: This figure plots gender-specific observed ADHD risk signals on predicted behavioral assessment probabilities from equation (9), with demeaned patient controls set to 0, for the set of patients with $Q_i = 1$. The figure also plots gender-specific exponential curves of best fit and the associated male and female intercept at 1.

Consistent with the theory, observed ADHD risk signals, x_i, are decreasing in exogenous behavioral assessment propensity, $\widehat{P_\theta(Q_i|Z_i)}$. A low value of $\widehat{P_\theta(Q_i|Z_i)}$ implies that child i is a patient of a PCP with generally low referral rates. Thus, these patients are ex-ante unlikely to schedule a behavioral assessment appointment. Despite this, the patient appears in the data as receiving a behavioral assessment anyway, which means that they must have a high ADHD risk draw, v_i, consistent with high observed signal, x_i. On the other hand, a large value of $\widehat{P_\theta(Q_i|Z_i)}$ implies the child is a patient of a PCP with conditionally high referral rates. These patients are more likely to schedule behavioral assessments regardless of true risk, and thus have lower *observed* risk signals on average.

The two dashed lines in Figure 3 represent the gender-specific lines of best fit through the data. These are obtained via non-linear least squares estimation, specifying an exponential functional form to ensure estimates above 0. Appendix Table A6 presents the estimated model fit coefficients for both males and females. The vertical intercept at one of the gender-specific curves provides an estimate of population mean ADHD risk, μ_θ. These values are

reported in the figure and again in Table 4 which presents the full set of parameters estimates. I estimate population mean ADHD risk for males to be $\mu_m = 0.130$ and mean ADHD risk for females to be $\mu_f = 0.064$, with bootstrap standard errors of 0.039 and 0.053, respectively.

5.2 Second Stage: Recovering Remaining Parameters

I estimate the remaining model parameters by matching moments defined by behavioral assessment rates and coefficients from a conditional diagnosis probit obtained via maximum likelihood estimation, separately for male and female patient groups.

With μ_θ estimated in first stage, it is clear how remaining parameters are identified up to ADHD risk dispersion, σ_θ. Gender-specific mean utilization cost, c_θ, is identified through variation in behavioral assessment rates *conditional* on mean ADHD risk parameter μ_θ. Both diagnostic uncertainty (ρ_θ) and diagnostic thresholds (τ_θ) are identified in the conditional physician diagnosis probability equation. The correlation between physician diagnosis, D_i, and patient ADHD match signal, x_i, identifies the signal strength ρ_θ. The diagnostic threshold, τ_θ, is identified by mean diagnosis rates *conditional* on ADHD signals, x_i, and mean risk, μ_θ.

Up to this point, the parameter identification has not relied on any functional form assumptions, and thus would follow through if instead ADHD risk and signals were modeled using alternative distributions (e.g., the Beta distribution). However, estimation of the final parameter, ADHD risk dispersion (σ_θ^2), requires an additional moment that depends on this parametric form. Specifically, I estimate σ_θ using the moment defined by equation 10 which follows from the truncated normality of selected risk signals. Thus σ_θ is identified by the difference between observed risk signals and population mean risk, adjusting for selection due to different healthcare utilization costs and signal strength by patient gender.

$$\overline{x_{obs}}|\theta = E[x_i|v_i > c_i] = \mu_\theta + \rho_\theta \sigma_\theta \frac{\phi\left(\Phi^{-1}(1 - \widehat{Q|\theta})\right)}{\widehat{Q|\theta}} \tag{10}$$

Table 4 presents the full set of results for male and female patients. The differences in model parameters in Table 4 are informative about which mechanisms lead to ADHD diagnostic disparities and in what direction. As discussed in Section 3.2, diagnostic disparities between male and female patients can be attributed to differences in prevalence, mental healthcare utilization, diagnostic uncertainty, and diagnostic thresholds. The results in Table 4 suggest that each of these channels play an important role in explaining diagnostic disparities.

Table 4: Model Parameter Estimates

	Male	Female	Difference
Pop. Mean Risk μ_θ	0.130	0.064	0.066***
	(0.037)	(0.047)	
Pop. Risk Dispersion σ_θ	0.384	0.375	0.009
	(0.067)	(0.067)	
Utilization Costs c_θ	0.459	0.463	-0.004*
	(0.041)	(0.053)	
Signal Quality ρ_θ	0.351	0.408	-0.057***
	(0.054)	(0.062)	
Diagnostic Threshold τ_θ	0.258	0.398	-0.140***
	(0.019)	(0.030)	

Note: Standard errors in parenthesis based on 1000 bootstrapped patient samples. Differences calculated as female parameter estimate subtracted from male parameter estimate with significance based on paired T-test difference in means using bootstrap sample estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

First, the population mean risk for males is significantly higher than that of females (difference of 0.066), which increases diagnostic disparities through both the patient selection (behavioral assessment scheduling) channel and through higher physician posterior beliefs. This finding is directionally consistent with the medical literature which notes higher ADHD symptom prevalence in boys than girls (AHRQ, 2011). Second, males and females have similar mental health utilization costs suggesting patient preferences do not drive differences in ADHD diagnosis rates. I find that physicians put more weight on female ADHD risk signals ($\rho_f > \rho_m$), which by construction measures the overlap between patient symptoms and DSM-V symptoms. This finding is consistent with the results in Bruchmüller et al. (2012), who show that physicians are more likely to follow DSM-V criteria when diagnosing female patients and rely on heuristics for male patients. Finally, I find that physicians use

lower diagnostic threshold for male patients ($\tau_m < \tau_f$). This means that physicians are more likely to diagnose a male patient than a female patient with identical posterior ADHD risk, suggesting that perceived cost of missed-diagnosis is higher for male patients.

6 ADHD Diagnosis Simulations

In the previous section, I presented estimates of model parameters and discussed differences by patient gender. I now use the model parameters in Table 4 and run ADHD diagnosis simulations using the structural model in Section 3. This allows me to (1) identify how much of the diagnostic disparity can be attributed to the different mechanisms of diagnosis, and (2) provide estimates of both missed and mis-diagnosis for male and female patients based on the DSM-V definition of ADHD. Appendix Table A7 shows how well the simulated model matches key moments of the observed data, both overall and for male and female subsets of patients. The simulated model does extremely well at predicting average diagnosis rates (D) and behavioral assessment rates (Q). It slightly over-estimates mean ADHD match signals ($x|Q$) and conditional diagnosis rates ($D|Q$), but the differences are small.

6.1 Mechanisms of Diagnostic Disparities

To show how the various mechanisms contribute to the ADHD diagnostic disparity measure, I analyze simulated diagnosis rates under counterfactual scenarios that place restrictions on the source of gender-specific variation. The results of this analysis are presented numerically in Table 5 and visually in Figure 4.

The first row of Table 5 shows no diagnostic disparity (1.00:1), in which parameters are restricted to be identical for both boys and girls. The second panel shows the results when only ADHD risk distribution parameters μ_θ and σ_θ are allowed to vary. The remaining parameters are held constant at either the male or female estimates. When only ADHD underlying risk varies by patient gender, the diagnostic disparity increases from 1.00:1 to 1.57:1 or 1.63:1 depending on at which estimates the remaining parameters are held. This represents 45.2% or 50.0% of the observed disparity, suggesting that at most half of the diag-

nostic disparity can be attributed to differences in underlying symptom prevalence between male and female patients.

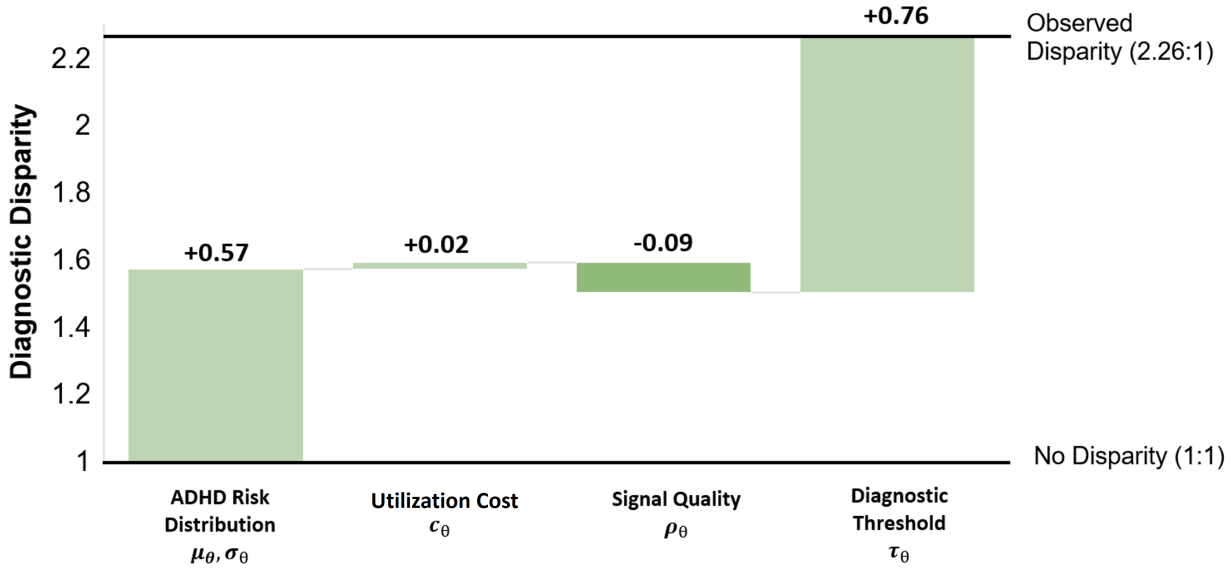
When patient utilization costs are also allowed to vary by patient gender, diagnostic disparities increase only slightly, suggesting that the very little of the diagnostic disparity can be attributed to differences in selection into mental health care (net of symptom prevalence differences). Finally, to analyze the physician decision making contribution, I relax the restrictions on signal quality and physician thresholds sequentially. The differences in signal quality actually reduces the diagnostic disparity, but this is more than made up for by different diagnostic thresholds which explain between 56.3% to 60.3% of the diagnostic gap between male and female patients.

Table 5: Disparity Mechanism Contribution

	Diagnostic Disparity	Disparity Effect	Relative Contribution
No Disparity	**1.00**	-	-
Prevalence Contribution			
ADHD Risk Distribution: μ_θ *and* σ_θ			
at Male estimates	1.57	+0.57	45.2%
at Female estimates	1.63	+0.63	50.0%
Patient Contribution			
Utilization Costs: c_θ			
at Male estimates	1.59	+0.02	1.6%
at Female estimates	1.65	+0.02	1.6%
Physician Contribution			
Signal Quality: ρ_θ			
at Male estimates	1.50	-0.09	-7.1%
at Female estimates	1.55	-0.10	-7.9%
Diagnostic Thresholds: τ_θ			
at Male estimates	2.26	+0.76	60.3%
at Female estimates	2.26	+0.71	56.3%
Observed Disparity	**2.26**	+1.26	100%

Note: This table presents results from diagnostic simulations with sequential restrictions the model parameters. Rows show which parameters are varied, starting with no variation, and adding variation until all parameters are at estimated value. Diagnostic disparity is calculated as simulated male diagnosis rate divided by simulated female diagnosis rate. Disparity effect calculates the net difference from disparities in previous simulation. Relative Contribution calculated as disparity effect divided by total effect of 1.26.

Figure 4: Cumulative Disparity Mechanism Effect



Note: This figure shows the cumulative effect of each mechanism in explaining ADHD diagnostic disparity. Values come from Column 2 of Table 5, where parameter restrictions in simulations are set at male parameter values.

6.2 Estimates of Mis(sed) Diagnosis

As less than one-half of the ADHD diagnostic disparity can be attributed to true underlying ADHD prevalence differences, the remaining difference in ADHD diagnosis rates between male and female patients is unwarranted, at least according to the DSM-V guidelines. In this section, I use the model estimates along with the DSM-V definition of ADHD, to determine the extent of over and under diagnosis for both male and female patients. I define ADHD diagnostic errors as any deviation from the DSM-V definition of ADHD.

I find that physicians are making diagnostic errors in the sense that they do not follow the DSM-V guidelines. However, I preface this section by noting that from a medical (or even an economic) standpoint, these errors may be justified. It may be the case that the DSM-V definition of ADHD is outdated or too terse, in which case physician discretion and variation from these guidelines is warranted. In fact, this is a common consensus among psychologists. A recent *Psychology Today* article written by a psychiatrist and pediatric neurologist states: "...behavioral issues that patients face are not so easily cataloged as medical books (including the DSM) might tempt a person to believe. The DSM is just a tool designed to categorize human behavior in a clinically useful way — but it is inherently artificial, and must be taken

with a grain of salt (and preferably used by a well-trained clinician with plenty of practical experience and good judgment)" (Cheyette and Cheyette, 2020). Therefore, while I estimate rates of ADHD diagnostic errors, I remain agnostic about the resulting policy implications. It may be that physicians require more training in recognizing ADHD, or it may imply a need to adjust DSM-V definition of this condition. I leave the interpretation and implications of the following estimates to the medical profession.

Defining 'True' ADHD

Recall that while ADHD risk, v_i, presents itself on a continuum, the DSM-V definition of ADHD is binary by construct. I follow the DSM-V definition of ADHD and assume that a child has ADHD, $S_i = 1$, if and only if they meet all the requirements for diagnosis outlined in the DSM-V. In other words, $S_i = \mathbb{1}(v_i > \overline{v})$ where $\overline{v}$ is implicitly defined as the DSM-V minimum requirement of diagnosis, which by definition does not differ by patient gender.

Thus far I have remained agnostic about the value of $\overline{v}$ as it is not necessary to estimate sources of diagnostic disparities. However, to examine inaccuracies in diagnosis according to guidelines, it is important to use this value. For purposes of classifying ADHD diagnostic inaccuracies, I refer back to the DSM-V guidelines for ADHD that requires a patient meets 6 (or more) of the 9 specified ADHD symptoms (see Table 1). As ADHD signal, x_i, and therefore ADHD risk, v_i, measures the fraction of DSM-V symptoms experienced by patient i (see construction of x_i in Section 4.2), the DSM-V defined minimum threshold is $6/9 = .66$, corresponding to a $\overline{v}$ value of 0.66.

Estimates of DSM-V defined errors

Using $\overline{v} = 0.66$ along with population risk distribution parameters, μ_θ and σ_θ, I can simulate DSM-V defined ADHD prevalence rates by patient gender. Combining this with the full diagnosis model allows me to simulate the extent of over/under diagnosis for both boys and girls, as well as potential sources of error. I present the results of this simulation exercise in Table 6.

Table 6: Mis(sed) Diagnosis Simulations

	% Misdiagnosed	% Missed Diagnosis
Panel A: Total		
DSM-V defined ADHD: 6.99%		
Clinical Dx: 6.05%		
Overall	1.90	2.46
Patient Effect	-	1.59
Physician Effect	1.90	0.86
Panel B: Male		
DSM-V defined ADHD: 8.39%		
Clinical Dx: 8.49%		
Overall	2.65	2.68
Patient Effect	-	1.77
Physician Effect	2.65	0.91
Panel c: Female		
DSM-V defined ADHD: 5.63%		
Clinical Dx: 3.62%		
Overall	1.16	2.26
Patient Effect	-	1.44
Physician Effect	1.16	0.81

Note: This table shows simulated diagnosis rates D_i based on simulated diagnosis decisions and S_i based on simulated risk v_i larger than $\overline{v} = 0.66$. DSM-V defined ADHD is then proportion of children with $S_i = 1$ and Clinical Dx is proportion with $D_i = 1$. Misdiagnosis is defined by $S_i = 0, D_i = 1$ and Missed Diagnosis by $S_i = 1, D_i = 0$. Within column 3, the Patient Effect denotes set of patients with $S_i = 1, D_i = 0, Q_i = 0$ and Physician Effect set of patients with $S_i = 1, D_i = 0, Q_i = 1$. Panel A shows results for full sample, and Panel B and C for male/female subsamples, respectively.

There are three key takeaways from this table. First, comparing simulated DSM-V defined ADHD and clinical diagnosis decisions allows me to estimate net over and under diagnosis. Based on the simulation results in Panel A, approximately 7% of children meet the diagnostic criteria for ADHD, 1.90% of children are misdiagnosed, and 2.46% of children have ADHD but do not receive clinical diagnosis, resulting in a small net under-diagnosis estimate of 0.94%. Both the prevalence rates and error rates are heterogeneous across patient gender, as shown in Panels B and C. 8.39% of males and 5.63% of females meet the DSM-V defined requirement for ADHD, however on net, 0.10% of males are over-diagnosed compared to a net female under-diagnosis of 2.01%.

The second insight from Table 6 is the source of diagnostic errors. Whereas a misdiagnosis falls on the physician decision, a missed diagnosis can be attributed to either physician error

or patient error, with the latter coming from the high cost of mental healthcare utilization. Panel A shows that 1.59% of children who have ADHD do not seek care from a physician, and 0.86% of children who have ADHD do seek care, but do not receive an appropriate diagnosis. This suggests that the majority of missed diagnosis is due to patients not appropriately seeking care as opposed to physicians missing a warranted diagnosis. This is true in the male and female sub-samples as well.

Finally, the simulations also provide insight on the impacts of heterogeneous physician decision making. In total, physicians are much more likely to misdiagnose than to miss a diagnosis (1.90% to 0.86% in Panel A). While this is true for both male and female patients, the relative difference in error rates in heterogeneous. The rate of missed diagnosis from a physician error is similar for both male and female patients (0.91% and 0.81, respectively); however, the misdiagnosis rate is much higher for male patients than female (2.65% and 1.16%, respectively). These findings suggest that the perceived cost of *missed diagnosis* is larger than cost of *misdiagnosis* on average, with a larger relative cost for male patients.

6.3 Economic Impact of ADHD Diagnostic Errors

Thus far, the literature that monetizes the economic impact of ADHD has only provided evidence of incremental costs associated with having an ADHD *clinical diagnosis*. Adjusting to 2019 U.S. dollars, Doshi et al. (2012) estimate the annual economic impact of ADHD diagnoses to be between $168 to $312 billion dollars. However, this estimate is based on diagnosis rates alone and therefore does not consider how much of the estimated costs come from misdiagnosis, and additionally excludes costs associated with missed diagnoses. Both of these types of diagnostic errors are costly to individuals, families, and society. A *misdiagnosis* can lead to excess medical and educational spending, along with indirect costs associated with treatment side effects and psychological stigmatization. A *missed diagnosis* can lead to decreased educational attainment (Currie and Stabile, 2006) and lower earnings/employment (Fletcher, 2014). However, in order to accurately quantify these costs, one would need to identify individuals with diagnostic errors and subsequently link to educational attainment,

medical expenditures, and long run economic outcomes.

While I am able to simulate rates of ADHD diagnostic errors, it is not possible to obtain the level and detail of data necessary to determine the observed economic impact of these errors. Instead, I provide a rough approximation of the economic impact associated with both over and under diagnosis of ADHD using per-person cost components from the literature combined with rates of ADHD diagnostic errors shown in Table 6.

I use ADHD cost estimates from Doshi et al. (2012), Table 2 (pg 996), which provides monetized ranges of ADHD economic impact based on a comprehensive literature review. Importantly, the authors break up the over-all economic impact into different categories: health care, productivity/income loss, justice system, and education. As these are based on those with an ADHD clinical diagnosis, I make some assumptions about how these categories carry over unto those with ADHD diagnostic inaccuracies. I assume that those who are misdiagnosed incur the health care costs (e.g., through treatment and follow-up visits) and the educational costs, which includes special education services used for children with diagnosed ADHD. I assume that those whose ADHD is missed (missed diagnosis) do not have to incur the direct medical spending for treatment in childhood, but as a result experience the productivity and income loss as adults.

Appendix Table A9 provides the relevant table from Doshi et al. (2012), and highlights the costs I consider for this analysis. I make necessary adjustments to the 'Per-Person Incremental Costs' column in order to re-monetize accounting for inflation and rates of diagnostic errors. I first inflate costs to 2019 U.S. dollars based on CPI and medical care CPI from the U.S. Bureau of Labor Statistics.[23] As the literature has not fully explored differential costs by patient gender, I must assume per-person costs within each category are the same for males and females. Therefore, differences in costs across gender comes from differences in diagnostic error rates. I determine the number of population incurring cost by multiplying the diagnostic error rates in Table 6 with 2019 population estimates from the U.S. Census. Finally, I calculate national incremental costs of ADHD diagnostic errors by

[23]Health care costs are adjusted using medical care component of CPI and all others using CPI-U.

multiplying the per-person cost by the number of children in each ADHD diagnostic error category. Table 7 presents the results from this back-of-the-envelope calculation.

Table 7: Cost of ADHD Mis(sed) Diagnosis

	Population Incurring Cost	Per-Person Cost of Error	National Cost of Errors (billions)
Misdiagnosis	1,400,440	\$3402-\$8989	\$4.8-\$12.6
Males	977,266		\$3.3-\$8.8
Females	427,784		\$1.5-\$3.8
Missed Diagnosis	1,814,395	\$12,593-\$22,156	\$22.8-\$40.2
Males	988,329		\$12.4-\$21.9
Females	833,442		\$10.5-\$18.5

Note: Table reflects estimates of costs associated with ADHD diagnostic errors, separated into misdiagnosis and missed diagnoses, by patient gender. All costs reported in 2019 U.S. dollars. Population counts based on 2019 Census population estimates and rates of errors in Table 6. Per-Person costs from Doshi et al. (2012), and are the same for males and females within each category.

The annual economic impact of ADHD diagnostic errors is \$27.6-\$52.8 billion U.S. dollars, with \$4.8-\$12.6 due to excess medical and education spending for those misdiagnosed, and \$22.8-\$40.2 due to productivity and income loss following a missed diagnosis. My findings suggest that the national estimate provided by Doshi et al. (2012) underestimates the cost of ADHD by at least \$10.2-\$35.4 billion dollars.[24]

The per-person cost of missed diagnosis is about 3 times larger than the cost of misdiagnosis. This suggest that physicians may in fact be optimal in their average diagnostic threshold, which recall reflects a higher relative cost of missed diagnosis. However, as these per-person cost estimates were not broken down by patient gender, this table does not yet provide support for why physicians use significantly lower thresholds for males, suggesting higher relative per-person costs for male patients. Future research analyzing differences in per-person excess expenditures by patient gender is warranted.

Interestingly, while females are under-diagnosed more than males on net, almost two-thirds of the economic impact is incurred by males. This comes from the important breakdown of net diagnosis rates in Table 6 which shows males have more misdiagnoses and missed

[24]This underestimate is determined by subtracting cost of misdiagnosis and adding cost of missed diagnosis to Doshi et al. (2012) estimates.

diagnoses than females. The former is attributed to higher diagnostic uncertainty for male patients (i.e., lower signal quality estimate ρ_θ), and the latter comes from lower diagnostic thresholds. This demonstrates the extreme importance of examining both *misdiagnosis* and *missed diagnosis* as opposed to net rates of errors, and further exploring the differential impact by patient gender.

These cost estimates may underestimate the true cost of misclassified ADHD as they do not include the potential spill-over effects of misdiagnosis (Persson et al., 2021) or the productivity loss of family members (Birnbaum et al., 2005). They also do not reflect health costs associated with over-use of stimulants, or personal costs through hindered peer relationships and self-esteem (Coghill, 2010). On the other hand, these estimates would overstate the true cost of diagnostic errors if physicians use the DSM-V with discretion and adjust the definition to fit each patient accordingly. Given that the estimates of diagnostic errors are significant, how the DSM-V defines errors and how additional indirect costs affect children and society are important topics for future research.

7 Conclusion

Attention Deficit Hyperactivity Disorder is the most diagnosed child mental health condition in the United States. Yet, recent research presents evidence of improper ADHD diagnosis decisions and documents heterogeneous national diagnosis rates by patient gender, with 14.8% of males diagnosed with ADHD and 6.7% of females. In this paper I combine structural modeling, selection estimation techniques, and text analysis procedures, to explore mechanisms of ADHD diagnosis and show how these contribute to the significant diagnostic disparity between male and female patients.

I develop a model of ADHD diagnosis, composed of three distinct stages, to demonstrate how both patient and physician factors contribute to the ADHD diagnosis rate. Importantly, each stage of the model depends on an unobservable patient ADHD risk value, coming from a gender-specific risk distribution, which accounts for variation in true ADHD prevalence between male and female children. My model highlights four key mechanisms of ADHD

diagnostic disparities: (1) differences in patient selection into mental health care, (2) varying rates of diagnostic uncertainty, (3) heterogeneous physician preferences for ADHD diagnosis, and (4) underlying differences in the true prevalence of ADHD symptoms between boys and girls.

I estimate the gender-specific model parameters using electronic health records and clinical doctor notes. I address the lack of necessary observable mental health variables by using clinical doctor note data combined with natural language processing and text analysis techniques to create proxies for two mental health related variables- the patient decision to schedule behavioral assessment and an ADHD match signal measuring how closely the behavioral assessment aligns with DSM-V criteria. In a first stage selection approach, I use quasi-exogenous variation coming from primary care physician referral rates to estimate population mean ADHD risk for males and females. I then back out the remaining model parameters using observed behavioral assessment rates and maximum likelihood estimates from a gender-specific conditional diagnosis probit. I find that males have higher ADHD prevalence, higher diagnostic uncertainty, and lower diagnostic thresholds than their female counterparts.

I then use these estimated parameters and structural model to simulate ADHD diagnosis rates in order to (1) identify the mechanism contribution in explaining ADHD diagnostic disparities and (2) provide estimates of over and under diagnosis for males and females. The raw ADHD male-to-female diagnostic disparity is 2.26:1. I show that less than half of this disparity can be explained by differences in true underlying symptom prevalence. The remaining difference is due to variation in physician decision-making based on patient gender.

Using the DSM-V definition of ADHD, I show that males are slightly over-diagnosed and females under-diagnosed on net. This can be broken down into heterogeneous rates of misdiagnoses (2.7% males and 1.2% females) and missed-diagnoses (2.7% males and 2.3% females). I conduct back-of-the-envelope calculations and estimate an annual economic impact of ADHD diagnostic error in the range of $27.6 to $52.8 billion U.S. dollars. The cost of *missed* diagnosis is more than 3 times larger than the estimated cost of *mis*-diagnosis. This

finding suggests that physicians may be acting optimally by internalizing these costs (on average) and setting diagnostic thresholds lower than that specified by the DSM-V guidelines. However, I also find that physicians use lower diagnostic thresholds for male patients than female patients with identical ADHD risk, implying that physicians perceive the relative cost of type II vs type I diagnostic error (as explained in Section 2) to be higher for male patients. The clinical support for these heterogeneous costs should be explored further, and perhaps even warrant a re-evaluation of how ADHD is defined in the DSM-V, noting its associated effects on male and female clinical diagnoses and subsequent treatment.

I also decompose ADHD missed diagnosis into physician and patient decisions. On the demand side, I find that approximately 80% of under-diagnosis for both male and females can be attributed to selection- i.e., high mental health care utilization costs limiting number of warranted appointments. As missed diagnoses are extremely costly, this suggests a potential policy response through targeted mental health education to reduce associated stigmas.

It is important to note the limitations of interpreting the results in this paper. First, identification of mean ADHD risk for each gender relies on the assumption that patients do not select primary care physicians in a way that is correlated with their underlying ADHD risk. In an ideal (econometric) setting, patients would be assigned to PCPs randomly. However, in application, families may select their primary care physician. If this choice is correlated with unobserved ADHD risk, then my estimates of population mean risk will be biased, though the direction depends on the sign of this correlation which is theoretically ambiguous. The ADHD prevalence rates derived from my estimates align with the medical literature, which helps alleviate this concern; however, it is still important to note the limitations. Although not feasible in this paper due to data constraints, an alternative source of exogenous behavioral assessment scheduling costs would be primary care physician time pressures. If a patient has a wellness visit on a "busy" day, the PCP may be less able to provide a thorough evaluation and thus less likely to suggest follow-up mental health care. This idea is motivated by the recent work by Freedman et al. (2021), and should be explored further, especially in relation to mental health care.

Finally, I emphasize that the suggested policy responses and diagnostic error estimates

are likely sample-location dependent. The in-sample ADHD diagnosis rate of 6.3% is lower than the national average during this time period, suggesting a potential under-estimate of misdiagnosis and over-estimate of missed diagnoses when compared to national rates. This is likely due to the fact that a large portion of the population in Arizona is of Hispanic ethnicity, and research suggests a significantly lower diagnosis rate for this group coming from cultural biases (Morgan et al., 2013). This is consistent with my large estimates of patient utilization costs, which include mental health stigma levels that may be lower in more nationally representative samples.

Despite the limits to external validity, the proposed model and methods are general enough to be applied to a variety of other applications. This paper addresses an understudied yet important area of research: mental health diagnostic errors and disparities. Mental health conditions are costly to both the individual and society. Thus, understanding mechanisms across additional geographies, other disparities (e.g., by race/ethnicity), and alternative mental health conditions is an important goal for future research.

References

Abaluck, J., Agha, L., Kabrhel, C., Raja, A., and Venkatesh, A. (2016). The determinants of productivity in medical testing: Intensity and allocation of care. *American Economic Review*, 106(12):3730–64.

AHRQ (2011). Attention Deficit Hyperactivity Disorder: Effectiveness of Treatment in At-Risk Preschoolers; Long-Term Effectiveness in All Ages; and Variability in Prevalence, Diagnosis, and Treatment. Available at: www.effectivehealthcare.ahrq.gov/reports/final.cfm.

AHRQ (2019). National Healthcare Quality and Disparities Report. Available at: https://www.ahrq.gov/sites/default/files/wysiwyg/research/findings/nhqrdr/2018qdr-final-es.pdf.

American Academy of Pediatrics (2011). Adhd: clinical practice guideline for the diagnosis, evaluation, and treatment of attention-deficit/hyperactivity disorder in children and adolescents. Subcommittee on Attention-Deficit/Hyperactivity Disorder, Steering Committee on Quality Improvement and Management.

American Psychiatric Association (2013). *Diagnostic and Statistical Manual of Mental Disorders*. Washington, DC, 5 edition.

Anwar, S. and Fang, H. (2012). Testing for the role of prejudice in emergency departments using bounceback rates. *The BE Journal of Economic Analysis & Policy*, 13(3).

Arnold, D., Dobbie, W. S., and Hull, P. (2020). Measuring racial discrimination in bail decisions. NBER Working Paper 26999, National Bureau of Economic Research.

Balsa, A. I., McGuire, T. G., and Meredith, L. S. (2005). Testing for statistical discrimination in health care. *Health Services Research*, 40(1):227–252.

Birnbaum, H. G., Kessler, R. C., Lowe, S. W., Secnik, K., Greenberg, P. E., Leong, S. A., and Swensen, A. R. (2005). Costs of attention deficit–hyperactivity disorder (adhd) in the us: excess costs of persons with adhd and their family members in 2000. *Current medical research and opinion*, 21(2):195–205.

Bruchmüller, K., Margraf, J., and Schneider, S. (2012). Is adhd diagnosed in accord with diagnostic criteria? overdiagnosis and influence of client gender on diagnosis. *Journal of consulting and clinical psychology*, 80(1):128.

Chamberlain, G. (1986). Asymptotic efficiency in semi-parametric models with censoring. *Journal of Econometrics*, 32(2):189–218.

Chan, D. C., Gentzkow, M., and Yu, C. (2021). Selection with variation in diagnostic skill: Evidence from radiologists. NBER Working Paper 26467, National Bureau of Economic Research.

Chan, E., Hopkins, M. R., Perrin, J. M., Herrerias, C., and Homer, C. J. (2005). Diagnostic practices for attention deficit hyperactivity disorder: a national survey of primary care physicians. *Ambulatory Pediatrics*, 5(4):201–208.

Chandra, A. and Staiger, D. O. (2010). Identifying provider prejudice in healthcare. NBER Working Paper 16382, National Bureau of Economic Research.

Cheyette, B. and Cheyette, S. (2020). The relationship between autism spectrum disorder and adhd. *Psychology Today*.

Clemens, J. and Rogers, P. (2020). Demand shocks, procurement policies, and the nature of medical innovation: Evidence from wartime prosthetic device patents. NBER Working Paper 26679, National Bureau of Economic Research.

Coghill, D. (2010). The impact of medications on quality of life in attention-deficit hyperactivity disorder. *CNS drugs*, 24(10):843–866.

Cronin, C. J., Forsstrom, M. P., and Papageorge, N. W. (2020). What good are treatment effects without treatment? mental health and the reluctance to use talk therapy. NBER Working Paper 27711, National Bureau of Economic Research.

Cuddy, E. and Currie, J. (2020). Rules vs. discretion: Treatment of mental illness in us adolescents. NBER Working Paper 27890, National Bureau of Economic Research.

Currie, J., Kleven, H., and Zwiers, E. (2020). Technology and big data are changing economics: Mining text to track methods. In *AEA Papers and Proceedings*, volume 110, pages 42–48. American Economic Association.

Currie, J. and MacLeod, W. B. (2017). Diagnosing expertise: Human capital, decision making, and performance among physicians. *Journal of labor economics*, 35(1):1–43.

Currie, J., MacLeod, W. B., and Van Parys, J. (2016). Provider practice style and patient health outcomes: the case of heart attacks. *Journal of health economics*, 47:64–80.

Currie, J. and Stabile, M. (2006). Child mental health and human capital accumulation: the case of adhd. *Journal of health economics*, 25(6):1094–1118.

Cutler, D., Skinner, J. S., Stern, A. D., and Wennberg, D. (2019). Physician beliefs and patient preferences: a new look at regional variation in health care spending. *American Economic Journal: Economic Policy*, 11(1):192–221.

Doshi, J. A., Hodgkins, P., Kahle, J., Sikirica, V., Cangelosi, M. J., Setyawan, J., Erder, M. H., and Neumann, P. J. (2012). Economic impact of childhood and adult attention-deficit/hyperactivity disorder in the united states. *Journal of the American Academy of Child & Adolescent Psychiatry*, 51(10):990–1002.

Elder, T. E. (2010). The importance of relative standards in adhd diagnoses: evidence based on exact birth dates. *Journal of health economics*, 29(5):641–656.

Epstein, A. J. and Nicholson, S. (2009). The formation and evolution of physician treatment styles: an application to cesarean sections. *Journal of health economics*, 28(6):1126–1140.

Epstein, J. N. and Loren, R. E. (2013). Changes in the definition of adhd in dsm-5: subtle but important. *Neuropsychiatry*, 3(5):455.

Fletcher, J. M. (2014). The effects of childhood adhd on adult labor market outcomes. *Health economics*, 23(2):159–181.

Freedman, S., Golberstein, E., Huang, T.-Y., Satin, D. J., and Smith, L. B. (2021). Docs with their eyes on the clock? the effect of time pressures on primary care productivity. *Journal of Health Economics*, 77:102442.

Gowrisankaran, G., Joiner, K. A., and Léger, P.-T. (2017). Physician practice style and healthcare costs: evidence from emergency departments. NBER Working Paper 24155, National Bureau of Economic Research.

Heckman, J. (1990). Varieties of selection bias. *The American Economic Review*, 80(2):313–318.

Herrerias, C. T., Perrin, J. M., and Stein, M. T. (2001). The child with adhd: Using the aap clinical practice guideline. *American Family Physician*, 63(9):1803.

Hinshaw, S. P. (2018). Attention deficit hyperactivity disorder (adhd): controversy, developmental mechanisms, and multiple levels of analysis. *Annual review of clinical psychology*, 14.

Jensen, P. S., Hinshaw, S. P., Swanson, J. M., Greenhill, L. L., Conners, C. K., Arnold, L. E., Abikoff, H. B., Elliott, G., Hechtman, L., Hoza, B., et al. (2001). Findings from the nimh multimodal treatment study of adhd (mta): implications and applications for primary care providers. *Journal of Developmental & Behavioral Pediatrics*, 22(1):60–73.

Knapp, M., King, D., Healey, A., and Thomas, C. (2011). Economic outcomes in adulthood and their associations with antisocial conduct, attention deficit and anxiety problems in childhood. *Journal of mental health policy and economics*, 14(3):137–147.

Layton, T. J., Barnett, M. L., Hicks, T. R., and Jena, A. B. (2018). Attention deficit–hyperactivity disorder and month of school enrollment. *New England Journal of Medicine*, 379(22):2122–2130.

Marquardt, K. (2021). Identifying physician practice style for mental health conditions. available at: `www.kellimarquardt.com`.

Morgan, P. L., Staff, J., Hillemeier, M. M., Farkas, G., and Maczuga, S. (2013). Racial and ethnic disparities in adhd diagnosis from kindergarten to eighth grade. *Pediatrics*, 132(1):85–93.

Morley, C. P. (2010). The effects of patient characteristics on adhd diagnosis and treatment: A factorial study of family physicians. *BMC Family Practice*, 11(1):1–10.

Persson, P., Rossin-Slater, M., and Qiu, X. (2021). Family spillover effects of misdiagnosis: The case of adhd. NBER Working Paper 28334, National Bureau of Economic Research.

Rushton, J. L., Fant, K. E., and Clark, S. J. (2004). Use of practice guidelines in the primary care of children with attention-deficit/hyperactivity disorder. *Pediatrics*, 114(1):e23–e28.

Sciutto, M. J. and Eisenberg, M. (2007). Evaluating the evidence for and against the over-diagnosis of adhd. *Journal of attention disorders*, 11(2):106–113.

Visser, S. N., Zablotsky, B., Holbrook, J. R., Danielson, M. L., and Bitsko, R. H. (2015). Diagnostic experiences of children with attention-deficit/hyperactivity disorder. *National health statistics reports*, (81):1–7.

Data: The data were purchased using funds awarded via the University of Arizona Graduate and Professional Student Council Research and Project Grant 2019. Data provided by The University of Arizona Center for Biomedical Informatics & Biostatistics- Department of Biomedical Informatics Services.

Appendices

A Additional Tables and Figures

Table A1: Additional Patient Demographics

	Mean	Std. Dev.	Minimum	Maximum
Medicaid	0.540	0.498	0	1
Private Ins.	0.419	0.493	0	1
White-Non Hispanic	0.345	0.475	0	1
Black-Non Hispanic	0.070	0.255	0	1
Hispanic	0.489	0.500	0	1
Psych Physician	0.069	0.254	0	1
Age	10.312	3.535	5	18
# of Appt.	3.248	4.043	1	85
# of Physicians	1.927	1.491	1	15
# Yrs. in Sample	1.693	0.891	1	4
N	11,397			

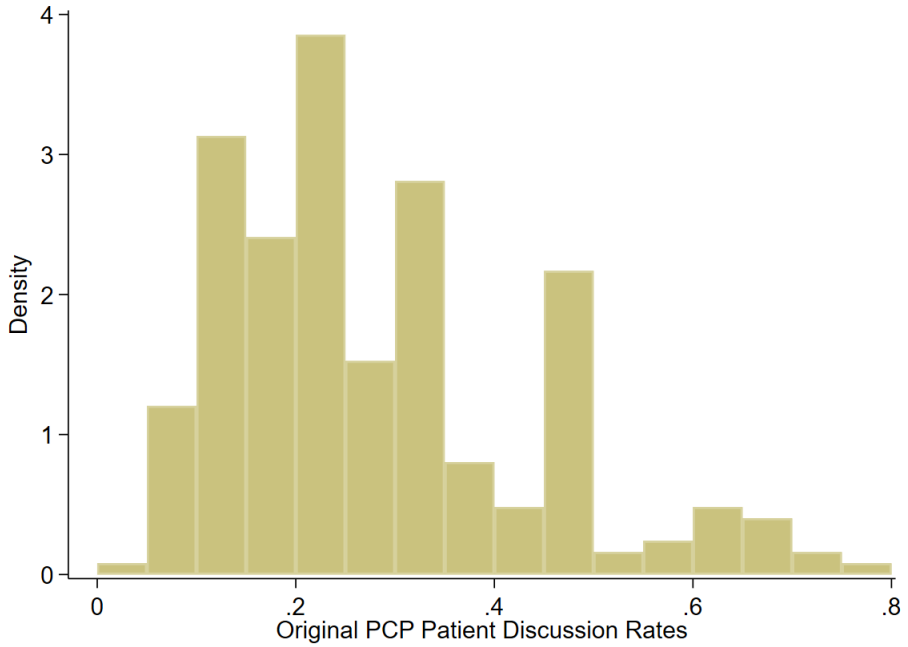
Note: Table presents summary statistics for full set of patients included in sample. Psych Physician indicates whether patient has an appointment with psychiatrist. Age is based on age at last appointment in sample. # of physicians indicates the number of unique physicians the patient sees over sample period. Alternative insurance category includes 'self-pay' and 'other'.

Table A2: Male/Female Difference in Observables

	Male	Female	Difference
Full Sample			
Age	10.165	10.463	-0.298***
Medicaid	0.535	0.545	-0.010
Private Ins.	0.421	0.417	0.005
White	0.346	0.345	0.001
Hispanic	0.483	0.496	-0.013
N	5,786	5,611	
Behavioral Assessment Sample			
Age	10.227	11.757	-1.529***
Medicaid	0.519	0.497	0.022
Private Ins.	0.437	0.477	-0.040*
White	0.412	0.447	-0.035
Hispanic	0.466	0.440	0.026
N	1,120	803	

Note: Table presents gender-specific means and difference in means for full sample and Behavioral Assessment subsample ($Q_i = 1$). Significance based on two-sample T test with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: *Original PCP* Referral Rate Distribution



Note: This figure plots histogram of *original primary care physicians* referral rates. PCP referral rate calculated as the fraction of patients of each original PCP that eventually appear in the electronic health record with $Q_i = 1$.

Table A3: Test of First Stage PCP Relevance

Wald Test for PCP Fixed-Effect Significance			
	Total	Male	Female
	(1)	(2)	(3)
Wald Chi-Squared Test Statistic	1773***	1352***	1378***
Degrees of Freedom	205	146	128
Patients	8934	4363	4258
Mean Behavioral Assessment Rates	.173	.198	.150
Patient Controls			
Male, Age, Psych Referral, Medicaid, Private Ins., Hispanic, White, Appt. Type, # of Physicians, #of Appts. Year FE			

Note: This table shows results from Wald Chi-squared joint test of significance on original PCP fixed effects in a probit regression of patient behavioral assessment indicator on set of patient controls and PCP fixed effects. Results shown for three separate regressions based on total sample, male sample, and female sample, respectively. The coefficients and construction of patient controls presented in Table A4. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: First Stage Behavioral Assessment Coefficients

	Total (1)	Male (2)	Female (3)
Male	0.120		
	(0.036)		
Age	0.021	-0.005	0.053
	(0.005)	(0.007)	(0.008)
Psych Referral	2.039	2.051	2.389
	(0.111)	(0.153)	(0.217)
Medicaid	-0.065	-0.136	0.099
	(0.099)	(0.135)	(0.159)
Private Ins.	-0.159	-0.212	-0.011
	(0.101)	(0.139)	(0.162)
Hispanic	0.119	0.103	0.139
	(0.055)	(0.076)	(0.085)
White	0.365	0.309	0.442
	(0.060)	(0.083)	(0.092)
Behavioral Appt.	2.352	2.478	2.198
	(0.185)	(0.256)	(0.286)
Wellness Appt.	0.058	-0.034	0.110
	(0.074)	(0.107)	(0.108)
# of Phys.	-0.010	-0.029	0.020
	(0.024)	(0.035)	(0.036)
# of Appt.	-0.247	-0.257	-0.266
	(0.033)	(0.048)	(0.049)
$\mathbb{1}$(2014)	0.292	0.300	0.313
	(0.034)	(0.049)	(0.049)
$\mathbb{1}$(2015)	0.258	0.276	0.263
	(0.034)	(0.050)	(0.049)
$\mathbb{1}$(2016)	0.136	0.138	0.133
	(0.038)	(0.055)	(0.055)
PCP Fixed Effects	Y	Y	Y
Observations	8934	4363	4258

Note: This table shows patient control coefficients from probit regression of patient behavioral assessment indicator on demeaned patient controls and PCP fixed effects. Results shown for three separate regressions based on total sample, male sample, and female sample, respectively. All controls are based on the average (or max) across patient appointments prior to and *including* behavioral assessment appointment. All controls demeaned using sample average. Behavioral Appt, indicator based on previous other mental health diagnoses, and Wellness Appt. indicator based on broad appointment type categories. Psych Referral indicates whether patient was seen by a psychiatrist during first behavioral assessment visit. Year fixed effect included to control for changes in mental health trends over time. Robust standard errors in parenthesis.

Table A5: Test of PCP Selection

	Full (1)	Male (2)	Female (3)
Male	0.002		
	(0.003)		
Age	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.000)
Medicaid	-0.005	-0.006	-0.005
	(0.007)	(0.007)	(0.007)
Hispanic	0.001	0.005	-0.003
	(0.004)	(0.004)	(0.005)
White	0.005	0.011	-0.002
	(0.004)	(0.006)	(0.005)
N	8929	4463	4466
Joint F-Test (p-value)	.849	.320	.813

Note: This table presents results from patient level regression of leave-one-out PCP referral rates on demeaned patient demographics. Leave-one-out PCP referral rates determined using data from all other patients of the patient's PCP and calculated as the percent of other patients from each PCP that eventually receive behavioral assessment in the data (i.e., percent with $Q_i = 1$). Robust standard errors in parenthesis, clustered at the PCP level. The table also reports the p-value associated with a joint test of patient demographic significance. Regression results provided for full sample and male/female subsambles.

Table A6: Male/Female Exponential Fit

	Male (1)	Female (2)
$\widehat{\alpha_0}$	0.364	0.376
	(0.013)	(0.018)
$\widehat{\alpha_1}$	-1.030	-1.778
	(0.200)	(0.324)
N	878	668
Adj. R-sq.	0.811	0.759
Fitted μ_θ	0.130	0.064

Note: This table shows coefficients from non-linear least squares regression with exponential functional form: $Y = \alpha_0 exp(\alpha_1 X)$ where Y is the observed ADHD risk signal for patients who receive behavioral assessment and X is the predicted probability of behavioral assessment coming from quasi-exogenous variation in scheduling costs using patient primary care physician referral rates. This fits the data in text Figure 3 for male and female subset of patients separately. Fitted μ_θ denotes the intercept at 1 (i.e., $\mu_\theta = \widehat{\alpha_0} exp(\widehat{\alpha_1})$). Standard errors in parenthesis.

Table A7: Observed verses Simulated Rates

	Observed			Simulated		
	Total	Male	Female	Total	Male	Female
ADHD Dx. (D)	0.063	0.088	0.037	0.062	0.086	0.038
Behavioral Appt. (Q)	0.170	0.195	0.144	0.169	0.196	0.143
ADHD match ($x|Q$)	0.305	0.320	0.305	0.314	0.319	0.308
Cond. Dx. ($D|Q$)	0.357	0.433	0.250	0.365	0.439	0.265

Note: This table presents average values across patients of ADHD diagnosis, behavioral assessment, ADHD risk signals, and conditional diagnosis. Means are calculated for full set, and subset of male/female patients. Those in the Observed columns are based on the EHR data and those in the Simulated columns based on diagnostic simulations using model parameters in Table 4 and model outlined in Section 3.1.

Table A8: Independent Disparity Effects

	Diagnosis Rates		Diagnostic
	Male	Female	Disparity
Baseline Differences	**0.086**	**0.038**	**2.26**
Panel A: Prevalence			
ADHD Risk Distribution: μ_θ and σ_θ			
at Male estimates	0.086	0.061	1.41
at Female estimates	0.055	0.038	1.44
Panel B: Patient Preferences			
Utilization Costs: c_θ			
at Male estimates	0.086	0.039	2.23
at Female estimates	0.848	0.038	2.24
Panel c: Physician Decision-Making			
Signal Quality: ρ_θ			
at Male estimates	0.086	0.035	2.46
at Female estimates	0.091	0.038	2.40
Diagnostic Thresholds: τ_θ			
at Male estimates	0.086	0.057	1.50
at Female estimates	0.059	0.038	1.55

Note: This table reflects diagnosis rates from a model simulation exercise that restricts variation in only one set of model parameters. The simulated gender-specific diagnosis rates are reported in columns 1 and 2 with the ratio in column 3. For reference, Panel A presents simulations that restrict ADHD risk distribution parameters to be equal for male and female patients and all other parameters allowed to vary and equal their estimated values in text Table 4. I include diagnosis rates when equalization is based on male estimate and female estimate. Panel B restricts variation in patient utilization costs, and Panel C restricts variation in physician parameters, signal quality and diagnostic thresholds, respectively.

Table A9: ADHD Cost Estimate Table: (Doshi et al., 2012)

TABLE 2 National Incremental Costs of Attention-Deficit/Hyperactivity Disorder (ADHD) by Cost Category and Age Group

Cost Category	Age Group of Patients with ADHD	Number of Studies	Age Range across Studies	Population corresponding to Age Range[31,33]	ADHD Prevalence for Age Range	Other Multipliers[a]	Population Incurring Cost	Per-Person Incremental Cost, 2010 U.S. Dollars	National Incremental Cost, 2010 U.S. Dollars (Billions)
Health care									
Health care (patient)	children and adolescents	9	0–21	92,140,979	7.2%[3]	—	6,634,150	$621[37]–$2,720[23]	$4.12–$18.04
Health care (patient)	adults	6	18–64	194,296,087	4.4%[8]	—	8,549,028	$137[(NS)46]–$4,100[42]	$1.17–$35.05
Health care (family)	children and adolescents	2	0–18	74,181,467	7.2%[3]	2.92	15,595,912	$1,088[10]–$1,658[25]	$16.97–$25.86
Health care (family)	adults	1	19–44	108,305,787	4.4%[8]	2.92	13,915,128	$1,051[10]	$14.62
								subtotal	$37B–94B
Productivity and income losses									
Income losses (lower wages)	adults	1	19–25	30,433,583	4.4%[8]	—	1,339,078	$(3,744)[26]	$(5.01)
Income losses (unemployment and lower wages)	adults	1	18–64	194,296,087	4.4%[8]	—	8,549,028	$10,532[34]–$12,189[34]	$90.04–$104.20
Productivity losses (patient)	adults	6	18–64	194,296,087	4.4%[8]	67.6%	5,779,143	$209[45]–$6,699[41]	$1.21–$38.71
Productivity losses (family)	children and adolescents	2	0–18	74,181,467	7.2%[3]	2.0, 67.6%	7,221,121	$142[10]–$339[25]	$1.03–$2.45
Productivity losses (family)	adults	1	19–44	108,305,787	4.4%[8]	1.0, 67.6%	3,221,447	$174[10]	$0.56
								subtotal	$88B–$141B
Education	children	1	3–4	8,182,210	5.5%[3]	—	450,022	$12,447[35]	$5.60
	children and adolescents	2	5–18	58,480,960	7.2%[3]	—	4,210,629	$2,222[23]–$4,690[36]	$9.36–$19.75
								subtotal	$15B–$25B
Justice system	adolescents	1	13–17	21,238,249	9.3%[3]	—	1,975,157	$267[(NS)23]	$0.53
	adults	1	18–28	47,550,861	4.4%[8]	—	2,092,238	$1,204[24]–$2,742[24]	$2.52–$5.74
								subtotal	$3B–$6B
								total	$143B–$266B

Note: B = billions; NS = difference was not statistically significant in the original study.
[a]Figures used in "Other Multipliers" are described in the Method section.

Note: This table based on screenshot of Table 2 in Doshi et al. (2012) which reflects estimates ADHD diagnostic costs decomposed into categories and age. The highlighted estimates are the ones used in back of the envelope cost calculations in text Section 6.2. The "+" denotes which costs are used for misdiagnosis and the "-" denotes which costs are used for missed diagnoses.

B Variable Construction using Clinical Texts

In this appendix I present the Machine Learning Algorithm used to construct a proxy for the behavioral assessment indicator, Q_i. This closely follows the *Text Analysis Appendix* in Clemens and Rogers (2020).

I first break the appointment level data into a labeled and un-labeled subsets, where i denotes patient and j denotes appointment. The labeled set is determined by icd9 codes where an appointments receive a positive label ($Q_{ij} = 1$) if the appointment is associated with an icd9 diagnosis related to mental health (Q1 Codes in table B10). An appointment receives a negative label ($Q_{ij} = 0$) if the appointment is associated with an idc9 diagnosis related to physical ailments (Q0 Codes in table B10). To ensure that there is no overlap with patients in both groups, I restrict the negative labeled set to only those patients that never receive a mental health diagnosis during the sample period. The un-labeled set contains all appointments in which there is no associated diagnoses or appointments with ambiguous icd9 codes that could be related to either mental or physical health concerns (e.g., abdominal pain can be associated with anxiety or a virus). This hand coded separation procedure results in 40,917 appointments and 14,092 patients in the labeled set (31,716 appointments with $Q_{ij} = 0$ and 9,200 with $Q_{ij} = 1$) and 105,054 appointments of 28,403 patients in the un-labled set.[25]

Q0 Codes	Q1 Codes
034, 055, 058, 078, 079, 080, 111, 113, 171, 192, 204, 250, 251, 273, 277, 278, 283, 287, 288, 289, 363-383, 389, 390, 462, 463, 466, 473, 474, 478, 486, 488, 493, 494, 529, 537, 599, 600, 608, 612, 682, 683, 693, 697, 703, 707, 709, 710, 715, 719, 720, 725, 728, 729, 730, 733, 734, 744, 760, 781-791, 849, 907, 919, 920, 960	293-319, 331, V11, V15, V40 V41, V61, V62, V71, V79

Table B10: ICD-9 Labeled Dataset Codes

[25]These sample sizes are larger than the estimation sample as I choose not to make any sample restrictions in building the machine learning algorithm. Within the estimation sample, 6,711 appointments of 2658 patients are un-labeled.

I next prepare the doctor notes for feature extraction. This includes traditional text pre-processing procedures: replace contractions, remove special characters and stop words, conversion to lowercase and stemming. For both computational and prediction purposes, I consider only 41 features: note length, relative frequency of top 20 predictive words in the positive labeled set, and relative frequency of top 20 predictive words in the negative labeled set. I determine these top predictive words by their "tf-idf" value in a constructed document term matrix.[26]

- Positive-label word stems: *school, mother, behavior, parent, report, current, social, disord, anxieti, famili, examin, activ, treatment, therapi, sleep, adhd, psychotherpi, tablet, feel, diagnosi*
- Negative-label word stems: *pain, fever, list, care, cough, blood, exam, address, rash, skin, return, vaccin, left, rang, bilater, ml, resid, hour, puls, record*

For cross-validation, I split the labeled data into a training and test set using 90-10 split. Using the training set, I define a random forest learner and tune hyperparameters using random grid search with hold-out re-sampling. I use false discovery rate (FDR) as the objective measure for hyperparameter tuning. The main hyperparameters and their tuned values are: number of trees to grow (ntree=398), number of variables at node split (mtry=3), and maximum number of observations in terminal nodes (nodesize=3).

Using the tuned hyperparameters, I then train the model on the training set, again specifying false discovery rate as the objective measure. The confusion matrix applied to the test set is presented below, with false discovery rate of 0.03487.

	Predicted-0	Predicted-1
True-0	3,153	28
True-1	129	775

Before analyzing the final model predictions, I look for issues with *context specificity*, or

[26] A document term matrix consists of documents i as rows, words j as columns, and matrix elements t_{ij} representing frequency of word j in document i. The tf-idf value is defined as $\frac{t_{ij}}{T_i} ln(\frac{D}{D_j})$ where T_i denotes the number of terms in document i, D denotes the total number of documents, and D_j denotes the number of documents with term j.

"limitations on a model's validity outside of its training set" (Clemens and Rogers, 2020). I take a random sample of 96 notes from the unlabeled dataset, read the unprocessed notes, and determine the appropriate hand label for behavioral assessment using own discretion. Then using the training random forest algorithm, I obtain the model's predictions for these notes. I specify a probability threshold of 0.5. The confusion matrix is presented in the table below. 88 of the notes were correctly determined via the random forest algorithm. 7 notes were incorrectly specified, with only 1 non-mental health related appointment receiving a positive label.

	Predicted-0	Predicted-1
True-0	70	1
True-1	6	18

I consider this performance and validity to be satisfactory, and thus apply the trained random forest algorithm to the full un-labeled set of appointments to obtain the complete set of predictions for behavioral assessment. Approximately 9% of appointments receive a positive predicted label. Results at the patient level are shown in text Table 3.

C Econometric Appendix

C.1 Physician Diagnostic Threshold

In this appendix, I present a physician utility framework that results in a risk-threshold diagnosis decision rule, where the threshold is a function of physician perceived cost of diagnostic errors.[27]

Let physician utility be defined by:

$$u_i|\theta = \begin{cases} -1 & \text{if } D_i = 0,\ S_i = 1 \\ -\beta_\theta & \text{if } D_i = 1,\ S_i = 0 \\ 0 & \text{otherwise} \end{cases} \tag{C1}$$

The utility of correct diagnoses are normalized to 0 so that physicians receive *disutility* from errors. With utility of missed diagnoses ($D_i = 0, S_i = 1$) standardized to -1, β_θ captures the potentially gender-specific disutility of misdiagnosis *relative* to missed diagnoses.

The physician chooses $D_i = 0$ or $D_i = 1$ in order to maximize his expected utility, where expectation is based on the posterior probability of $S_i = 1$. Let $p(x, \theta)$ denote this probability. $p(x, \theta)$ is expressed in equation C2, and follows from posterior ADHD risk in (4) and the DSM-V defined minimum diagnostic requirement, $\overline{v}$.

$$p(x, \theta) = Pr(v_i|x > \overline{v}) = \Phi\left(\frac{\rho_\theta x + (1 - \rho_\theta)\mu_\theta - \overline{v}}{\sigma_\theta\sqrt{1 - \rho_\theta^2}}\right) \tag{C2}$$

The doctor will choose to diagnose a patient with ADHD if the expected utility of $D_i = 1$ is larger than the expected utility of $D_i = 0$. Based on the utility function (C1), $E[u_i|D_i = 1, \theta] = -\beta_\theta(1 - p(x, \theta)) + 0(p(x, \theta))$ and $E[u_i|D_i = 0, \theta] = -1(p(x, \theta)) + 0(1 - p(x, \theta))$.

[27] This is similar to the utility in Chan et al. (2021), but with variation in cost across patient gender as opposed to variation across physicians.

Assuming misdiagnoses are costly (i.e., $\beta_\theta > 0$), then the doctor will choose $D_i = 1$ iff

$$\begin{aligned} & E[u_i|D_i = 1, \theta] \geq E[u_i|D_i = 0, \theta] \\ \implies & -\beta_\theta + \beta_\theta p(x, \theta) \geq -p(x, \theta) \\ \implies & p(x, \theta) \geq \frac{\beta_\theta}{1 + \beta_\theta} \end{aligned}$$

Plugging in equation (C2) for $p(x, \theta)$, a physician will diagnose if $\Phi\left(\frac{\rho_\theta x + (1-\rho_\theta)\mu_\theta - \overline{v}}{\sigma_\theta\sqrt{1-\rho_\theta^2}}\right) \geq \frac{\beta_\theta}{1+\beta_\theta}$. Re-writing with posterior ADHD risk mean on the right-hand side results in the following gender-specific threshold value:

$$\tau_\theta = \overline{v} + \sigma_\theta\sqrt{1-\rho_\theta^2}\Phi^{-1}\left(\frac{\beta_\theta}{1+\beta_\theta}\right)$$

For $\beta_\theta \in (0, 1)$, $\Phi^{-1}\left(\frac{\beta_\theta}{1+\beta_\theta}\right) < 0$ which implies $\tau_\theta < \overline{v}$. In words, physicians will use thresholds lower than the DSM-V defined definition so that they diagnose patients on the margin of meeting ADHD criteria. Intuitively, this suggests that physicians view missed diagnoses as costlier than misdiagnosis, which is consistent with $\beta_\theta \in (0, 1)$ in (C1).

On the other hand, $\beta_\theta > 1$ implies $\tau_\theta > \overline{v}$. In this case, physicians will use higher thresholds and will *not* diagnose patients on the margin of meeting ADHD criteria. This suggests that physicians view misdiagnosis as costlier than missed diagnosis, which is consistent with $\beta_\theta > 1$ in (C1).

C.2 Modeling Assumptions and Implications

In this appendix, I discuss in the detail the key assumptions made throughout the main text. While I cannot test for the validity of each assumption, I discuss what would happen if the assumption fails, and in most cases determine the direction of the resulting estimation bias.

Full Documentation Assumption

In Section 4, I show how ADHD risk signal x_i can be constructed using clinical doctor

note text. This relies on the assumption that physicians accurately document behavioral symptoms in their notes. There are two situations in which this assumption might fail. First, it may be the case physicians do not conduct a thorough behavioral assessment and thus do not learn about all the symptoms that the patient is experiencing. Alternatively, it may be the case that the physician does learn about the patient symptoms, but does not write these down in the note. In both cases, x_i is a downward biased proxy of individual symptoms such that $x_i^{true} = x_i^{obs} + \zeta_i$ where $\zeta_i > 0$. While ζ_i is only unobserved to the physician in the first case but to the econometrician in both, the implications of the assumption are likely the same.

Because x_i is downward biased, then I underestimate mean ADHD risk in the first stage. As a result, I also underestimate mental healthcare utilization costs. Assuming the full documentation assumption fails for both boys and girls equally, then $\hat{\mu}_\theta < \mu_\theta$ and $\hat{c}_\theta < c_\theta$ for $\theta \in \{m, f\}$.

It is unlikely that the other parameters will be impacted as these are estimated from the physician diagnosis decision. In the first case, physicians do not know ζ_i and therefore use x_i^{obs} and $\hat{\mu}_\theta$ in the decision making process, which means $\hat{\rho}_\theta = \rho_\theta$ and $\hat{\tau}_\theta = \tau_\theta$. In the second case, physicians know ζ_i and will use $x_i^{true} = x_i^{obs} + \zeta_i$ in their decision making process instead of x_i^{obs}. The ADHD diagnosis probit slope which identifies ρ_θ remains unchanged with respect to x_i^{obs}, therefore $\hat{\rho}_\theta = \rho_\theta$. The diagnostic threshold estimate becomes, $\hat{\tau}_\theta = (1-\rho_\theta)\hat{\mu_\theta} + \rho_\theta\overline{\zeta} - k_\theta$ for gender-specific constant k_θ. Because physicians know ζ_i, it is reasonable to assume that they will replace $\hat{\mu_\theta}$ with $\mu_\theta = \hat{\mu_\theta} + \overline{\zeta}$ as their prior belief, thus cancelling out the unobserved mean $\overline{\zeta}$ and leaving $\hat{\tau}_\theta = \tau_\theta$.

In sum, if the full documentation assumption fails, then I underestimate mean ADHD risk and mean utilization costs, with no effect on the other parameter estimates. Because this is true for both boys and girls, the mechanism contribution table and graph (Table 5 and Figure 4) remain the same. However, since mean ADHD risk is underestimated, then I also under-estimate the rate of missed diagnosis for both boys and girls in Table 6. This comes from the patient effect entirely.

Physician Prior Assumption

In Section 3, I present a model of ADHD diagnosis that incorporates both patient selection and physician decision making under uncertainty. In the second stage, physicians learn about patient ADHD risk and update their prior beliefs. The key assumption here is that physicians have unbiased and normally distributed prior beliefs for both males and females: $v_i \sim N(\mu_\theta, \sigma_\theta^2)$.

I make this assumption for two reasons. First, the normality of the prior allows for computational ease and clearer interpretation of the model parameters. One could argue that a more complete mathematical model would have physicians update their beliefs twice: once after patient selection but before behavioral assessment, and then again after patient assessment. This complicates estimation as it would now require twice-updating where the second prior has a truncated normal distribution, with an unknown truncation point for each patient c_i. It is still possible to recover the model parameters via simulated maximum likelihood estimation, but it would require another assumption that physicians know the distribution of patient mental healthcare utilization costs for males and females, c_θ, which is likely false in this application. Therefore, I argue that a normally distributed prior belief with single updating is well suited for this application, and the computation and interpretation benefits outweigh the costs of a more complication physician learning model.

Second, the accuracy of the prior mean is necessary for parameter identification. As is common with these types of decision-making under uncertainty models, it is not possible to separately identify both the agent's prior beliefs *and* the agent's preferences without making additional assumptions. Therefore, I assume that physicians know the gender-specific ADHD risk parameter μ_θ (which is identified and estimated in the selection first stage) in order to separate out the diagnostic threshold parameter τ_θ in the conditional diagnosis equation 6.

While the accuracy of the prior distribution is a common assumption, it is likely not satisfied in practice. In what follows, I show that if physicians have inaccurate (albeit normally distributed) prior beliefs, this will only impact the bias of one model parameter, τ_θ, which measures the perceived cost of misdiagnosis relative to missed diagnosis. The estimated diagnostic threshold will now contain both physician perceived cost of diagnostic

errors and/or their inaccurate priors. Policy implications will depend on this distinction, but the main results presented in the paper are unaffected.

Suppose physician prior beliefs follow the distributed defined by equation C3, where γ determines the deviation from accurate prior mean.

$$v_i \sim N(\mu + \gamma, \sigma^2) \tag{C3}$$

If $\gamma > 0$, physicians overestimate population mean ADHD risk, and $\gamma < 0$ implies physicians underestimate population mean ADHD. I drop the θ subscript without loss as parameters are estimated separately for both males and females, so the thought experiment holds for both samples.

Recall that the true ADHD risk distribution parameters, μ and σ, and patient mental health utilization costs, c, are estimated in a first stage patient selection model (see Section 5.1), which does not depend on the physician decision-making process or their prior beliefs. Therefore, these parameters are accurately identified regardless of the physician prior assumption. If physicians have inaccurate priors (i.e., $\gamma \neq 0$), this can only impact parameters that are identified in the conditional ADHD diagnosis, in text equation 6.

After receiving the signal x_i, physicians update beliefs resulting in posterior distribution:

$$v_i \mid x_i \sim N\left(\left(\rho x_i + (1-\rho)\left(\mu + \gamma\right)\right), \sigma^2\sqrt{1-\rho^2}\right)$$

Using the same utility framework, and letting $k = \frac{1}{\sigma\sqrt{1-\rho^2}}$, the new conditional diagnosis rate is defined by equation C4, where $\tilde{\tau} = \tau - (1-\rho)\gamma$.

$$\begin{aligned} P(D_i = 1 \mid Q_i = 1, x_i) &= \Phi(k\rho x_i + k(1-\rho)(\mu+\gamma) - k\tau) \\ &= \Phi(k\rho x_i + k(1-\rho)\mu - k\tilde{\tau}) \end{aligned} \tag{C4}$$

The diagnostic uncertainty parameter, ρ, is also unaffected by γ as it is identified by the slope coefficient measuring correlation between diagnosis decision and patient signal,

x_i. Therefore, the only parameter that is impacted by inaccurate physician priors is the diagnostic threshold τ, and the bias of the estimate depends on whether physicians over or under-estimate mean ADHD risk in their priors. If physicians over-estimate mean ADHD risk with $\gamma > 0$, then $\tilde{\tau} < \tau$, meaning my estimates of the perceived costs associated with misdiagnosis are biased downwards. On the other hand, if physicians behave as if ADHD risk is lower than true risk, then $\tilde{\tau} > \tau$, and I over-estimate the perceived cost of a misdiagnosis.

Because the model parameters are identified and estimated separately for boys and girls, it is possible for the direction of the bias on τ to differ by sub-group. However, regardless of the inaccuracy in physician prior beliefs, it is still the case that diagnostic thresholds for male patients are lower than diagnostic thresholds for female patients, i.e., $\tilde{\tau_m} < \tilde{\tau_f}$. And, it is still the case that this difference explains a majority of the gender-specific diagnostic disparity. However, whether and how to eliminate the difference in diagnostic thresholds depends on if this difference comes from inaccurate physician priors or real differences in costs associated with diagnostic errors. Distinguishing between the two is outside the scope of this paper.

PCP Selection Assumption

The mean ADHD risk parameters, μ_θ, are estimated using a selection model approach described in Section 5.1. Identification relies on the independence between patient risk, v_i, and their chosen or assigned primary care physician. The main text argues for this assumption and provides empirical tests showing no selection on observables. There may still be concern that patients choose PCPs based on unobserved factors that are correlated with ADHD risk. This will only impact the parameters estimated in the first selection stage (μ_θ and c_θ) as this assumption does not change the decision-making process of the diagnosing physician, which is not usually the same as the original PCP (as noted in the main text).

The direction of the bias depends on the direction of unobserved correlation, which can theoretically be either positive or negative. If patients with high ADHD risk select into high referring PCPs, then my estimates of mean ADHD risk, μ_θ, are biased upwards. This can be seen visually in Figure 3. Under positive risk-referring selection, the patients who see high referring physicians (high x-axis value) have higher than average ADHD risk (high y-axis

value), leading to a biased upwards extrapolation point at $\widehat{P_\theta(Q_i|Z_i)} = 1$. Because utilization costs are identified off of mean risk, then estimates of c_θ are also biased upwards. Under the reasonable assumption that if boys positively select their PCP, then girls do as well, the mechanisms contribution table and graph (Table 5 and Figure 4) remain the same. In this case, I over-estimate the rate of missed diagnosis for both boys and girls, coming from the patient effect entirely.

Alternatively, if patients with high ADHD risk select into low referring PCPs, then my estimates of mean ADHD risk and utilization costs are biased downwards. In this case, I under-estimate the rate of missed diagnosis for both boys and girls, again coming from the patient effect entirely.

In sum, if the selection independence assumption fails, then my estimates of mean ADHD risk and mean utilization costs are biased. The mechanism contribution to diagnostic disparities does not depend on this assumption given that selection (if it exists) is in the same direction for boys and girls. The estimates of diagnostic errors do rely on unbiased ADHD risk parameter estimates, and are therefore either over-estimated or under-estimated depending on the direction of selection into PCPs which is theoretically ambiguous and untestable in this setting. Primary care physician choice and how it relates to the mental health referral process and child mental healthcare are important topics for future research.