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# ALL CHILDREN LEFT BEHIND:
# DRUG ADHERENCE AND THE COVID-19 PANDEMIC

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**ABSTRACT**

We study the effect of the COVID-19 pandemic on chronic disease drug adherence. Focusing on asthma, we use a database that tracks the vast majority of prescription drug claims in the U.S. from 2018 to 2020. Using a difference-in-differences empirical specification, we compare monthly drug adherence in 2019 and 2020 for the set of chronic patients taking asthma medication before the onset of the pandemic. We find that the pandemic increased adherence for asthmatic adults by 10 percent. However, we find a sustained decrease in pediatric drug adherence that is most severe for the youngest children. By the end of 2020, drug adherence fell by 30 percent for children aged 0 to 5, by 12 percent for children aged 6 to 12, and 5 percent for children aged 13 to 18. These negative effects are persistent regardless of changes in medical need, socioeconomic factors, insurance coverage and access to health services. We provide suggestive evidence that the observed pediatric changes are likely driven by parental inattention.

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# 1 Introduction

Prescription drug regimens are a primary tool used to manage chronic health conditions; yet, just 50 – 60 percent of patients adhere to their medication as prescribed (Burkhart and Dunbar-Jacob, 2002; Winnick et al., 2005; Matsui, 2007; Briesacher et al., 2008; Yeaw et al., 2009). Poor drug adherence increases the likelihood of negative clinical outcomes, including hospitalization and mortality, and increases the total cost of healthcare (Milgrom et al., 1996; Ordoñez et al., 1998; McCarthy, 1998; Bauman et al., 2002; Chandra et al., 2010; Osterberg and Blaschke, 2015). In light of these risks, prior literature has studied the mechanisms that underlie poor adherence such as access to health insurance and care, socioeconomic factors, patient characteristics, and health literacy (Bosworth et al., 2011; McQuaid and Landier, 2018; Stirratt et al., 2018). However, these studies have primarily focused on the adult population.

The COVID-19 (COVID) pandemic interacted with many of these mechanisms, potentially leading to significant impacts on drug adherence. The sign of this effect, however, is ex-ante unclear because the pandemic environment increased health literacy and emphasized the importance of self-managed healthcare at the same time that it reduced access to health care and induced macroeconomic instability. Any effect of the pandemic on drug adherence will likely have short and long-run consequences for disease management and, therefore, long-run health. Moreover, there is a general lack of evidence describing the mechanisms driving pediatric drug adherence, a population for whom the disruption of the pandemic was acutely felt and for whom negative long-run health consequences can be particularly impactful. These issues underscore the importance of empirical evidence that identifies pandemic-induced changes in adherence rates for both adults and children.

In this paper, we study the impact of the pandemic on drug adherence for both adults and children, including an analysis of underlying mechanisms. Our analysis relies on IQVIA's Longitudinal Prescription Claims (LRx) dataset. LRx, which contains near-population level prescription-level fill and refill information, captures more than 90 percent of retail channel claims, 60 to 85 percent of mail order claims, and 75 to 80 percent of long-term care claims. With this data, we build a patient-by-month panel and compute monthly adherence rates for roughly 25 million asthma patients in 2019 and 2020. We combine these data with a difference-in-differences empirical strategy to evaluate the impact of COVID on prescription drug adherence for patients who were already chronic users of asthma medication before the pandemic. Finally, the size and scope of our data permit sub-sample analyses that speak to the mechanisms that underlie the effect of the pandemic on drug adherence.

Our study focuses on chronic asthma patients because asthma is highly prevalent in the general population and is the single most prevalent chronic disease among children, affecting 25 million individuals and 4.2 million children in the U.S. (CDC).[1] Management of asthma symptoms almost always requires prescription drugs, delivered in either an aerosolized form (inhaler) or orally (pills). Furthermore, poor drug adherence among pediatric asthma patients has been shown to negatively affect long-term health, educational attainment, and income (Ordoñez et al., 1998; Bauman et al., 2002; Miller et al., 2009; Currie, 2009).

Overall, we find that average drug adherence increased during the pandemic. Not surprisingly, we detect stockpiling activity around the time of the state-level shutdowns in March 2020, when adherence rates increased by about 10 percent. Again not surprisingly, adherence rates slowly reverted back towards 2019 patterns by the end of 2020. These average estimates, however, mask significant differences between adults and children.

For adults, we find a *sustained increase* in adherence throughout 2020, consistent with a pandemic environment that emphasized self-management of health care and best health practices. In stark contrast to this, we find a *sustained decrease* among children, including a 30 percent decrease in adherence rates for children aged 0 to 5. Importantly, we also estimate a divergent change in adherence rates for adults and children with two other major chronic conditions, diabetes and depression. This suggests that differential behavior among adults and children is not limited to asthma patients or any interaction between asthmatic

[1] Detailed statistics are available at: `https://www.cdc.gov/asthma/most_recent_national_asthma_data.htm`.

symptoms and complications due to the contraction of COVID.[2]

Given the large and sustained decrease in pediatric adherence to asthma medication, we explore a number of potential mechanisms, which we categorize into four groups: (1) medical need, (2) socioeconomic status (SES) factors, (3) insurance and access to health services, and (4) school closures. These factors have been shown in the literature to be relevant for drug utilization and adherence.[3] However, we find that these combined factors are unable to account for a significant share of the overall observed response during the pandemic.

Having shown the limited quantitative significance of a set of traditional explanatory factors, our evidence suggests that parental inattention played a key role in pediatric adherence response to COVID.[4] Parental stress, which has increased during the pandemic (Marchetti et al., 2020), has been shown to lead to greater inattention and decreased adherence (Almogbel et al., 2019). In our study, estimates by age bands using the IQVIA data show the largest negative response in the youngest children, who are the least able to communicate symptoms to parents and would be most exposed to changes in parental attention. The mediating effect of age remains large and statistically significant even in a horse race analysis that includes all of the standard factors discussed above. In addition, we find the smallest negative percentage response for high-intensity users of asthma medication prior to the pandemic, consistent with the likelihood that pre-pandemic established routines would mitigate the effect of increased parental inattention.

[2]Our analysis provides a more complete picture than the findings in Kaye et al. (2020) and also stands in contrast to the findings in Yang et al. (2022). The former study documented improved asthma drug adherence, including in children, from January to March 2020. The analysis captures early stockpiling but not subsequent effects. The latter study is a meta-analysis showing improvements in pediatric asthma control during COVID. The authors acknowledge several important limitations to their meta-analysis including: (1) a limited sample size; and, (2) results based on observational studies, which can be susceptible to bias.

[3]Prior literature, for example, has shown that Medicaid expansion (Finkelstein et al., 2012; Ghosh et al., 2019), changes in insurance characteristics (Chandra et al., 2010; Brot-Goldberg et al., 2017), minority status (Lieu et al., 2002), environmental factors (Friedman et al., 2001; von Mutius and Smits, 2020), and health services at schools (Jones and Wheeler, 2004; McClure et al., 2020) are all relevant for drug utilization and adherence.

[4]Prior to COVID, research already demonstrated the negative role that parents can play in pediatric drug adherence (Conn et al., 2007). For example, parents admitted to adjusting or delaying medicine regimens, ignoring or not following medication instructions, and outright withholding medication (e.g. Aston et al., 2019).

Finally, we supplement these results by using Medical Expenditure Panel Survey (MEPS) to study within-family responses.[5] After replicating our finding that adherence rates diverged between adults and children during the pandemic using the MEPS data, we show that children whose parents also fill prescriptions for themselves exhibit smaller decreases in adherence during the pandemic.[6] Most compelling among our MEPS results, we find that the differential effect of the pandemic on adherence among children and adults is completely mitigated for those children whose parents fill any asthma medication in 2020.

Our findings contribute to existing studies of behaviors associated with prescription drug adherence. The literature has noted several sources of poor adherence, including cognitive impairment, poor patient-provider relationships, side effects, lack of insurance, and high out-of-pocket costs (Chandra et al., 2010; Finkelstein et al., 2012; Brot-Goldberg et al., 2017; Huskamp et al., 2003; Bosworth et al., 2011; Osterberg and Blaschke, 2015; McQuaid and Landier, 2018). In addition, the literature has documented several consequences of poor adherence, including worse clinical outcomes, and increased risk of hospitalization and death (Milgrom et al., 1996; Ordoñez et al., 1998; McCarthy, 1998; Bauman et al., 2002; Chandra et al., 2010; Osterberg and Blaschke, 2015). Finally, a nascent literature has studied the impact of the COVID pandemic on prescription drug adherence (Ferraro et al., 2021; Yang et al., 2022; Haapanen et al., 2022; Clement et al., 2021). Our evidence speaks to an understudied and influential factor related to pediatric adherence for chronic patients that was likely to be especially relevant during the pandemic: parental inattention.[7] The size of our estimated response within children is on par with, if not larger, than the responses to large changes in insurance parameters estimated in the literature.[8]

[5] The IQVIA database does not link individuals within the same household, so we are limited in our ability to study these mechanisms within these data.

[6] We also find some evidence, albeit imprecise, that children have worse adherence if their parents report worsening mental health status or experienced job loss in 2020. In addition, we find similar results when we repeat our adherence analysis for other common chronic pediatric medications, primarily ones treating allergies and attention-deficit disorders.

[7] Our findings on the importance of parental attention are consistent with survey evidence discussed in Matsui (2007).

[8] For example, Chandra et al. (2010) find a negative 20 percent quantity response after a significant increase in cost-sharing implemented by CalPERS (from $1 to $7 on average per month). Finkelstein et al.

In addition, our use of large-scale administrative prescription drug claims data contributes to a literature that directly studies measures of drug adherence (Chandra et al., 2010; Baicker et al., 2017; Brot-Goldberg et al., 2017; Stirratt et al., 2018). Subjective measures of drug adherence rates are based on a patient's or provider's evaluation of drug-taking behavior through self-reporting. Objective measures, which are generally seen to be an improvement over subjective measures, can be obtained through pill counts, electronic monitoring, biochemical measures, and secondary database analysis. Fortunately, we are able to calculate an objective measure of medication adherence using IQVIA's LRx database. The use of these data expands the scope of adherence behavior that can be studied because the database is both longitudinal and comprehensive. For example, the size and scope of these data allow us to precisely measure medication adherence rates by age group and in fine-grained geographic detail. This detail is especially important given the variation in the progression of the pandemic and its effects, both by age and by geographic region.

We also contribute to the large body of work documenting the effects of macroeconomic conditions on health behaviors. Studies of the 2001 recession (Cawley and Simon, 2005) and the Great Recession (Cawley et al., 2015) find that recession-driven unemployment increased the likelihood of uninsurance, especially for men. Burgard and Hawkins (2014) document decreases in healthcare use during the Great Recession, especially among African Americans and Hispanics and among those individuals with less education. Ruhm (2000) documents the pro-cyclical nature of mortality while subsequent work has examined mortality differences by age group (Dehejia and Lleras-Muney, 2004; Van Den Berg et al., 2006; Miller et al., 2009), by individuals' employment situation (Sullivan and Wachter, 2009), and has also delved into potential mechanisms such as risky behavior, nutrition, and cost of healthcare inputs (Stevens et al., 2015; Cutler et al., 2016). Our results forecast divergent, long-run health consequences for adults and children with chronic asthma as a result of the pandemic and

(2012) find a 15 percent increase in the probability of taking any prescription drugs from gaining Medicaid coverage. Brot-Goldberg et al. (2017) find a 17.8 percent reduction in drug quantity filled when a patient switches from a zero out-of-pocket spending plan to a high-deductible plan.

subsequent macroeconomic recession.

Finally, our findings contribute to the literature on pediatric health and the role of parents and families. The literature has documented a strong relationship between pediatric health and parental socioeconomic status, one that strengthens as children grow older (Case et al., 2002; Currie and Stabile, 2003; Conti et al., 2010). Fadlon and Nielsen (2019) provides quasi-experimental evidence of within-family spillovers, including drug adherence, but focuses on adults. Our analysis focuses on the management of asthma, the most common chronic condition among children (Currie, 2009). Importantly, our findings point to prescription drug adherence in younger children as being particularly sensitive to parental attention. Further, our results suggest that differences across children in their parents' attention to chronic disease management could be a driver of the increasing steepness of the health-SES gradient by age.

# 2 Background

## 2.1 Asthma Prevalence and Management

Asthma is a chronic respiratory condition that affects the airways in the lungs, with symptoms that include wheezing, coughing, shortness of breath, and tightness in the chest. Asthma affects 13.9 percent of adults aged 18–59, and it is the most common chronic condition among children.[9] A 2018 National Health Interview Survey (NHIS) found that 8.5 million (11.6 percent) children under 18 report ever having been diagnosed with asthma and 5.5 million (7.5 percent) children report still having asthma. Low-income and non-white children under 18 are 30 to 50 percent more likely to be diagnosed with asthma. These disparities are exacerbated for the youngest children aged 0–5. These low-income young children, defined as those living in households with income at or below the poverty level, are

[9] The summary statistics throughout this section are based on author's calculations using the 2018 National Health Interview Survey.

twice as likely to have been diagnosed with asthma and non-white children are five times more likely to have been diagnosed with asthma. Mild pediatric asthma can resolve with age. However, persistent disease has known, long-run health consequences, including reduced lung function, and negative impacts on educational attainment and labor market outcomes.

Asthma management can include a combination of short-term medications to help relieve symptoms during an asthma attack and long-term medications to help prevent and control symptoms by reducing airway inflammation and preventing the narrowing of airways. Seventy-two percent of young children with asthma reported using a prescription inhaler for quick relief of symptoms within the last three months, and 55 percent of young children with asthma reported taking preventative medication in 2018. Low-income young children are 33 percent more likely to report the use of a prescription inhaler but are 10 percent less likely to report the use of preventative medication. Additionally, non-white young children are 20 percent less likely to report the use of a prescription inhaler or the use of preventative medication. Notably, 52 percent of young children with asthma are covered by public insurance including either Children's Health Insurance Program (CHIP), Medicaid, or Medicare.[10] In terms of cost, asthma is estimated to have a yearly cost of $3,266 per person, of which 56 percent was attributable to the cost of prescription medication (Nurmagambetov et al., 2018).

A severe and sometimes sudden onset of asthmatic symptoms, referred to as an asthma attack, is commonly associated with health care utilization, either via an Emergency Room (ER) visit or hospitalization. During the past twelve months, seventy-one percent of young children with asthma reported having an asthma attack compared with 54 percent of children aged 6 to 12 and 42 percent of adults aged 19 to 59 (NHIS, 2018). In addition, non-white and low-income young children were two-to-three times more likely to report having had an asthma attack than white or non-low-income young children. Forty-four percent of young children with asthma report missing school due to their asthma. Finally, young children

[10] In the IQVIA data, CHIP and Medicaid are both labeled as Medicaid in the payer field.

with asthma were four times as likely as adults to report ER visits and hospitalizations due to asthma complications.

## 2.2 Drug Adherence

Drug adherence is a fundamental part of disease management, especially for chronic conditions. Drug adherence, or compliance, refers to the behavior of the patient in following a prescribed medication regimen. According to a 2003 World Health Organization (WHO) report, "increasing the effectiveness of adherence interventions may have a far greater impact on the health of a population than any improvement in specific medical treatment" (Sabate and World Health Organization., 2003).

Non-adherence to drug therapy is a common problem, both in the general chronic population and specifically among asthmatic individuals (Bender et al., 1997; Bush and Saglani, 2010). Poor adherence has been shown to have direct consequences for disease management, including increased risk of hospitalization and death. Among asthma patients, nonadherence rates have been shown to be less than 50 percent (Bender et al., 1997; Yawn et al., 2016). The costs associated with asthma control are substantial, driven by the cost of hospitalization and medication (Ungar and Coyte, 2001; Weiss and Sullivan, 2001; Gergen, 2001; Horne, 2006). In light of this, a large empirical body has focused on studying the mechanisms that underlie poor adherence (Matsui, 2007; Bosworth et al., 2011; McQuaid and Landier, 2018; Stirratt et al., 2018). In the context of asthma, empirical evidence has shown that disparities in drug adherence exist among racial and ethnic minorities, and these disparities are especially related to individual beliefs about taking drugs (McQuaid, 2018).

Adherence rates can be measured in several ways, including the use of self-reported measures, objective monitoring devices, and indirect methods such as viral loads or secondary databases. In this paper, we create a measure of adherence based on the LRx database which we describe in more detail in Section 3.1. Our measure is derived from patient-level longitudinal prescription refill patterns as opposed to direct measures of drug consumption.

These measures necessarily assume that refill adherence corresponds to drug-taking behavior, as is common in the drug adherence literature and also specifically within the context of asthma control (Lam and Fresco, 2015; Feehan et al., 2015). Moreover, objective measures drug adherence for asthmatic patients have been shown to be more accurate than subjective measures (Bender et al., 1997).

## 2.3 Timeline of Key COVID-19 Events in 2020

The WHO first announced the emergence of a mysterious coronavirus-related pneumonia in Wuhan, China on January 9, 2020, with the Centers for Disease Control (CDC) confirming the first U.S. coronavirus case on January 21, 2020. This patient had traveled to the U.S. from Wuhan on January 15, 2020. China subsequently placed Wuhan under quarantine on January 23, 2020, and the U.S. declared a public health emergency on February 3, 2020. The WHO declared COVID a pandemic on March 11, 2020, followed by a U.S. declaration of a national emergency on March 13, 2020. Six days later, on March 19, 2020, California became the first state to issue a stay-at-home order; other states quickly followed.

Several significant pieces of federal legislation were passed in quick succession. First, the Coronavirus Preparedness and Response Supplemental Appropriations Act was signed by President Trump on March 6, 2020. While this Act provided $8.3 billion in emergency funding for federal agencies, it also included a waiver removing restrictions on Medicare providers allowing them to offer telehealth services to beneficiaries regardless of whether the beneficiary was in a rural community. Importantly, Federal officials encouraged states and insurers to provide similar flexibility under private insurance, which many did (Volk et al., 2021).[11]

Second, the Families First Coronavirus Response Act was signed into law on March 18, 2020. This Act, among other things, mandated that states could not dis-enroll any

[11] Centers for Medicare and Medicaid Services, FAQs on Availability and Usage of Telehealth Services Through Private Health Insurance Coverage in Response to Coronavirus Disease 2019 (CMS, March 24, 2020).

beneficiary who had Medicaid coverage through the end of 2020. Around this time many states also increased the quantity limits on prescriptions, typically from 30 to 90 days, and relaxed limits on early refills. Third, the Coronavirus Aid Relief Act (CARES) was signed by the President on March 27, 2020. CARES provided $2 trillion across seven major areas, including benefits for individuals, unemployment assistance, small business relief, big and medium-sized business relief, tax breaks and credits, hospital and healthcare assistance, and state and local government. The first payments or 'stimulus checks' started on April 15, 2020. Collectively, this group of legislation likely expanded access to care, increased quantities of drugs per claim, and made time between claims more irregular.

Finally, school closures and re-openings were highly relevant events, especially as they relate to interpreting our estimates for the impact on children. After the national emergency declaration on March 13, 2020, all public schools in the U.S. were closed. These closures were recommended or mandated for the rest of the academic year in most states. By August 2020, some states had mandated at least some in-person schooling for the new academic year, with several other states lifting closures in September and October 2020.[12]

# 3 Data Collection and Empirical Methods

## 3.1 Data Sources

As mentioned previously, our primary data source is the IQVIA Longitudinal Prescription Claims dataset. Each entry in these data corresponds to a drug claim and includes anonymized patient identifiers, prescriber zip code, drug identifiers, fill date, days supplied, method of fill (mail, retail, or other), primary payer, and out-of-pocket payment amount. These data cover the vast majority of prescription drug claims in the U.S. market. We study an extract of these data that includes all prescriptions associated with the treatment

[12] Detailed statistics provided by Education Week are available at `https://www.edweek.org/ew/section/multimedia/map-covid-19-schools-open-closed.html`.

of asthma. The detail in these data permits us to generate a continuous adherence measure by combining information about fill and refill dates and days of medication supplied to each individual; we describe this measure in detail below. The scope of these data also allows us to derive representative results for the population and to precisely estimate heterogeneous effects, including by age and other factors.

We supplement these data with geographic information describing race, income, education, occupation, population density, asthma prevalence, access to health insurance, COVID case counts, population mobility, school closure, air quality, and the availability of mail-order and telehealth services prior to the pandemic using several external sources. All geographic information is matched to individual claimants based on their prescriber's zip code. In addition, we capture information about the development of the COVID pandemic based on measures of case counts, average weekly mobility levels, and school closure measures. We provide detailed variable descriptions for these supplemental data, including sources, in Table A1.

## 3.2 Constructing a Measure of Drug Adherence

We construct a monthly patient-level panel data set to study drug adherence in 2019 and 2020 using the LRx database. First, we restrict our population data to patients aged 0 to 59. Next, we draw a 25 percent random sample from the full population data.[13] We compute adherence rates for each patient based on prescription fill date and days of medication supplied. Specifically, we identify the earliest claim in the LRx database for each patient and we track their stock of medication across prescription claims, decreasing the stock by one each day and adding back additional medication with each new prescription observed. If a patient stock hits zero, all subsequent days are marked as non-adherent until the next prescription is filled. We aggregate this measure to describe the proportion of days covered

[13]We draw a random sample of the data to manage computing constraints within the context of our empirical analysis. In some specifications, we rely on a smaller random sample (1 in 20), again, to manage computing constraints. We show that our results are robust to different sample sizes in Table A2.

by drug for a given patient within each month. Our measure is similar to other continuous measures such as the Proportion of Days Covered (PDC), which is a common method to measure for assessing adherence in asthma pharmacy claims databases (Lam and Fresco, 2015; Asamoah-Boaheng et al., 2021).

We construct our sample to study the effect of the pandemic on adherence rates for those individuals who were already prescribed medication to manage asthma symptoms prior to the pandemic. This allows us to evaluate baseline adherence patterns before the pandemic and to avoid the confounding comparison of impacts on average drug adherence for those that may have newly developed respiratory symptoms as a result of a COVID infection. In particular, individuals in our sample in year $y$ must have filled at least one asthma prescription in year $y - 1$. We refer to this as the sample of continuing users of asthma medication. Our final sample contains roughly 6 million patients: 4 million adults and 2 million kids under 18.[14]

We characterize each patient and year based on the prescription characteristics for the final prescription filled in the previous year. First, we measure the intensity of usage in the previous year to separate infrequent and chronic users of asthma medication. Chronic (infrequent) users are those in the top (bottom) 25th percentile of total days covered by a prescription in the prior year. Second, we capture the payer for the last claim in the previous year (i.e., private insurance, Medicaid, Medicare, and cash). Fixing these measures allow us to obtain a clearer picture of heterogeneous effects that are not influenced by other effects of the pandemic. We match all geographic characteristics to patients based on the zip code of their provider for their last prescription in the prior year. Detailed variable descriptions for measures based on IQVIA LRx are reported in Table A3.

Table 1 reports summary statistics measured in January and February for adult (aged 18–59) and pediatric (aged 0–17) continuing users. We measure these summary statistics in

[14]Based on the 2018 National Health Interview Survey, there were roughly 33 million individuals under the age of 60 who report ever having been diagnosed with asthma: 25 million adults 18 to 59 and 8 million kids under 18. In addition, there were roughly 19 million individuals who report currently having asthma: 13 million adults and 6 million children. Our final sample is consistent with these estimates and reflects a full population of roughly 24 million continuing-use individuals: 9 million kids under 18 and 16 million adults.

January and February to capture pre-pandemic characteristics. Columns (1) and (2) report summary statistics for adults in 2019 and 2020, respectively. Columns (3) and (4) report summary statistics for children in 2019 and 2020, respectively. This table shows that the profile of asthma users is very similar in these months in 2019 and 2020.

Among adults, roughly two-thirds are female, 85 percent are covered by private insurance and 5 percent are covered by Medicaid. These adults had enough medication to supply roughly 100 days in the prior year. Average per-capita income based on zip code was roughly $33,000, 25 percent of the population was non-white, 21 percent had at least some college education, most lived in urban areas, and 59 percent lived in a Medicaid expansion state. Finally, asthma prevalence in the local population was roughly 14 percent.

By comparison, children are less likely to be female (44 percent compared with 64 percent) and are more likely to be covered by Medicaid (11 percent compared with 5 percent). Children were, on average, 8 years old with enough medication to supply roughly 80 days in the prior year. Generally, children lived in areas with comparable geographic characteristics to adult asthma patients.

### 3.3 Estimating the Effect of the Pandemic on Adherence Rates: Difference-in-Differences Specification

We capture the effect of the COVID pandemic on monthly drug adherence rates using a dynamic difference-in-differences (DD) empirical specification that compares monthly drug adherence in 2020 to 2019 for treated months, i.e., months that were affected by the pandemic (March–December), and control months, i.e., those that were not (January–February):

$$y_{imt} \quad = \quad \lambda_t + \mu_m + \phi_m \cdot \mu_m \times \lambda_{2020} + \gamma_s + X_{imt} + u_{imt} \tag{1}$$

where $y_{imt}$ captures monthly drug adherence rates for individual $i$ in month $m$ in year $t$. Here, $\mu_m$ captures monthly fixed effects in each month from March to December, where January and February serve as the control (pre-pandemic) reference category and $m = 3, ..., 12$. $\lambda_{2020}$ is an indicator for 2020. $X_{imt}$ collects control variables that capture state-by-month variation in the evolution of the pandemic including monthly COVID case counts, unemployment rates, and monthly mobility measures. Finally, in some specifications we include a state fixed effect, $\gamma_s$, where the state is defined based on the prescriber of the last prescription in the prior year, and in other specifications, we include individual fixed effects. Importantly, $\phi_m$ identifies differences in adherence rates in each month from March through December 2020 compared to these same months in 2019, using changes in adherence rates in January and February from 2019 to 2020 as control changes. All estimates are clustered based on the state of the last known provider.

In addition to the above dynamic difference-in-differences specification, we also estimate a traditional difference-in-differences empirical model that collapses the estimated effects in months 3 (March) through 12 (December), $\phi_m$, into one post period:

$$y_{imt} = \lambda_t + \text{POST} + \phi \cdot \text{POST} \times \lambda_{2020} + \gamma_s + X_{imt} + u_{imt} \tag{2}$$

where POST is a dummy variable equal to one for months 3 (March) through 12 (December) and $\phi$ captures the difference-in-differences estimate. In this model, $\phi$ reflects a weighted average of $\phi_m$ from Equation 1. We will take advantage of this simplification to conduct additional empirical tests of the relative importance of patient and geographic characteristics, $\pi_i$, in explaining $\phi$:

$$\begin{aligned} y_{imt} = {} & \lambda_t + \text{POST} + \phi \cdot \text{POST} \times \lambda_{2020} + \gamma_s + X_{imt} \\ & \pi_i + \pi_i \times \lambda_{2020} + \pi \times \text{POST} + \psi\pi_i \times \text{POST} \times \lambda_{2020} + u_{imt} \end{aligned} \tag{3}$$

For example, suppose $\pi_i$ is a dummy variable equal to one for female patients and zero for male patients. Then $\psi$ captures the estimate of the pandemic on drug adherence for female patients relative to male patients, or the relative difference-in-differences.

# 4 Empirical Evidence

## 4.1 Differential Impact on Adults and Children

Figure 1, Panel (a) plots the mean change in monthly drug adherence, scaled by the average adherence rate in January and February 2019, for all asthma patients aged 0 to 59 years. This figure reflects two distinct behaviors. First, we find evidence of a short-run increase in adherence at the start of the pandemic; this behavior is consistent with stock-piling behavior that was common at the time. Second, after the initial onset of the pandemic, we document a steady decline in adherence rates throughout 2020.

A more nuanced picture emerges, however, when we consider changes in adherence rates during the pandemic across age groups. In Figure 1, Panel (b) we group asthma patients by age: (1) children, under 6; (2) children, aged 6 to 17; and, (3) adults, aged 18 to 59. The first group roughly corresponds to children who are pre-kindergarten and the second group roughly corresponds to children in kindergarten through high school. The final group includes likely working, pre-Medicare adults. In this Panel, we again see two patterns emerge. First, as in the full population, all groups show evidence of stockpiling behavior in March 2020. Second, we show a clear divergence in the long-run change in adherence rates through the end of 2020 across our age groupings. Adult adherence returns to near-baseline rates by December 2020, whereas pediatric adherence, however, sharply declines and remains persistently below 2019 adherence rates the entire time period, impacting the youngest children the most.

Next, we estimate the effect of the pandemic on adherence rates based on the difference-in-differences model described in Equation 1. We report these results in Table 2. Columns 1, 4, 7, and 10 report estimates of the change in monthly drug adherence during the pandemic for the full sample, children (under 6), children (6-17), and adults (18-59), respectively, without any controls. Columns 2, 5, 8, and 11 report results across the same groupings but with the inclusion of controls and state fixed effects. Figure 1, Panels (c) and (d) plot these monthly estimates, scaled by adherence rates in January and February 2019. Importantly, the same trends we observed in Panels (a) and (b) remain present in Panels (c) and (d). In other words, the pandemic appears to have caused a large decline in pediatric drug adherence.

Interpretation of these results is complicated by the fact that we are studying asthma patients within the context of a respiratory pandemic. For example, many of the medications used to treat COVID-related respiratory symptoms are the same ones used to treat asthma. However, there are three reasons supporting our interpretation that the results are driven by behavioral changes caused by the pandemic rather than a direct result of the onset of COVID-related respiratory illness. First, any new onset of respiratory symptoms driven by the contraction of COVID should, all else equal, serve to abnormally increase, rather than decrease, drug adherence rates. Second, our analysis includes only those patients that had chronically used asthma medication *prior* to the onset of COVID. As such, any new patients that were prescribed asthma medication as part of a treatment regime for COVID in 2020, are excluded from our sample. Finally, we obtained additional data from IQVIA for diabetes and depression-related prescriptions, two highly-prevalent chronic conditions that are less likely to be treated by similar prescription regimens to COVID-related symptoms, and we replicate our core finding of divergent drug adherence rates for adults and children.

Figure 2 plots the monthly difference-in-differences estimates (Table A4), scaled by adherence rates in January and February 2019, for asthma (Panel (a)), diabetes (Panel (b)), and depression (Panel (c)). We include Panel (a) for comparative purposes. There are a limited number of very young patients in diabetes and depression data, so we group patients into two categories: (1) under 18 and (2) 18-59. With this grouping, we still see a similar divergence in adherence rates between children and adults in these other markets as we saw in asthma (Panel (a)). These findings provide complementary evidence that the respiratory and age-based nature of COVID is unlikely to account for our findings. Instead, these results suggest something more fundamental about the effect of the pandemic on adult and pediatric drug adherence rates.

Given the richness of our data, we are able to include individual-level fixed effects, which we do in Table 2, Columns 3, 6, 9, and 12, and in all regression analyses going forward. Figure 1, Panels (c) and (d) are replicated in Figure A1 with the inclusion of individual fixed effects. We find similar levels of stock-piling behavior on average, with about a 10% increase in drug adherence rates in April 2020, and also find a similar reversion to baseline adherence levels by the end of 2020. Importantly, in the sub-sample analysis, we continue to see starkly different behavior for adults and children. Pediatric adherence rates begin to fall immediately following March 2020, and this relative decrease persists throughout the rest of the year. Again, the decline in pediatric adherence rates is strongest for the youngest children.

As previously discussed, identification in our model requires that within-year seasonal variation in drug adherence rates would have been similar if not for the onset of the pandemic. While we cannot formally test this hypothesis, we can confirm that seasonal trends had otherwise been similar across years prior to the pandemic. Appendix Figure A2 plots monthly adherence rates for the population of users, regardless of continuous use.[15]

These plots reveal several facts. First, seemingly low drug adherence rates from January to March 2018 are mechanically related to how we measure drug adherence by building a stock variable (days supplied) based on a flow variable (prescriptions). This procedure requires several months of observations before stock variables are measured with consistency and our database begins in 2018.[16] Our difference-in-differences comparison avoids this issue by limiting our pre-COVID seasonality controls to 2019. Second, drug adherence rates are generally seasonal, with lower adherence in the summer months and higher adherence rates in the winter months. These seasonal patterns in drug adherence mirror seasonal trends in

[15] We note that we are unable to identify the subset of continuous users in 2018 because we do not have data from 2017.

[16] For example, some patients will be consuming medication in January to March 2018 that is linked to a prescription that was filled in 2017, given typical prescription supplies of 30 to 90 days. Our data does not include these 2017 prescriptions, so we calculate an abnormally low drug adherence rate. After March 2020, we are likely to see all new prescriptions, which enables us to accurately build a drug adherence rate.

environmental triggers that affect the severity of the presentation of asthma symptoms. Finally, and most importantly, seasonal trends were parallel in 2018 and 2019, lending support to the identifying assumption that seasonal trends would likely have continued in 2020 if not for the pandemic.

To illuminate the mechanics of our difference-in-differences analysis, Figure A3 plots raw trends in monthly adherence rates for adults (18 to 59) and children (0 to 18) in Panels (a) and (b), respectively. For adults, Panel (a), adherence rates rise sharply in March and April 2020 compared to typical trends seen in 2019, and adherence rates remain elevated throughout the year. By comparison, pediatric adherence rates rise in March 2020 but fall sharply thereafter, leveling out at abnormally low rates in July 2020. Moreover, these panels provide additional support for the parallel trends assumption; monthly adherence rates in January and February 2020 evolve similarly to these same months in 2019 for adults and children.

## 4.2 Exploring Potential Mechanisms

Given the large negative impact on pediatric adherence, we investigate factors that may contribute to the estimated response. We start by exploring a broad set of factors that cover policy-relevant issues raised in the healthcare literature, socioeconomic factors, and other changes caused by the COVID pandemic such as school closures. We use the zip code of the prescribing physician's practice to link individuals to county-level measures from additional data sources. As we will discuss below, we generally find persistent decreases in pediatric adherence across county-level characteristics and no factor offsets more than 20 percent of the mean response. Throughout our analysis, we control for local COVID prevalence in order to account for the direct effects of COVID cases on adherence.

We provide two exhibits that summarize our results in this section. First, Figure 3 provides a visualization of adherence responses by county. In short, no obvious geographic pattern appears to exist (i.e., North versus South, urban versus rural, etc.) when comparing changes in adherence rates in April and December 2020 across adults and children. Second, Table 3 introduces a "horse race" regression, based on Equation 3, that simultaneously incorporates all of the factors discussed below. We will reference these horse race estimates throughout the discussion that follows as a way to discuss the relative importance of various individual factors.

To summarize our results and provide context for the relative importance of each factor, Table 3, Columns 1, 3, and 5 report estimates of the average effect of the pandemic on adherence averaged across months 3 (March) through 12 (December) based on Equation 2. We estimate that the average adherence rate fell by 1.92 percentage points for children and increased by 0.98 percentage points for adults, or a 2.9 percentage point difference between adult and pediatric adherence rates. These average estimates serve as context for the subsequent discussion.[17]

### 4.2.1 Medical Need

We explore whether changes in medical need can explain both the divergent patterns and the sustained decrease in pediatric adherence. First, we compare differences between low and high-intensity users of asthma medication. We define low (high) intensity users as those in the bottom (top) 25th percentile of the distribution of total days supplied in the prior year. To provide context for the scale of this difference, low-intensity users had an average adherence rate of just 5.81 percent in January and February 2019, whereas high-intensity users had an average adherence rate of 72.4 percent in these same months. If our estimates are driven by low-intensity users, this speaks to the welfare implications of our findings. For example, decreased adherence might correct for a tendency for over-diagnosis of asthma among marginally affected patients. On the other hand, if we estimate a sustained decrease in adherence for high-intensity users, our results are more likely to foreshadow medium and long-run negative health consequences of poor asthma management for severely affected

[17]The average incorporates stockpiling behavior in March, so it will understate the negative response throughout the rest of 2020.

patients.

Figure 4, Panels (a) and (b) plot our scaled estimates among high-intensity and low-intensity users, respectively, and Table 4 reports point estimates. While we do estimate the largest absolute effects for high-intensity users, these estimates are relative to a much higher control mean. Scaled by control means, Figure 4 reveals large decreases in drug adherence across both low- and high-intensity pediatric users. Low-intensity pediatric users saw a greater than 50% reduction by December 2020 and high-intensity users exhibit more than a 10% reduction in drug adherence. In the horse race regression, Table 3, we see that high-intensity use offsets roughly 50 percent of the estimated pediatric effect (0.00881/-0.0173, Columns 3 and 4). In other words, the potential over-diagnosis of pediatric asthma does not fully explain our results.

For completeness, we also provide evidence by county-level pre-COVID asthma prevalence. We theorize that patients in counties with high prevalence of pre-COVID asthma may be predisposed to pay more attention to drug adherence. As a result, when confronted with an illness that has respiratory implications (*i.e.*, COVID) patients in these counties should experience smaller declines in adherence rates. We use pre-COVID county-level asthma prevalence data from Torch Insights, drawn from the Behavioral Risk Factor Surveillance System, to define high (low) prevalence counties as those in the top (bottom) 25th percentile of the distribution. Figure 4, Panels (c) and (d) provide a comparison between high- and low-prevalence counties, and Table 5 reports point estimates. We find similar responses across high- and low-prevalence counties. In the horse race regression, Table 3, we find that high prevalence counties have a less negative response, but the point estimate is only 16 percent of the average response (0.0031/-0.0192, Columns 3 and 4).

Next, we test whether changes in air quality mediate the adherence response in children. It is well documented that air quality improved in response to the shutdowns that occurred due to COVID (Berman and Ebisu, 2020; Slezakova and Pereira, 2021; Venter et al., 2020). Figure 5, Panels (a) and (b) present results broken down by whether a county experienced an increase or decrease in environmental pollutants in April to August 2020, based on Air Quality Index (AQI) data from the Environmental Protection Agency. Higher AQI reflects worsening air quality. In particular, we calculate county-level changes in the AQI in April through August 2020 compared to 2019, relative to changes that would be predicted based on AQI changes from 2018 to 2019.[18] We divide counties into those that experienced an increase (Figure 5, Panel (a)) or decrease (Figure 5, Panel (b)) in AQI. Point estimates are reported in Table 6. In addition, we further focus on urban counties that experienced an increase (Figure 5, Panel (c)) or decrease (Figure 5, Panel (d)) because changes in air quality should be more acute in urban areas. Point estimates for these urban counties are presented in Table 7.

Across all four panels, we find minimal differences in patterns across our two groups of children. We see little difference between adherence rates in counties with worsening air quality (Panel (a)) and those counties with improvements in air quality (Panel (b)). In both cases, our core pattern still emerges between adults and children. We again see similar patterns when we focus solely on urban counties (Panels (c) and (d)). In short, it does not appear that improvements in AQI had any impact on pediatric adherence rates. In our horse race regression, Table 3, we estimate that the mediating effect of AQI is only 21 percent of the mean change in pediatric adherence (-0.004/-0.0192, Columns 3 and 4).

#### 4.2.2 Measures of Socioeconomic Status

We next focus on responses to numerous county-level measures of socioeconomic status (SES). Measures of SES may proxy for changes to family budgets, changes in work routine, and general ability to adjust to the pandemic. We focus on four separate measures relating to: (1) income, (2) education level, (3) occupation type, and (4) race. We start with income as financial instability could lead to reduced adherence if families re-prioritized their family budgets in ways that negatively impacted the purchase of medication. Evidence suggests that

[18] Specifically, we calculate the county-level change in air quality from April to August 2019 to 2020, differencing out the change in air quality that occurred from 2018 to 2019.

even with stimulus payments, a significant number of families still faced financial struggles (Cox et al., 2022). We use data from the American Community Survey to separate counties into high (low) income counties, defined as those in the top (bottom) 25th percentile of the distribution of per-capita income. We break out our adherence estimates by the pre-pandemic, per capita income by zip code and county, and report the results in Figure 6, Panels (a) and (b). Point estimates are presented in Table 8.

Overall, we find very minimal differences in the average adherence response between high-income and low-income counties. In both cases, our core results hold; pediatric adherence is still significantly lower than adults. Turning to our horse race regression, Table 3, we see that children in high-income counties experience a quantitatively and statistically significant additional decrease, about 34 percent of the average effect size (-0.0065/-0.0192, Columns 3 and 4). In other words, and somewhat curiously, children in high-income counties experience a *larger* decrease in pediatric adherence. Thus, it appears that families may very well have been re-prioritizing their budgets, they just may have been doing so in ways that we are unable to capture with this measure.

We next test whether differences in parental education influence adherence rates. In general, the education levels of parents may impact their beliefs about medications and the need for adherence (Conn et al., 2007). Using the same data source as we used for our income measure, we divide counties into high (low) education counties, defined as those in the top (bottom) 25th percentile of the distribution of the population with at least some college experience. Results are reported in Figure 6, Panels (c) and (d), and point estimates are reported in Table 9. We again find minimal quantitative differences. In our horse race regression, Table 3, we find that higher education levels in a county are actually associated with slightly more negative adherence changes, about 3 percent of the average decrease (-0.0006/-0.0192, Columns 3 and 4), although these results are statistically noisy.

The pandemic likely had differential impacts on high-skilled and low-skilled workers, particularly in the prevalence of remote work and the likelihood of unemployment. Although we control for state-by-month unemployment rates, these factors could contribute to possible time, attention, and resources that parents may have been able to provide to their children. Using county-level occupation data from BEA REIS we classify counties as "white collar" if they are in the top 25th percentile of the distribution in terms of the share of jobs that are in professional occupations. Likewise, we classify counties as "blue collar" if they are in the bottom 25th percentile.[19] As reported in Figure 6, Panels (e) and (f), and Table 10, we again find minimal differences in adherence rates between areas with predominately white collar employment versus those with blue collar employment. In our horse race regression, Table 3, we find that counties with higher levels of white-collar employment have a smaller drop in pediatric adherence, accounting for about 17 percent of the baseline decrease (0.0033/0.0192, Columns 3 and 4). The estimate, however, is statistically insignificant.

Finally, we consider whether race is a potential factor in explaining the change in pediatric adherence. As we documented previously, disparities exist in both the prevalence of pediatric asthma, where non-white children are 50 percent more likely to be diagnosed, are 25 percent less likely to report the use of a prescription inhaler, and are two-to-three times more likely to report having an asthma attack.[20] More broadly, research has also documented a higher level of skepticism towards prescription drugs in minority populations (Adams et al., 2018) and differences in the rates at which minority patients fill prescriptions (Reed and Hargraves, 2003). In the recent pandemic, mortality rates due to COVID infection were significantly higher among the minority population (Hill and Artiga, 2022).

Using data from the American Community Survey, we calculate the share of the population in a given county that is non-white. We categorize counties as mostly non-white (white) if the share of the population is in the top (bottom) quartile of this distribution. Results are reported in Figure 7, Panels (a) and (b) with point estimates reported in Table

[19]Specifically, we classify occupations based on the line code variable in BEA REIS. We exclude government occupations (2000s), classify line codes 900-1600 as professional occupations ("white collar"), and classify the rest as non-professional ("blue collar"). We then use the jobs variable in BEA REIS to compute the fraction of jobs in the "white collar" categories by county.

[20]National Health Interview Survey, Center for Disease Control, 2018: https://www.cdc.gov/nchs/nhis/index.htm

11. In contrast to what might be implied by the extant literature, we find minimal differences across these two regions. The decline in pediatric adherence persists, regardless of race. Knowing that minority populations tend to be higher in urban areas, in Panels (c) and (d) and Table 12 we focus solely on urban counties. Again, we find minimal differences. Finally, turning to our horse race regression, Table 3, we see some limited evidence that high minority population areas have a slightly larger drop in adherence. This additional effect, however, is only 18 percent of the average effect (-0.0034/-0.0192, Columns 3 and 4).

### 4.2.3 Insurance and Access

Prior literature has documented the importance of insurance coverage (Chandra et al., 2010; Finkelstein et al., 2012; Brot-Goldberg et al., 2017) and access to care (Brown and Bussell, 2011) on prescription drug adherence. During the pandemic, we saw both state and federal governments implement various insurance-related policies, including mandating continuing coverage for individuals covered by Medicaid. There was also increased use in both mail-order delivery of prescriptions and expansions in the use of telehealth services (Volk et al., 2021). Presumably, all of these changes should moderate the pediatric adherence results that we have thus far documented.

We start by documenting adherence responses by insurance type, Medicaid (public) or Third Party Insurers (private), which was provided by IQVIA. Results are reported in Figure 8, Panels (a) and (b) with point estimates reported in Table 13. In all cases, insurance status is determined by a patient's payer on their final prescription in the prior year. We find large decreases in pediatric adherence in both groups, with a slightly larger decline in children covered by Medicaid. This suggests that policies that were put in place to aid Medicaid recipients, while securing coverage, did little to impact drug adherence. The horse race estimates, Table 3, suggest minimal quantitative differences across the two groups. Children covered by Medicaid have smaller decreases in adherence, but the moderating effect size is only 8 percent of the average effect (0.0016/-0.0192, Columns 3 and 4) and is statistically insignificant.

The Affordable Care Act (ACA) was passed in 2010. One provision of ACA was the expansion of thresholds for Medicaid eligibility, which increased access to medical coverage for low-income individuals. This expansion, however, was not universal in that states had to opt-in to the program. As of January 1, 2020, 15 states still had not adopted and implemented the ACA Medicaid expansion.[21] As a result, the uninsurance rate in expansion states was half of that in non-expansion stats (9.8 compared with 18.4) among adults aged 19 to 64 (American Community Survey, 2019).[22]

We compare the Medicaid expansion and non-expansion states in Figure 8, Panels (c) and (d), and Table 14. In this case, the increased access afforded by Medicaid expansion did not translate into better adherence. There remains little difference across the two groups of states; pediatric adherence still declined. Again, in the horse race regression, Table 3, we find similar responses in pediatric adherence, with horse race estimates showing a negligible coefficient relative to the mean response (0.0004, Column 4).

Beyond insurance, we also investigate other access factors that may have changed during the pandemic. Specifically, we focus on the mail order channel since this is a delivery channel that, if available, would have remained accessible throughout the pandemic. Certainly, mail-order would be available for both adults and pediatric prescription drugs, so if we observed any differences, it would point to explanations beyond simple access. Using data from IQVIA, we group patients based on whether their last prescription in 2019 was filled through mail order rather than at a retail pharmacy. Presumably, this group of patients would already be set up and familiar with the mail-order system and we would therefore be the least affected by any disruptions that may have occurred with retail pharmacies. Results are presented in Figure 9, Panels (a) and (b) with point estimates reported in Table 15. Interestingly, we find some imprecise evidence that the mail-order group exhibits a smaller decrease in

[21] These states include: Wyoming, South Dakota, Kansas, Texas, Oklahoma, Missouri, Nebraska, Wisconsin, Tennessee, Mississippi, Alabama, Georgia, Florida, South Carolina and North Carolina. See: https://www.kff.org/medicaid/issue-brief/status-of-state-medicaid-expansion-decisions-interactive-map/

[22] https://www.census.gov/programs-surveys/acs

adherence rates. However, once we control for chronic users in the horse race regression, Table 3, which is strongly associated with mail-order usage, the differences become much smaller, around 25 percent of the average effect (0.0048/-0.0192, Columns 3 and 4), and statistically insignificant.

Finally, we consider whether geography matters for access to retail pharmacies. Namely, we consider differences between urban and rural counties. According to the Rural Policy Research Institute at the University of Iowa, from 2003 to 2018, over 1,200 retail pharmacies closed in rural areas leaving over 600 areas with no pharmacy.[23] We see in Figure 9, Panels (c) and (d) and Table 16, that stockpiling behavior appears to be slightly stronger in urban counties, but children in both groups exhibit similar and large declines in adherence later in the year. In the horse race regression, Table 3, urban counties are 10 percent of the average effect (-0.00197/-0.0173, Columns 3 and 4) but the estimate is statistically insignificant.

Thus far, we have ruled out access to insurance and access to prescription drugs as possible explanations for the trend we see in pediatric adherence. Next, we consider the direct effect of access to medical services during the pandemic. While many physician offices were closed and hospital admissions were dominated by COVID patient care, telehealth not only remained available throughout the pandemic but thrived. Using data from the Commonwealth Fund Issue Brief, we identified those states that had policies in place that required insurers to cover telehealth services prior to 2020; the subset of patients using these services prior to the pandemic should have been the least affected by disruptions due to closures of physician offices. Panels (a) and (b) of Figure 10 plot relative estimates for patients in states without and with pre-pandemic telehealth policies in place, respectively with point estimates reported in Table 17. While there appears to be some positive moderating effect in those states that had pre-pandemic telehealth policies, the overall trends are still negative, and the cumulative effect of these policies is negligible (-0.00016/-0.0192, or less than 1% of the mean effect).

[23]Policy Brief 2018-2, July 2018: http://www.public-health.uiowa.edu/rupri/

### 4.2.4 School Closures

Schools play an important role in the maintenance of asthma for a multitude of reasons. For those students taking medication, schools provide reminders to students to take their medication and reminders to parents to refill expiring or fully consumed prescriptions (McClure et al., 2020). In addition, many schools are able to provide inhalers for emergency situations for asthmatic students (Jones and Wheeler, 2004). At the same time, the physical activity associated with school attendance, both through physical education and recreational physical activity during recess periods, may increase the likelihood of environmental triggers for asthmatic episodes. During the early months of the pandemic, schools in most areas closed to in-person learning through the end of the 2019 to 2020 school year, and there was significant variation in in-person schooling once the new 2020 to 2021 school year started. These closures and subsequent re-openings could explain the variation that we see in pediatric drug adherence rates.

To investigate this hypothesis, we identify zip codes that were highly exposed to school closures and those that were not. Specifically, we use county-level data on in-person schooling from the U.S. School Closure and Distance Learning Database (Parolin and Lee, 2021) to create a county-level distribution of the share of schools with at least a 50 percent reduction in year-on-year attendance from September 2019 to September 2020. We categorize counties as low (high) school closure counties if they fall in the bottom (top) 25th percentile of this distribution.

Figure 11, Panels (a) and (b), and Table 18 report results for these two groups. Interestingly, we see some positive moderating effects for schools with lower levels of closure, reinforcing the roles that schools might play in terms of monitoring. The overall trends, however, are still negative for both groups. This pattern is confirmed by the horse race regression, Table 3. The coefficients suggest that high school closure counties have a larger drop in pediatric adherence, but the coefficient is quantitatively small (-0.0032, Columns 3 and 4), statistically insignificant, and explains only 17 percent of the overall response.

#### 4.2.5 Evidence on Parental Inattention

A distinguishing factor for pediatric drug adherence is the role that parents play in filling and administering these prescriptions (e.g., Conn et al., 2005). Moreover, the importance of adult intervention is likely to be inversely related to age; the youngest children rely the most on adult caretakers to follow prescription drug regimes. Therefore, a decrease in parental attention may lead to reduced pediatric adherence without necessarily affecting adults. In this section, we provide evidence that our existing results are consistent with parental inattention as the key driver of negative pediatric drug adherence that we observe during to the pandemic.

Although we cannot link prescriptions within households using the IQVIA database, we nonetheless revisit the horse race regressions (Table 3). In particular, we focus on the role that age plays in explaining the divergent effect of COVID on drug adherence among adults and children after controlling for all other observable patient-level and geographic proxies. In this analysis, we find that the explanatory power of age is entirely consistent with our divergent findings regarding the effect of the pandemic on adult and pediatric drug adherence rates.

Among pediatric patients, we estimate that age tends to reduce the negative effect of COVID in both a quantitatively and statistically significant way. As reported in Table 3, Column 4 an increase in *Age* by ten years offsets the average effect by 67 percent (0.0013 point estimate per year; t-statistic of 15.8), and the full variation from age 1 to age 17 accounts for all of the observed negative response. As a robustness check and to ensure that our linearity assumption is not driving this finding, we also non-parametrically estimate responses by age and find a monotonic pattern, shown in Figure A4.

In contrast, among adult patients, we find that age plays no role in explaining the positive effect of COVID on adult drug adherence. In this case, the coefficient on *Age* (-0.0000424) reflects a precisely estimated zero effect. The divergent explanatory power of age across these two samples, combined with the sign and magnitude of the effect of age for children, is consistent with a hypothesis of parental inattention. The youngest children are likely the least able to communicate symptoms or need to parents, making them the most sensitive to changes in parental attention to their health needs. Our estimates suggest that the youngest children experience the strongest decline in drug adherence and that this effect shrinks by half around age eight and entirely disappears by age 18.

Because our IQVIA evidence is necessarily indirect, we complement our findings with an analysis based on a panel data set constructed from the nationally representative Medical Expenditure Panel Survey (MEPS). The advantage of MEPS over IQVIA is that it links parents and children. This allows us to directly measure parental socio-economic status and other contextual factors, such as the number of parental prescriptions. A disadvantage of MEPS, however, is the sample size; this survey only tracks about fifteen thousand individuals over the 2019 to 2020 time period. As such, the number of pediatric patients identified as taking asthma medication is only 330. This is in contrast to over 7 million pediatric patients in 2019 with asthma prescriptions in IQVIA.

Notwithstanding this limitation, we proceed in two steps. First, we replicate our core finding that drug adherence responses diverge for adults and children in the MEPS sample. To do so, we create an individual-by-year panel for users of asthma medication in 2019 and who continue to be surveyed in 2020.[24] We compute total asthma-related prescriptions (Rx) and days supplied (Q) for each individual and year.[25] We run a simple difference-in-differences specification comparing adherence rates in 2020 (post-COVID) and 2019 (pre-COVID) for children (treated) and adults (control):

$$Y_{it} = \alpha_i + \delta_t + \beta \cdot I_{t=2020} \cdot I_{age2020_i < A} + \epsilon_{it}$$

where $i$ indexes the individual and $t$ the year (2019 or 2020). Here, $Y$ is the outcome of interest, $age2020$ the age of the individual in 2020, and $A$ the cutoff for separating kids and

[24] Although MEPS contains rounds of surveys within a given year, the dates of the scripts are not available, making it difficult to conduct a monthly analysis.

[25] Appendix A provides additional information about our data construction and empirical design.

adults.

Table 19, Panel (a) shows large differences between adults and children in the number of prescriptions (Rx) and days filled (Q), consistent with our core analysis. Columns (1) and (2) focus on children under the age of five, Columns (3) and (4) focus on children under the age of 12, and Columns (5) and (6) focus on children under the age of 18. Children under 18 exhibit a 28.2 percent decrease in asthma prescriptions relative to adults and a -1.013 log point decrease in days filled (Columns 5 and 6). Results are similar for children under 12 (Columns 3 and 4) as well as children under five (Columns 1 and 2).

Second, we show that children whose parents are also taking medication experience a smaller drop in adherence. We focus on children within the panel constructed above and then construct a set of parental measures based on MEPS data. These measures include: (1) whether any parent was taking asthma medication in 2020, (2) total number of prescriptions for parents in 2020, (3) change in self-reported mental health state from 2019 to 2020 averaged across parents, (4) whether any adult lost employment in 2020, (5) whether any adult in the family lost health insurance coverage in 2020, (6) the highest education level of any parent, and (7) hourly wages.[26]

Formally, we run the following specification within the set of children under the age 18:

$$Y_{it} = \alpha_i + \delta_t + \sum_j \gamma_j \cdot I_{t=2020} \cdot X_i^j + \epsilon_{it}$$

where $X^j$ are the seven factors discussed above. Results are reported for these factors in Table 19, Panel (b).

Focusing on the individual factors, we find that parental usage of asthma medication offsets almost the entire observed drop in pediatric adherence (0.937 log points, panel (b), Column 1). Moreover, parental usage of asthma medication offsets almost all of the gap between adults and children (0.937, Panel (b), Column 1 versus -1.013, Panel (a), Column

[26] Values for self-reported mental health states are on a 1 to 5 scale, with lower (higher) values representing better (worse) health.

6). Similarly, we find that the total number of prescriptions for adults in the family also offsets a significant part of the observed gap (0.352, Column 2). Both of these results are consistent with the hypothesis that parental inattention towards their children's prescriptions is attenuated when parents themselves are obtaining and taking prescription medication.

We next consider the impact of changes in parental mental health. Research suggests that parental depression doubles the odds of child neglect (Friedman and Billick, 2015). We find a negative point estimate suggesting that worse parental mental health leads to worse pediatric adherence. The effect of a 1-point shift on the 5-point scale is only 15 percent of the overall adult-children gap (-0.149/-1.013, Panel (b), Column 3, Panel (a), Column 6). While not significant, the direction of the effect is consistent with Friedman and Billick (2015).

The loss of a job or health insurance represent significant household disruptions. It is natural to assume that these kinds of disruptions could plausibly impact parental attention and as a result pediatric drug adherence. We find a large negative association between parental job loss and pediatric adherence (-0.319, Column 4) but a minimal association between parental insurance loss and pediatric adherence (-0.0033, Column 5). Both estimates, however, are again statistically insignificant.

The final two factors test measures of socioeconomic status which have been shown in the extant literature to affect drug adherence and parental inattention. Importantly, MEPS allows us to connect children to measures of their parent's socioeconomic status rather than county-level measures. As reported in Columns (6) and (7), we find that higher education and higher hourly wage are *negatively* associated with changes in pediatric adherence from 2019 to 2020, although the estimates are not statistically significant.

Finally, we repeat our horse race regression (Table A5). The offsetting effect of adult prescriptions is the most precisely-estimated factor (0.293, t-statistic 2.03), with some imprecisely-estimated large additional effects for parents taking asthma medication (0.564, t-statistic 1.23), changes in mental health (-0.131, t-statistic 0.34), and job loss (-0.374, t-statistic

0.81). Collectively, this evidence is consistent with parental inattention as a key driver of the large decrease in pediatric adherence.

As an additional check, we repeat the same analysis within the set of other common chronic pediatric medications, which include allergy medications and medications for attention deficit disorders. We again find significant divergence between adults and children. Parents filling medication again significantly offset the gap, whereas children whose parents lose employment in 2020 experience a larger drop in adherence. Appendix A provides detailed methodology and results.

## 5 Conclusion

In this paper, we have documented the effect of the COVID pandemic on prescription drug adherence rates by combining comprehensive prescription drug claims data with a difference-in-differences empirical identification strategy. Across all ages, our data suggest a minimal average long-run impact of the pandemic on adherence rates for chronic asthma patients, with the exception of predictable stock-piling behavior in March and April of 2020. However, these findings mask substantial heterogeneity by age: we find a sustained *increase* in adherence rates for adults but a sustained *decrease* for children.

We find minimal evidence that several well-documented mechanisms associated with drug adherence are behind the sustained decrease in pediatric adherence. These include how the pandemic affected medical need, SES factors, access to health care, and schooling. Instead, we find evidence that parental inattention is likely to be a key mechanism. Specifically, we show that age, as opposed to changes in medical need, insurance, access to retail pharmacies, affordability, and school attendance, is the only factor that can account for the magnitude of the decrease in pediatric adherence. We supplement this evidence by studying the role of intra-family medical behaviors using the MEPS database. In this case, we provide direct evidence of the role of parental inattention: parental prescription drug fills during the same period significantly offset the average negative response in children.

Prior to the pandemic, the WHO identified poor drug adherence in the treatment of chronic diseases as a "worldwide problem of striking magnitude" (Sabate and World Health Organization., 2003). Recent evidence suggests that during the 2008–2013 period, asthma was responsible for $3 billion in losses due to missed work and school days, $29 billion in losses associated with asthma-related mortality, and $50.3 billion in direct medical costs (Nurmagambetov et al., 2018). This same study finds that, on a per-person basis, the incremental medical cost of asthma was $3,226 (2015 dollars), 56% of which is attributable to prescription medicine. In addition, the medical literature has shown that poor asthma adherence has both short-run (increased likelihood of severe complications that require hospitalization) and long-run health risks (reduced lung function and onset of other comorbidities that increase the risk of mortality) (Milgrom et al., 1996; Ordoñez et al., 1998; McCarthy, 1998; Bauman et al., 2002; Chandra et al., 2010; Osterberg and Blaschke, 2015). Given these risks, there is significant interest and medical research focusing on identifying the mechanisms that underlie poor adherence to asthma medication in order to recommend interventions (Bosworth et al., 2011; McQuaid and Landier, 2018; Stirratt et al., 2018).

Our estimate of a sustained decrease in pediatric adherence rates during the pandemic provides new, large-scale evidence of the important role played by parents in the maintenance and management of drug therapies used to treat chronic pediatric conditions. The pandemic, unfortunately, provided a novel opportunity to observe the effect of widespread, sustained disruption to typical behaviors on drug adherence, including a documented worsening of mental health issues related to the unstable macroeconomic and childcare environment. Our findings underscore the critical role that families play and provide a unique opportunity to focus on behavioral interventions that can help mitigate these effects. These could include reminders, automatic mail delivery, and other forms of assistance to help parents of children who are prescribed chronic medication.

Finally, our findings suggest that there may be long-term effects of the pandemic on children's health and also speak to the broader literature on the health-SES gradient in children. Adherence to asthma medication is important for pediatric development and long-term health. Although we find the largest effects among children who are infrequent users, both chronic and infrequent users appear to have been negatively impacted, with effects worsening towards the end of 2020. More generally, we find that parental attention likely matters most for adherence in younger children. Differences in drug adherence can potentially accumulate and contribute to the significant health differences across parental socioeconomic status among teenagers documented in the literature.

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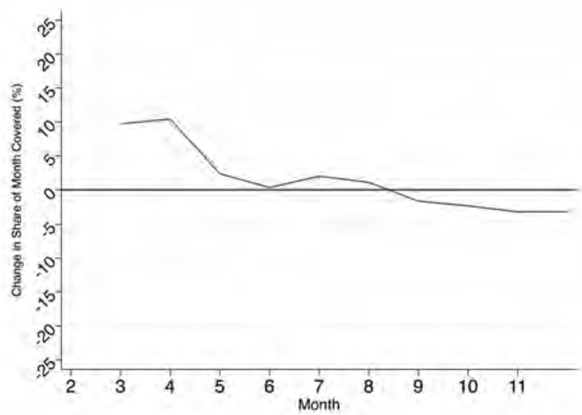
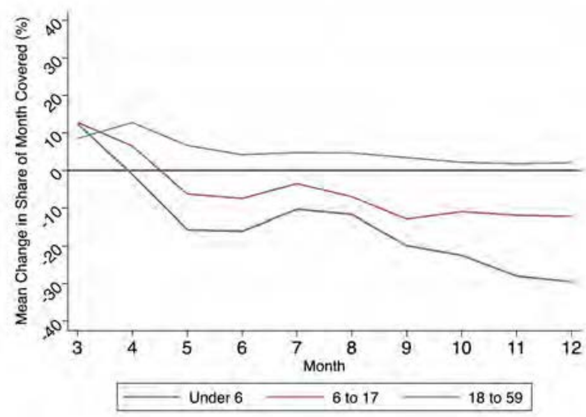
Figure 1: Change in Monthly Drug Adherence During Pandemic: Variation By Age

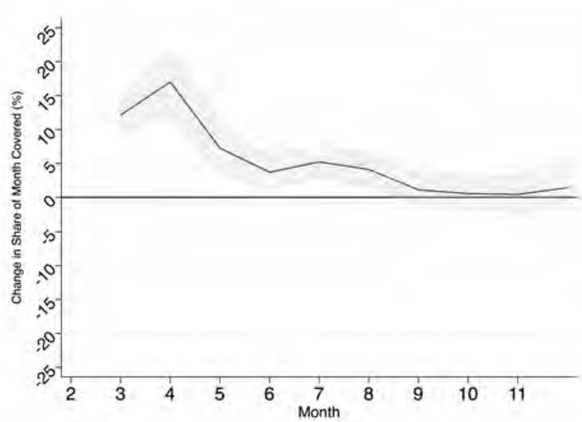
(a) Mean Adherence, 0 – 59 years old



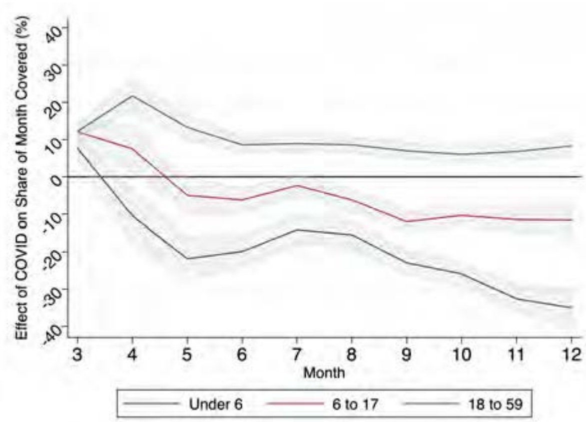

(b) Mean Adherence: Heterogeneity by Age




(c) State Fixed Effects, 0 – 59 years old



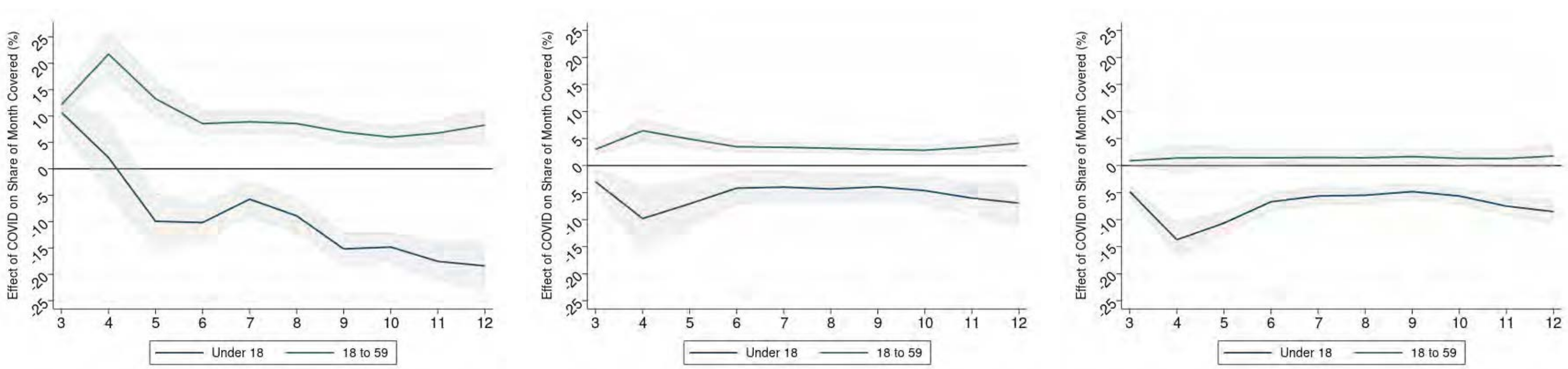

(d) State Fixed Effects: Heterogeneity by Age




*Notes:* Figure (a) plots mean changes in drug adherence rates for chronic asthmatic patients based on a 1 in 4 random sample of the full population of continuing users. Figure (b) depicts mean changes in drug adherence based on age. Figures (c) and (d) plot changes in drug adherence based on equation 1 and including controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes state fixed effects for the full population and based on age, respectively.

Figure 2: Effect of Pandemic on Monthly Adherence: Variation by Disease

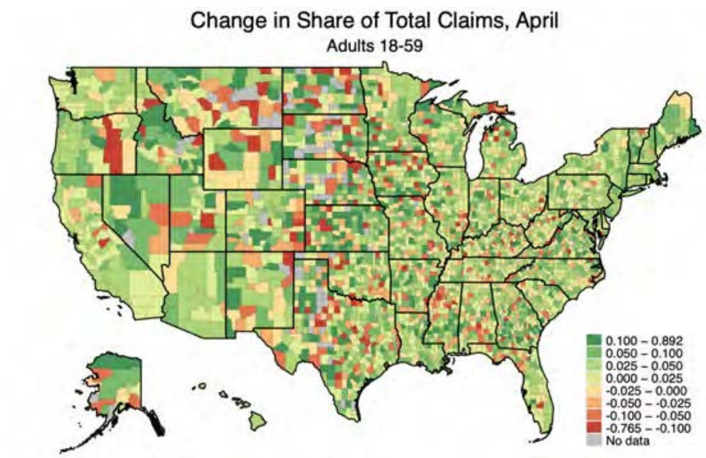
(a) Asthma Patients (b) Diabetes Patients (c) Depression Patients



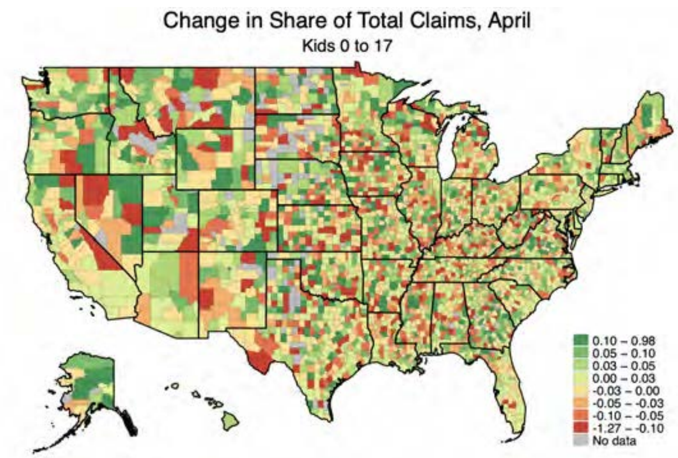

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes state fixed effects. Panel (a) plots estimates for the population of continuing user asthma patients by age. Panel (b) plots estimates for the population of continuing user diabetes patients by age. Panel (c) plots estimates for continuing user depression patients by age.

Figure 3: Effect of Pandemic On Monthly Adherence: Variation by Geography

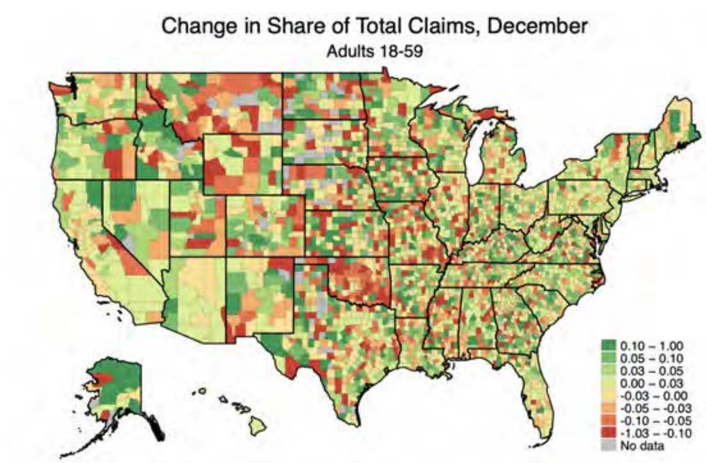
(a) April, Adults



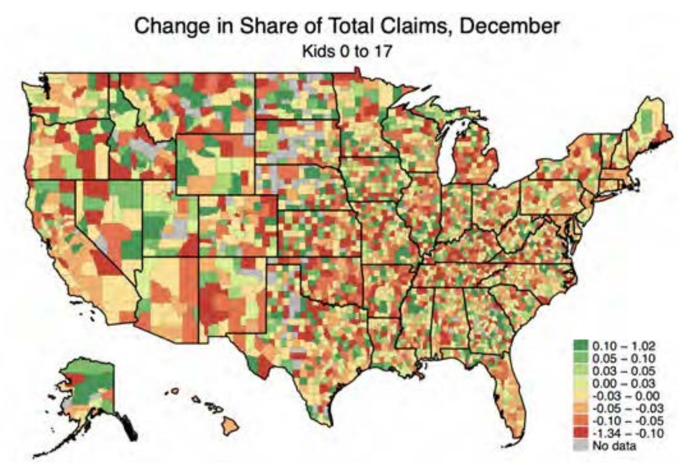

(b) April, Kids 0–17




(c) December, Adults



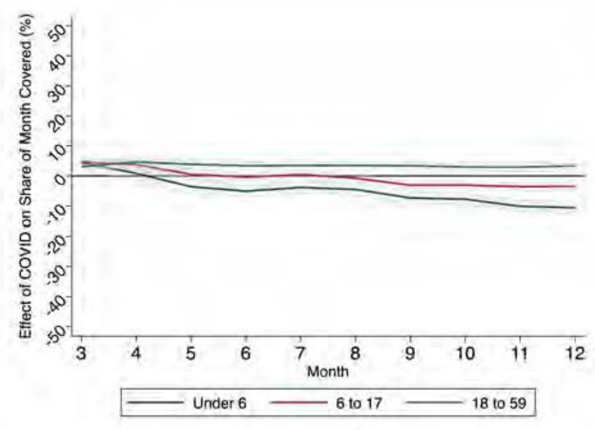

(d) December, Kids 0–17



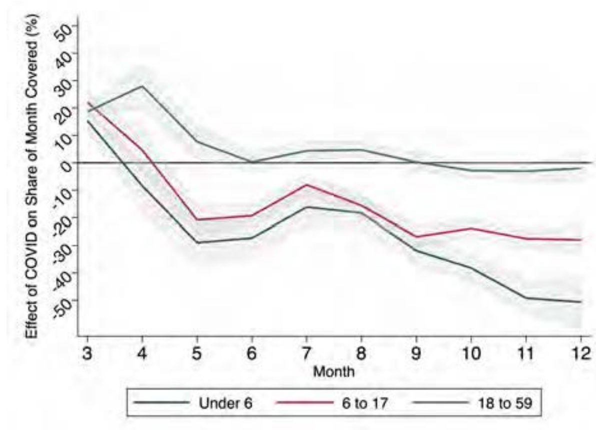

*Notes:* Figures (a) – (d) plot the difference-in-difference estimate within zip code, scaled by within-zip code average adherence rates in January and February 2019. Estimates are based on a 1 in 25 sample to manage computing constraints. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects.

Figure 4: Effect of Pandemic On Monthly Adherence: Heterogeneity in Disease Severity

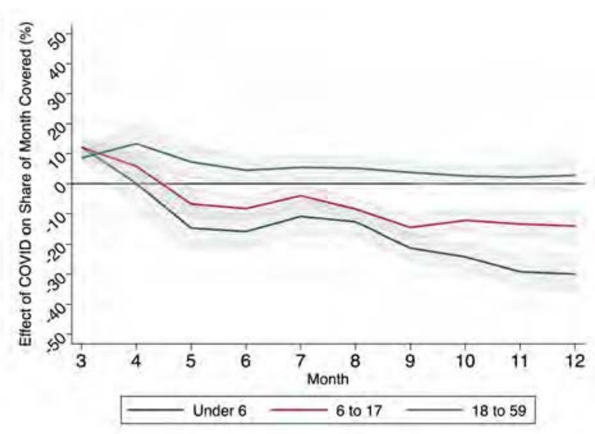
(a) Frequent Users



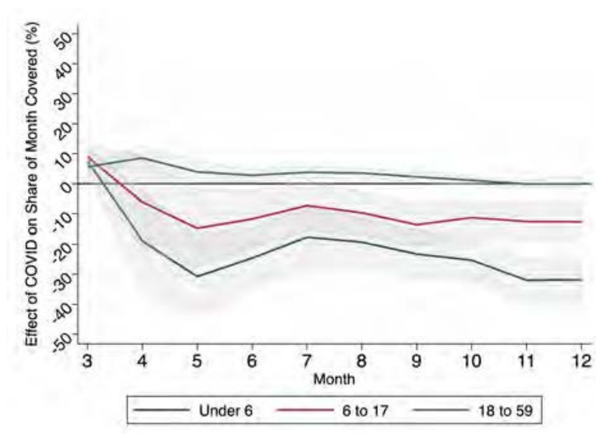

(b) Infrequent Users




(c) Low Asthma Prevalence, by County



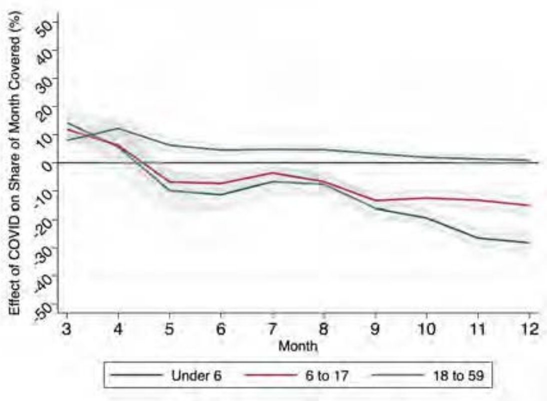

(d) High Asthma Prevalence, by County



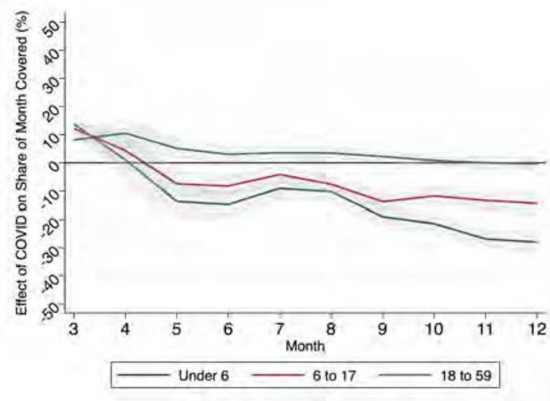

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panels (a) and (b) are limited to those patients in the top and bottom 25th percentile of the distribution of total days supplied in the prior year, or chronic and infrequent users, respectively. Panels (c) and (d) are limited to those patients in counties in the top and bottom 25th percentile of the distribution of asthma prevalence, respectively.

Figure 5: Effect of Pandemic On Monthly Adherence: Environmental Factors

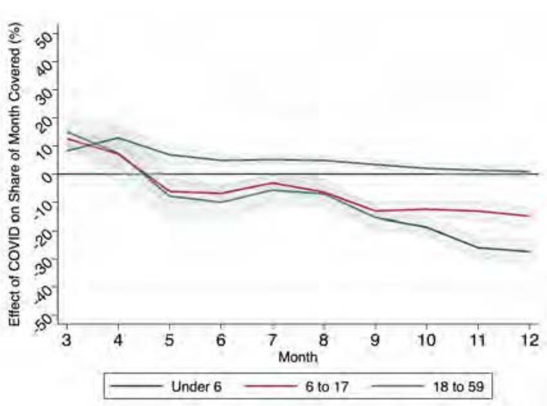
(a) Counties with Increase in Environmental Pollutants, April - August 2022



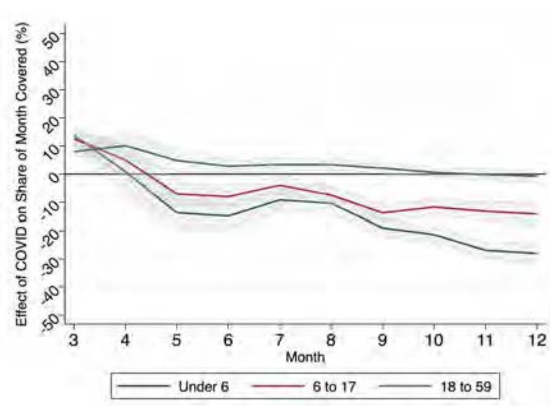

(b) Counties with Decrease in Environmental Pollutants, April - August 2022




(c) Urban Counties with Increase in Environmental Pollutants, April - August 2022



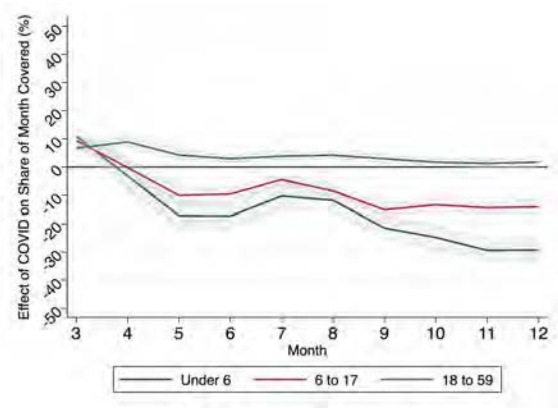

(d) Urban Counties with Decrease in Environmental Pollutants, April - August 2022



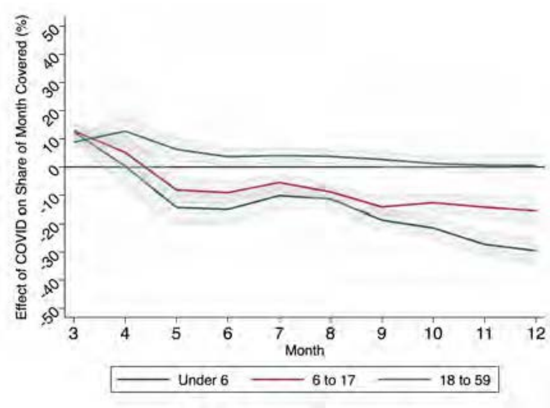

*Notes:* All figures plot the monthly difference-in-difference estimates for a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panels (a) and (b) are limited to those patients located in counties that experienced an increase and decrease in the Air Quality Index, respectively between April and August of 2020. Panels (c) and (d) are limited to those patients located in urban counties that experienced an increase and decrease in the Air Quality Index, respectively between April and August of 2020. Locations are determined based on the zip code of the last known prescriber in the prior year.

Figure 6: Effect of Pandemic On Monthly Adherence: Socioeconomic Status

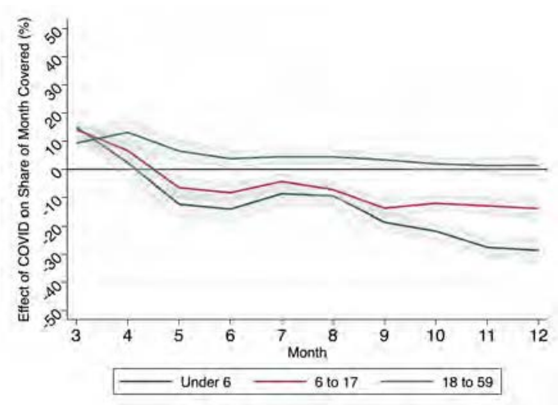
(a) Low Income Zip Codes



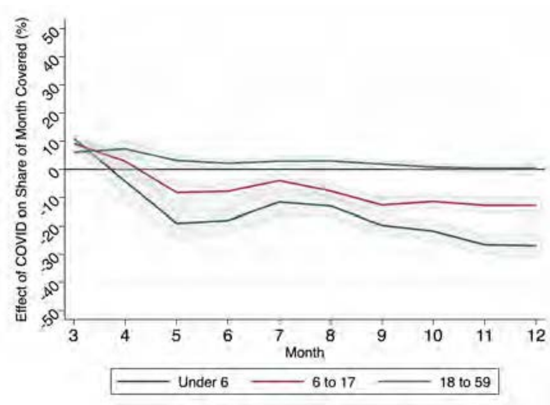

(b) High Income Zip Codes



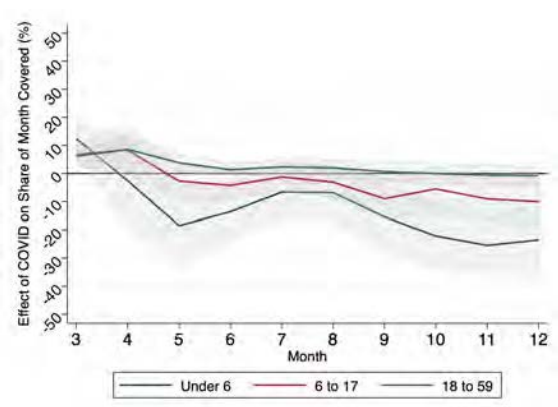

(c) Low Education Zip Codes



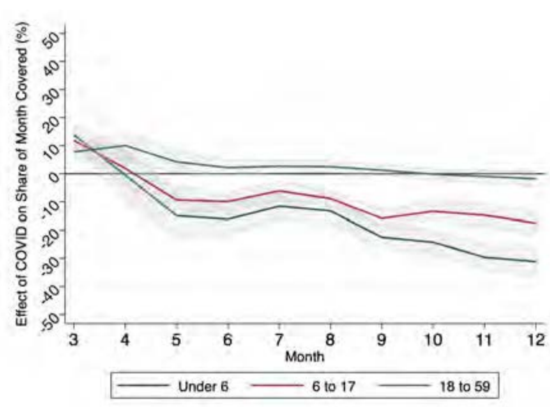

(d) High Education Zip Codes




(e) Low Prevalence White Collar Jobs



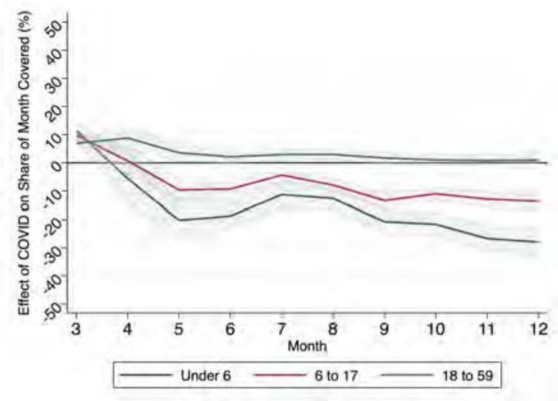

(f) High Prevalence White Collar Jobs



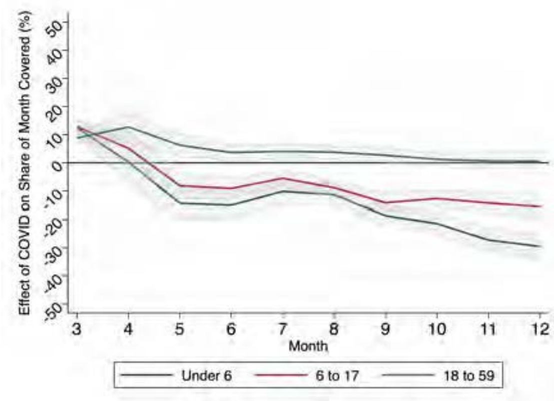

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panels (a) and (b) are limited to those patients located in the bottom and top 25th percentile counties ranked based on income per-capita using ACS data in 2018. Panels (c) and (d) are limited to those patients located in the bottom and top 25th percentile counties ranked based on the prevalence of white-collar jobs using BEA data from 2019. Panels (e) and (f) are limited to those patients located in the bottom and top 25th percentile counties ranked based on the share of the population with some college education using ACS data in 2018. Locations are determined based on the zip code of the last known prescriber in the prior year.

Figure 7: Effect of Pandemic On Monthly Adherence: Race

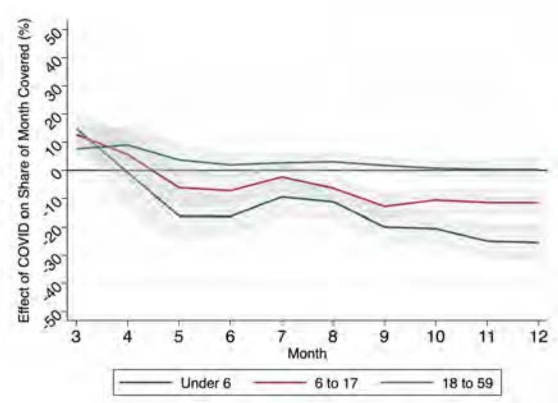
(a) Mostly White Counties



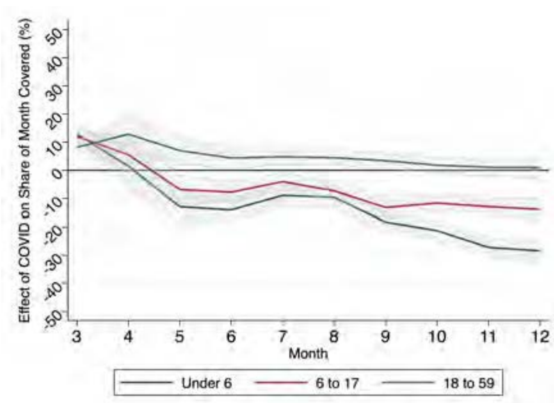

(b) Mostly Non-White Counties




(c) Mostly White, Urban Counties



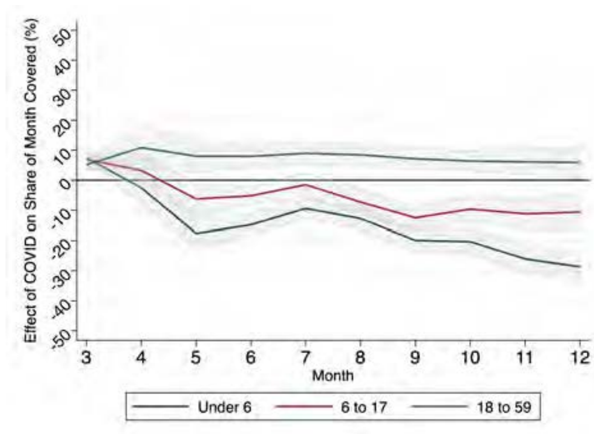

(d) Mostly Non-White, Urban Counties



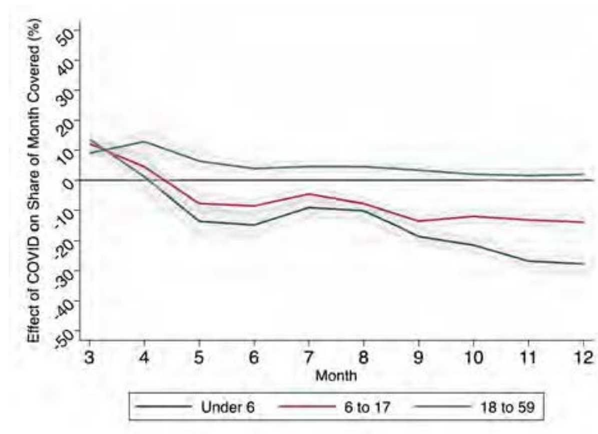

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panels (a) and (b) are limited to those patients located in the bottom and top 25th percentile counties ranked based on the share of the population that is non-white using TORCH data in 2018. Panels (b) and (c) are limited to those patients located in the bottom 25th percentile of counties ranked based on the share of the population that is non-white in urban counties using TORCH data in 2018. Locations are determined based on the zip code of the last known prescriber in the prior year.

Figure 8: Effect of Pandemic On Monthly Adherence: Access Based on Insurer

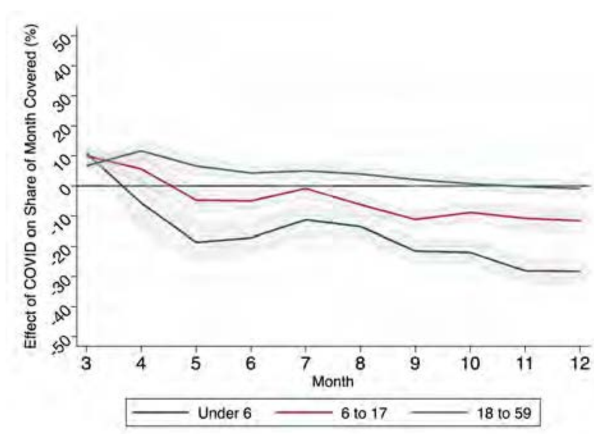
(a) Medicaid



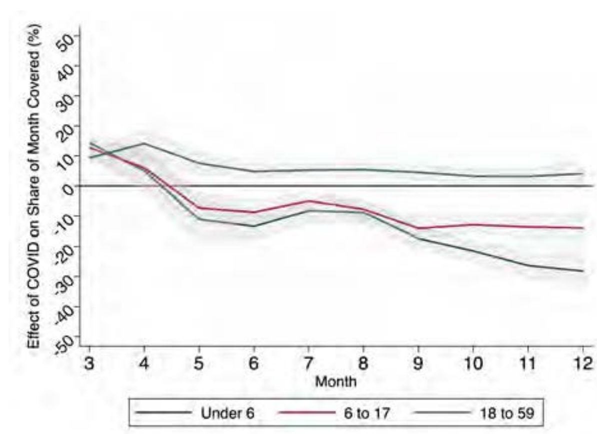

(b) Third Party




(c) Medicaid Non-Expansion States



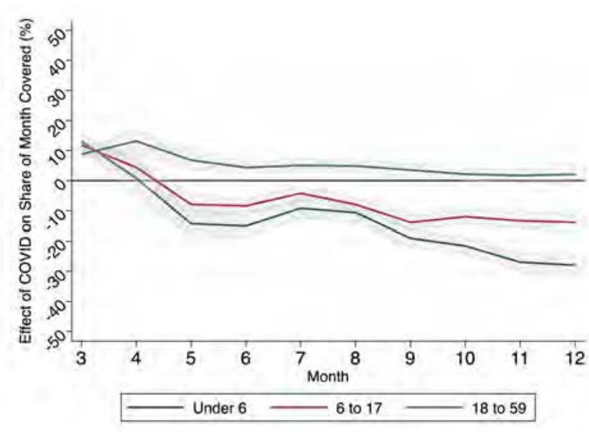

(d) Medicaid Expansion States



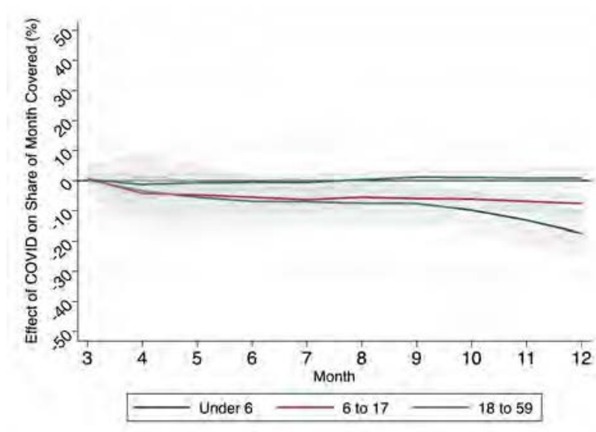

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panels (a) and (b) are limited to those patients with a last payer of either Medicaid or Third Party, respectively, based on their last prescription fill in the prior year. Panels (c) and (d) are limited to those patients fill in prescriptions in Medicaid Non-expansion and Expansion states, respectively, based on their last prescription refill in the prior year.

Figure 9: Effect of Pandemic On Monthly Adherence: Access

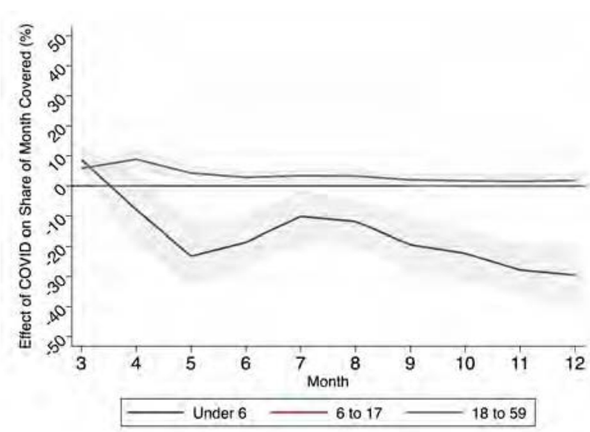
(a) Non-Mail Order



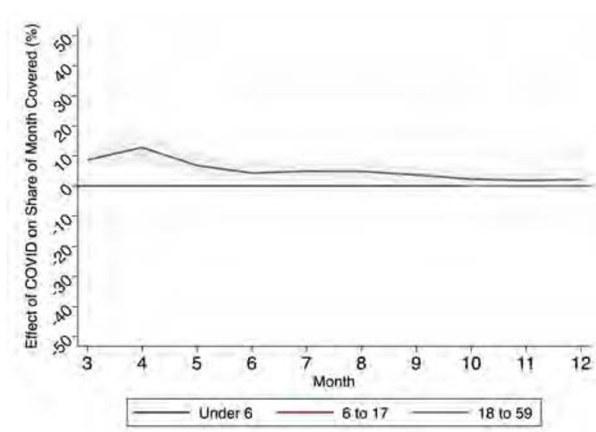

(b) Mail Order




(c) Rural



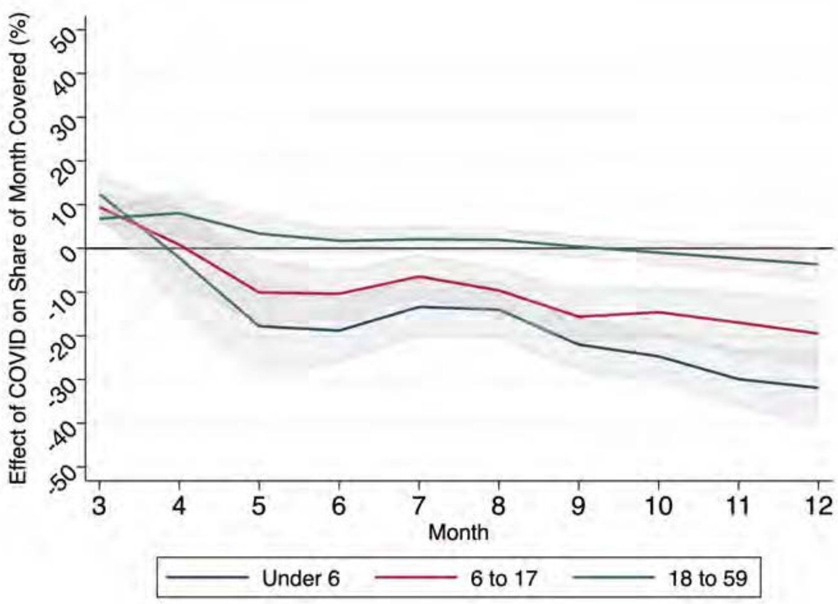

(d) Urban



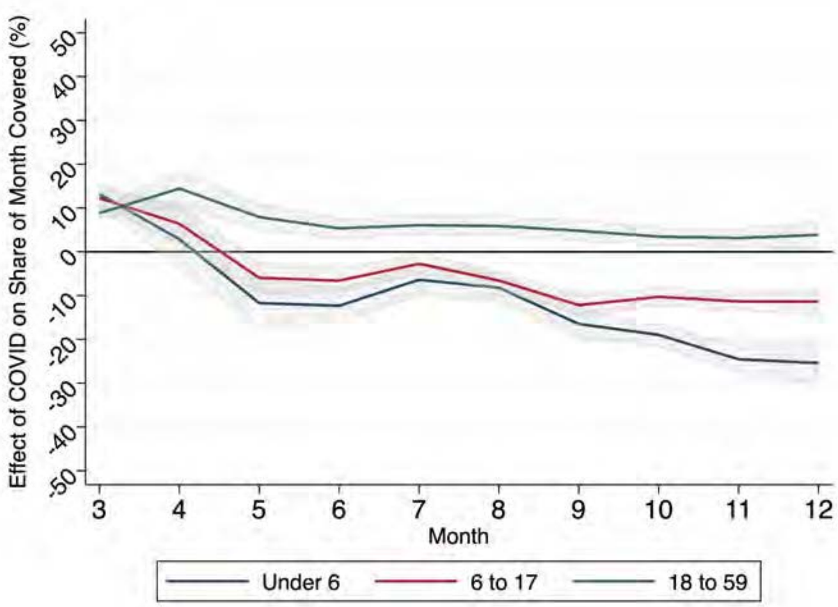

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panels (a) and (b) are limited to those patients who did not and did fill a prescription via mail order based on their last prescription fill in the prior year. Panels (c) and (d) are limited to those patients who live in rural and urban areas, respectively, based on the zip code of their last known prescriber in 2019.

Figure 10: Effect of Pandemic On Monthly Adherence: Variation by Telehealth Readiness

(a) No Pre-Pandemic Telehealth Policies



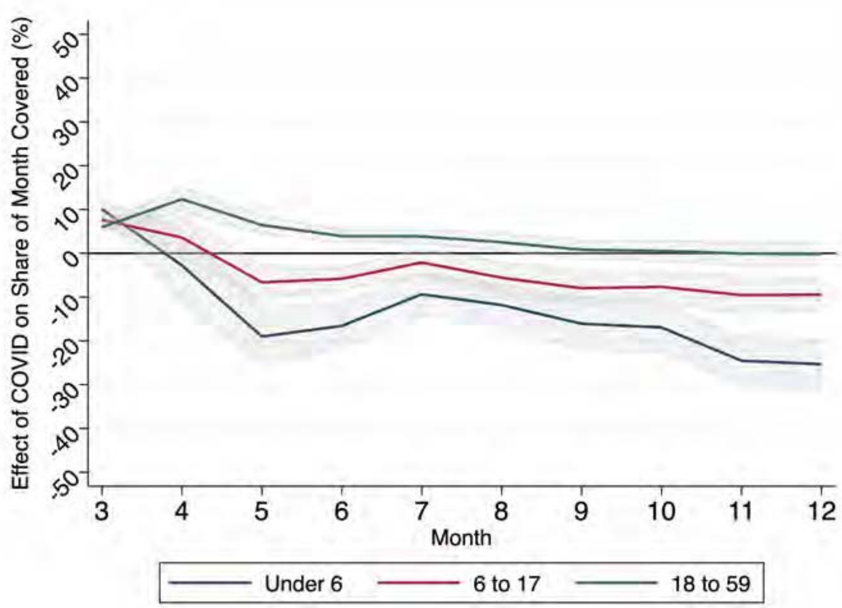

(b) Pre-Pandemic Telehealth Policies



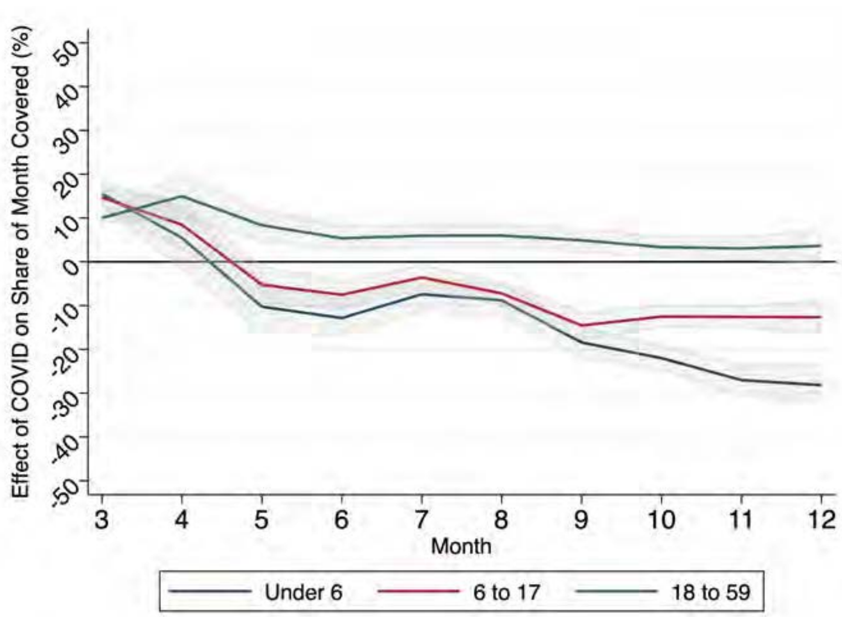

*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panel (a) limits analysis to those individuals who lived in states that did not have telehealth policies in place prior to the pandemic, and panel (b) limits analysis to individuals in those states that required insurers to cover telehealth services prior to the pandemic. Difference-in-Difference coefficients are scaled by average adherence rates in 2019 in January and February (Control months and years).

Figure 11: Effect of Pandemic On Monthly Adherence: School Attendance

(a) Low School Closure Counties, September 2020




(b) High School Closure Counties, September 2020




*Notes:* All figures plot the monthly difference-in-difference estimates based on a 1 in 4 random sample and scaled by adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes individual fixed effects. Panel (a) limits analysis to counties in the bottom 25th percentile when ranked on the share of schools with at least a 50% drop in attendance in September 2020. Panel (b) limits analysis to counties in the top 25th percentile when ranked on the share of schools with at least a 50% drop in attendance in September 2020. Difference-in-Difference coefficients are scaled by average adherence rates in 2019 in January and February (Control months and years).

Table 1: Sample Statistics, January and February

| | Adults 18–59 | | Kids 0–17 | |
|---|---|---|---|---|
| | 2019 (1) | 2020 (2) | 2019 (3) | 2020 (4) |
| | *Individual Characteristics* | | | |
| Adherence Rate | 0.252 | 0.265 | 0.182 | 0.188 |
| Patient Age | 41.34 | 41.34 | 8.31 | 8.36 |
| Share Female | 0.636 | 0.636 | 0.438 | 0.439 |
| Medicaid Payer | 0.045 | 0.043 | 0.114 | 0.107 |
| Third Party Payer | 0.853 | 0.867 | 0.857 | 0.873 |
| Number Days Supplied, Prior Year | 95.3 | 103.6 | 73.39 | 76.20 |
| | *Geographic Characteristics* | | | |
| Per-Capita Income, 2018 | 32,719 | 32,685 | 32,300 | 32,262 |
| Asthma Prevalence Rate, 2017 | 0.137 | 0.137 | 0.135 | 0.134 |
| Minority Share of Population, 2018 | 0.248 | 0.249 | 0.269 | 0.269 |
| Share Population with Some College, 2018 | 0.210 | 0.210 | 0.209 | 0.210 |
| Share of Population in Urban Area | 0.920 | 0.920 | 0.937 | 0.936 |
| Medicaid Expansion State | 0.586 | 0.584 | 0.511 | 0.514 |
| N | 7,849,780 | 7,838,419 | 4,428,587 | 4,296,259 |

*Notes:* This table provides summary statistics for a 1 in 4 sample of the population of continuing asthma prescription users. Columns (1) and (2) are limited to the adult subpopulation aged 18–59, where means capture January and February. Likewise, columns (3) and (4) reflect the subpopulation aged 0–17. Individual characteristics are based on prescription-level information captured in the IQVIA LrX database. Adherence rate measures the share of the month that is covered by the days supplied by the relevant prescription. Payer information is based on the last prescription filled in the previous year. Geographic characteristics are based on the zip code of the prescriber who wrote the last prescription filled in the prior year.

Table 2: Estimated Effect of Pandemic on Adherence: Variation By Age

| | Main | | | 0–6 | | | 6–17 | | | 18–59 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| March DD | 0.0219*** | 0.0273*** | 0.0211*** | 0.0175*** | 0.0108*** | 0.0182*** | 0.0251*** | 0.0237*** | 0.0225*** | 0.0216*** | 0.0308*** | 0.0207*** |
| | (0.000137) | (0.00260) | (0.00147) | (0.000361) | (0.00249) | (0.00166) | (0.000298) | (0.00285) | (0.00174) | (0.000170) | (0.00252) | (0.00157) |
| Apr DD | 0.0236*** | 0.0384*** | 0.0224*** | -0.00150*** | -0.0147** | 0.00118 | 0.0127*** | 0.0147* | 0.00851 | 0.0323*** | 0.0550*** | 0.0308*** |
| | (0.000162) | (0.00590) | (0.00486) | (0.000402) | (0.00542) | (0.00447) | (0.000344) | (0.00643) | (0.00441) | (0.000205) | (0.00579) | (0.00530) |
| May DD | 0.00532*** | 0.0164*** | 0.00463 | -0.0221*** | -0.0308*** | -0.0199*** | -0.0123*** | -0.00976 | -0.0149*** | 0.0169*** | 0.0336*** | 0.0160*** |
| | (0.000167) | (0.00443) | (0.00380) | (0.000406) | (0.00431) | (0.00368) | (0.000348) | (0.00494) | (0.00353) | (0.000213) | (0.00434) | (0.00407) |
| June DD | 0.000737*** | 0.00832** | 0.000438 | -0.0227*** | -0.0281*** | -0.0210*** | -0.0146*** | -0.0122*** | -0.0160*** | 0.0106*** | 0.0217*** | 0.0102*** |
| | (0.000171) | (0.00293) | (0.00262) | (0.000411) | (0.00310) | (0.00264) | (0.000352) | (0.00327) | (0.00247) | (0.000219) | (0.00302) | (0.00287) |
| July DD | 0.00450*** | 0.0118*** | 0.00432 | -0.0146*** | -0.0199*** | -0.0129*** | -0.00689*** | -0.00460 | -0.00821** | 0.0121*** | 0.0225*** | 0.0118*** |
| | (0.000174) | (0.00285) | (0.00256) | (0.000413) | (0.00291) | (0.00250) | (0.000357) | (0.00312) | (0.00240) | (0.000224) | (0.00301) | (0.00282) |
| Aug DD | 0.00244*** | 0.00926** | 0.00232 | -0.0165*** | -0.0218*** | -0.0149*** | -0.0138*** | -0.0122*** | -0.0152*** | 0.0118*** | 0.0217*** | 0.0116*** |
| | (0.000179) | (0.00282) | (0.00246) | (0.000423) | (0.00282) | (0.00230) | (0.000368) | (0.00312) | (0.00232) | (0.000230) | (0.00292) | (0.00272) |
| Sept DD | -0.00380*** | 0.00245 | -0.00378 | -0.0281*** | -0.0324*** | -0.0265*** | -0.0254*** | -0.0235*** | -0.0265*** | 0.00863*** | 0.0176*** | 0.00856** |
| | (0.000184) | (0.00280) | (0.00262) | (0.000443) | (0.00254) | (0.00224) | (0.000383) | (0.00303) | (0.00247) | (0.000235) | (0.00291) | (0.00292) |
| Oct DD | -0.00538*** | 0.00122 | -0.00538* | -0.0317*** | -0.0365*** | -0.0301*** | -0.0215*** | -0.0203*** | -0.0230*** | 0.00548*** | 0.0152*** | 0.00536 |
| | (0.000189) | (0.00259) | (0.00230) | (0.000457) | (0.00232) | (0.00197) | (0.000390) | (0.00274) | (0.00227) | (0.000241) | (0.00276) | (0.00272) |
| Nov DD | -0.00736*** | 0.000947 | -0.00745** | -0.0395*** | -0.0460*** | -0.0376*** | -0.0234*** | -0.0224*** | -0.0255*** | 0.00455*** | 0.0171*** | 0.00431 |
| | (0.000194) | (0.00315) | (0.00273) | (0.000473) | (0.00278) | (0.00223) | (0.000399) | (0.00348) | (0.00254) | (0.000249) | (0.00314) | (0.00307) |
| Dec DD | -0.00731*** | 0.00317 | -0.00716 | -0.0416*** | -0.0494*** | -0.0391*** | -0.0240*** | -0.0227*** | -0.0265*** | 0.00524*** | 0.0209*** | 0.00518 |
| | (0.000201) | (0.00416) | (0.00385) | (0.000485) | (0.00387) | (0.00300) | (0.000409) | (0.00455) | (0.00333) | (0.000258) | (0.00417) | (0.00436) |
| Constant | 0.226*** | 0.225*** | 0.259*** | 0.141*** | 0.144*** | 0.166*** | 0.196*** | 0.199*** | 0.234*** | 0.253*** | 0.251*** | 0.286*** |
| | (0.000146) | (0.00153) | (0.00181) | (0.000322) | (0.00142) | (0.00106) | (0.000279) | (0.00135) | (0.00141) | (0.000193) | (0.00156) | (0.00210) |
| State FE | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes | No |
| Individual FE | No | No | Yes | No | No | Yes | No | No | Yes | No | No | Yes |
| Controls | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Observations | 146,477,976 | 146,477,976 | 146,477,905 | 18,077,112 | 18,077,112 | 18,077,099 | 34,272,151 | 34,272,151 | 34,272,138 | 94,128,713 | 94,128,713 | 94,128,660 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Estimates based on variation in age of patient. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility. Columns 2, 5, 8, and 11 include state fixed effects. Columns 3, 6, 9, and 12 include individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 3: Impact of Covariates on Estimated Effect: Horse Race

| | Main | | 0–17 | | 18–59 | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| DD | 0.0000793 | -0.0221*** | -0.0192*** | -0.0232*** | 0.00981*** | 0.00211 |
| | (0.00204) | (0.00231) | (0.00222) | (0.00273) | (0.00204) | (0.00241) |
| Chronic x DD | | 0.0129*** | | 0.00865*** | | 0.0152*** |
| | | (0.00147) | | (0.00239) | | (0.00123) |
| High Asthma Prevalence x DD | | 0.00104 | | 0.00314* | | -0.000401 |
| | | (0.00106) | | (0.00152) | | (0.00151) |
| AQI Drop x DD | | -0.00235** | | -0.00407* | | -0.00158 |
| | | (0.000808) | | (0.00156) | | (0.000793) |
| High Income x DD | | -0.00444*** | | -0.00647*** | | -0.00392*** |
| | | (0.000833) | | (0.00114) | | (0.000772) |
| High Education x DD | | 0.000727 | | -0.000557 | | 0.00152 |
| | | (0.000669) | | (0.000907) | | (0.000762) |
| White Collar x DD | | 0.00324 | | 0.00328 | | 0.00324 |
| | | (0.00173) | | (0.00225) | | (0.00191) |
| High Minority Population x DD | | -0.00211* | | -0.00338* | | -0.00144 |
| | | (0.00104) | | (0.00156) | | (0.000863) |
| Medicaid Payer x DD | | 0.00446** | | 0.00157 | | 0.00922*** |
| | | (0.00129) | | (0.00158) | | (0.00188) |
| Medicaid Expansion x DD | | 0.00205 | | 0.000448 | | 0.00174 |
| | | (0.00173) | | (0.00219) | | (0.00161) |
| Mail Order x DD | | 0.00200 | | 0.00479 | | 0.00178 |
| | | (0.00207) | | (0.00431) | | (0.00229) |
| Urban x DD | | -0.00233* | | -0.00194 | | -0.00253* |
| | | (0.000969) | | (0.00136) | | (0.00105) |
| Telehealth x DD | | -0.00112 | | -0.000160 | | -0.00143 |
| | | (0.00192) | | (0.00213) | | (0.00188) |
| High School Closure x DD | | -0.000552 | | -0.00318 | | 0.000788 |
| | | (0.00120) | | (0.00172) | | (0.00118) |
| Age x DD | | 0.000588*** | | 0.00128*** | | -0.0000424* |
| | | (0.0000183) | | (0.0000810) | | (0.0000181) |
| Observations | 146,477,976 | 146,477,905 | 52,349,263 | 52,349,243 | 94,128,713 | 94,128,660 |

*Notes*: This table reports estimates based on a difference-in-different model that collapses the dynamic effect from March through December into one post period, reflected in the coefficient "DD." Columns (1), (3), and (5) report the average DD estimate across months March – December. Columns (2), (4), and (6) are fully saturated to capture the differential difference in difference estimate based on observable characteristics. Variable definitions provided in Table A3 and A1. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 4: Estimated Effect of Pandemic on Adherence: Variation By Asthma Severity

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | Low | High |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0110*** | 0.0257*** | 0.00812*** | 0.0286*** | 0.0117*** | 0.0304*** | 0.0115*** | 0.0228*** |
| | (0.000753) | (0.00231) | (0.000998) | (0.00487) | (0.00103) | (0.00307) | (0.000758) | (0.00230) |
| Apr DD | 0.0104*** | 0.0335*** | -0.00446 | 0.00558 | 0.00246 | 0.0252** | 0.0172*** | 0.0348*** |
| | (0.00247) | (0.00856) | (0.00241) | (0.0120) | (0.00226) | (0.00764) | (0.00259) | (0.00895) |
| May DD | -0.00207 | 0.0227** | -0.0153*** | -0.0233* | -0.0110*** | 0.00375 | 0.00474* | 0.0288*** |
| | (0.00183) | (0.00679) | (0.00217) | (0.00937) | (0.00151) | (0.00635) | (0.00198) | (0.00697) |
| June DD | -0.00457*** | 0.0181*** | -0.0144*** | -0.0330*** | -0.0102*** | -0.00268 | 0.000176 | 0.0254*** |
| | (0.00115) | (0.00507) | (0.00184) | (0.00740) | (0.00105) | (0.00473) | (0.00130) | (0.00519) |
| July DD | -0.000707 | 0.0204*** | -0.00855*** | -0.0250*** | -0.00426*** | 0.00314 | 0.00269* | 0.0260*** |
| | (0.000991) | (0.00517) | (0.00185) | (0.00703) | (0.00101) | (0.00494) | (0.00105) | (0.00523) |
| Aug DD | -0.00164 | 0.0186*** | -0.00966*** | -0.0294*** | -0.00826*** | -0.00510 | 0.00290** | 0.0261*** |
| | (0.000934) | (0.00499) | (0.00164) | (0.00728) | (0.00103) | (0.00493) | (0.000966) | (0.00508) |
| Sept DD | -0.00596*** | 0.0139* | -0.0169*** | -0.0477*** | -0.0142*** | -0.0205*** | 0.000145 | 0.0255*** |
| | (0.00104) | (0.00520) | (0.00146) | (0.00732) | (0.00106) | (0.00517) | (0.00110) | (0.00527) |
| Oct DD | -0.00739*** | 0.0114* | -0.0202*** | -0.0504*** | -0.0126*** | -0.0204*** | -0.00174 | 0.0221*** |
| | (0.000859) | (0.00511) | (0.00143) | (0.00658) | (0.000914) | (0.00486) | (0.000950) | (0.00527) |
| Nov DD | -0.00897*** | 0.0102 | -0.0260*** | -0.0657*** | -0.0146*** | -0.0236*** | -0.00190 | 0.0219*** |
| | (0.00107) | (0.00581) | (0.00169) | (0.00716) | (0.000948) | (0.00510) | (0.00103) | (0.00604) |
| Dec DD | -0.00873*** | 0.0130 | -0.0268*** | -0.0688*** | -0.0148*** | -0.0233*** | -0.00124 | 0.0251** |
| | (0.00168) | (0.00788) | (0.00242) | (0.00686) | (0.00145) | (0.00631) | (0.00171) | (0.00818) |
| Constant | 0.0570*** | 0.794*** | 0.0502*** | 0.744*** | 0.0533*** | 0.753*** | 0.0586*** | 0.809*** |
| | (0.00124) | (0.00364) | (0.00131) | (0.00353) | (0.00101) | (0.00214) | (0.00143) | (0.00384) |
| Control Mean | 0.0581 | 0.724 | 0.0529 | 0.650 | 0.0529 | 0.664 | 0.0616 | 0.747 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 47,009,165 | 27,322,577 | 8,987,379 | 1,386,284 | 9,824,524 | 5,515,240 | 28,197,258 | 20,421,003 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose total days supplied in the previous year was in the bottom 25th percentile (infrequent users. Likewise, columns (2), (4), (6), and (8) are limited to those whose total days supplied in the previous year was in the top 25th percentile (chronic users). Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 5: Estimated Effect of Pandemic on Adherence: Variation By Geographic Disease Severity

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Low Prevalence (1) | High Prevalence (2) | Low Prevalence (3) | High Prevalence (4) | Low Prevalence (5) | High Prevalence (6) | Low Prevalence (7) | High Prevalence (8) |
| March DD | 0.0222*** | 0.0152*** | 0.0172*** | 0.0107** | 0.0234*** | 0.0176*** | 0.0211*** | 0.0140*** |
| | (0.00211) | (0.00209) | (0.00270) | (0.00332) | (0.00226) | (0.00451) | (0.00234) | (0.00126) |
| Apr DD | 0.0264*** | 0.0101 | 0.000126 | -0.0268* | 0.0113 | -0.0121 | 0.0329*** | 0.0214*** |
| | (0.00743) | (0.00825) | (0.00655) | (0.0121) | (0.00587) | (0.0155) | (0.00859) | (0.00506) |
| May DD | 0.00771 | -0.00404 | -0.0207*** | -0.0436*** | -0.0130* | -0.0292* | 0.0178* | 0.00981* |
| | (0.00614) | (0.00724) | (0.00532) | (0.0100) | (0.00516) | (0.0131) | (0.00696) | (0.00456) |
| June DD | 0.00188 | -0.00389 | -0.0223*** | -0.0348*** | -0.0160*** | -0.0231* | 0.0110* | 0.00701* |
| | (0.00451) | (0.00506) | (0.00405) | (0.00718) | (0.00394) | (0.00978) | (0.00515) | (0.00301) |
| July DD | 0.00623 | 0.000973 | -0.0153*** | -0.0250** | -0.00771 | -0.0143 | 0.0134* | 0.00949*** |
| | (0.00459) | (0.00441) | (0.00409) | (0.00755) | (0.00387) | (0.00856) | (0.00525) | (0.00268) |
| Aug DD | 0.00333 | -0.00103 | -0.0177*** | -0.0273*** | -0.0163*** | -0.0191* | 0.0127** | 0.00890*** |
| | (0.00411) | (0.00349) | (0.00350) | (0.00564) | (0.00354) | (0.00725) | (0.00470) | (0.00213) |
| Sept DD | -0.00342 | -0.00579 | -0.0297*** | -0.0330*** | -0.0282*** | -0.0269*** | 0.00926 | 0.00568* |
| | (0.00410) | (0.00350) | (0.00346) | (0.00582) | (0.00360) | (0.00722) | (0.00471) | (0.00254) |
| Oct DD | -0.00462 | -0.00695* | -0.0338*** | -0.0358*** | -0.0235*** | -0.0222*** | 0.00639 | 0.00283 |
| | (0.00364) | (0.00299) | (0.00340) | (0.00497) | (0.00358) | (0.00601) | (0.00437) | (0.00197) |
| Nov DD | -0.00643 | -0.0105** | -0.0407*** | -0.0453*** | -0.0259*** | -0.0247*** | 0.00536 | -0.000218 |
| | (0.00418) | (0.00312) | (0.00388) | (0.00535) | (0.00405) | (0.00642) | (0.00481) | (0.00184) |
| Dec DD | -0.00564 | -0.0106** | -0.0419*** | -0.0451*** | -0.0272*** | -0.0250*** | 0.00682 | -0.000232 |
| | (0.00583) | (0.00386) | (0.00469) | (0.00597) | (0.00512) | (0.00638) | (0.00681) | (0.00358) |
| Constant | 0.254*** | 0.262*** | 0.167*** | 0.165*** | 0.229*** | 0.234*** | 0.280*** | 0.290*** |
| | (0.00301) | (0.00336) | (0.00125) | (0.00218) | (0.00257) | (0.00524) | (0.00349) | (0.00337) |
| Control Mean | 0.219 | 0.224 | 0.140 | 0.142 | 0.193 | 0.197 | 0.246 | 0.249 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 43,670,446 | 7,224,025 | 5,499,158 | 873,534 | 10,519,349 | 1,671,549 | 27,651,937 | 4,678,941 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber in the previous year was located in a county in the bottom 25th percentile of asthma prevalence. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber in the previous year was in the top 25th percentile or asthma prevalence. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 6: Estimated Effect of Pandemic on Adherence: Variation By Covid-Induced Changes in Pollutants

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | AQI Increase | AQI Decrease | AQI Increase | AQI Decrease | AQI Increase | AQI Decrease | AQI Increase | AQI Decrease |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0214*** | 0.0222*** | 0.0204*** | 0.0200*** | 0.0234*** | 0.0243*** | 0.0205*** | 0.0207*** |
| | (0.00236) | (0.00192) | (0.00282) | (0.00207) | (0.00272) | (0.00235) | (0.00218) | (0.00212) |
| Apr DD | 0.0242*** | 0.0210*** | 0.00803 | 0.00153 | 0.0123* | 0.00877 | 0.0316*** | 0.0269*** |
| | (0.00537) | (0.00582) | (0.00729) | (0.00582) | (0.00527) | (0.00603) | (0.00484) | (0.00642) |
| May DD | 0.00551 | 0.00335 | -0.0141* | -0.0199*** | -0.0135** | -0.0149** | 0.0161*** | 0.0130** |
| | (0.00385) | (0.00438) | (0.00547) | (0.00436) | (0.00412) | (0.00471) | (0.00352) | (0.00476) |
| June DD | 0.00210 | -0.000947 | -0.0162*** | -0.0215*** | -0.0145*** | -0.0165*** | 0.0117*** | 0.00772* |
| | (0.00259) | (0.00300) | (0.00387) | (0.00321) | (0.00304) | (0.00352) | (0.00253) | (0.00325) |
| July DD | 0.00500* | 0.00290 | -0.00951* | -0.0132*** | -0.00709* | -0.00831* | 0.0123*** | 0.00918** |
| | (0.00208) | (0.00276) | (0.00358) | (0.00300) | (0.00300) | (0.00330) | (0.00194) | (0.00298) |
| Aug DD | 0.00331 | 0.000809 | -0.0108** | -0.0149*** | -0.0133*** | -0.0152*** | 0.0120*** | 0.00888*** |
| | (0.00197) | (0.00249) | (0.00344) | (0.00267) | (0.00224) | (0.00313) | (0.00184) | (0.00254) |
| Sept DD | -0.00360* | -0.00588* | -0.0229*** | -0.0276*** | -0.0265*** | -0.0275*** | 0.00840*** | 0.00573* |
| | (0.00171) | (0.00243) | (0.00244) | (0.00250) | (0.00285) | (0.00310) | (0.00176) | (0.00242) |
| Oct DD | -0.00596*** | -0.00764*** | -0.0276*** | -0.0312*** | -0.0247*** | -0.0235*** | 0.00498** | 0.00209 |
| | (0.00162) | (0.00215) | (0.00212) | (0.00228) | (0.00272) | (0.00315) | (0.00184) | (0.00225) |
| Nov DD | -0.00841*** | -0.0105*** | -0.0378*** | -0.0391*** | -0.0262*** | -0.0266*** | 0.00350 | 0.0000496 |
| | (0.00204) | (0.00249) | (0.00229) | (0.00233) | (0.00293) | (0.00347) | (0.00237) | (0.00263) |
| Dec DD | -0.0103*** | -0.0119*** | -0.0402*** | -0.0407*** | -0.0300*** | -0.0288*** | 0.00241 | -0.00106 |
| | (0.00242) | (0.00284) | (0.00332) | (0.00281) | (0.00327) | (0.00407) | (0.00278) | (0.00308) |
| Constant | 0.267*** | 0.262*** | 0.171*** | 0.171*** | 0.239*** | 0.237*** | 0.295*** | 0.289*** |
| | (0.00126) | (0.00186) | (0.00249) | (0.00124) | (0.00180) | (0.00197) | (0.00133) | (0.00205) |
| Control Mean | 0.230 | 0.228 | 0.142 | 0.145 | 0.197 | 0.200 | 0.258 | 0.255 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 19,503,199 | 77,960,736 | 2,369,589 | 9,746,891 | 4,442,908 | 18,386,978 | 12,690,702 | 49,826,866 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in an area that experienced a worsening in environment air quality in April - Aug, 2020 as measured by the Air Quality Index (AQI). Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in an area that experienced an improvement in environmental air quality. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 7: Estimated Effect of Pandemic on Adherence: Variation By Covid-Induced Changes in Pollutants in Urban Areas

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | AQI Increase (1) | AQI Decrease (2) | AQI Increase (3) | AQI Decrease (4) | AQI Increase (5) | AQI Decrease (6) | AQI Increase (7) | AQI Decrease (8) |
| March DD | 0.0200*** | 0.0194*** | 0.0217*** | 0.0184*** | 0.0195*** | 0.0231*** | 0.0200*** | 0.0175*** |
| | (0.00377) | (0.00215) | (0.00300) | (0.00247) | (0.00538) | (0.00247) | (0.00382) | (0.00245) |
| Apr DD | 0.0220** | 0.0167** | 0.0123 | 0.00183 | 0.00611 | 0.00487 | 0.0312*** | 0.0227** |
| | (0.00745) | (0.00567) | (0.00840) | (0.00546) | (0.00921) | (0.00557) | (0.00767) | (0.00675) |
| May DD | 0.00504 | 0.000967 | -0.00749 | -0.0178*** | -0.0155* | -0.0160** | 0.0163** | 0.0101* |
| | (0.00578) | (0.00426) | (0.00703) | (0.00478) | (0.00687) | (0.00465) | (0.00604) | (0.00493) |
| June DD | 0.000676 | -0.00261 | -0.0105 | -0.0203*** | -0.0173** | -0.0169*** | 0.0104* | 0.00564 |
| | (0.00380) | (0.00291) | (0.00534) | (0.00402) | (0.00498) | (0.00336) | (0.00406) | (0.00329) |
| July DD | 0.00345 | 0.000414 | -0.00514 | -0.0135*** | -0.0101* | -0.0102** | 0.0110** | 0.00662* |
| | (0.00335) | (0.00276) | (0.00463) | (0.00357) | (0.00442) | (0.00343) | (0.00375) | (0.00313) |
| Aug DD | 0.00247 | -0.00178 | -0.00534 | -0.0169*** | -0.0150*** | -0.0152*** | 0.0111** | 0.00572* |
| | (0.00320) | (0.00248) | (0.00382) | (0.00344) | (0.00370) | (0.00334) | (0.00361) | (0.00263) |
| Sept DD | -0.00350 | -0.00862*** | -0.0172*** | -0.0288*** | -0.0246*** | -0.0284*** | 0.00757* | 0.00243 |
| | (0.00275) | (0.00230) | (0.00421) | (0.00303) | (0.00349) | (0.00303) | (0.00352) | (0.00243) |
| Oct DD | -0.00692* | -0.00977*** | -0.0214*** | -0.0307*** | -0.0248*** | -0.0234*** | 0.00313 | -0.000904 |
| | (0.00274) | (0.00236) | (0.00394) | (0.00303) | (0.00343) | (0.00371) | (0.00349) | (0.00257) |
| Nov DD | -0.00842* | -0.0128*** | -0.0291*** | -0.0379*** | -0.0279*** | -0.0262*** | 0.00342 | -0.00323 |
| | (0.00357) | (0.00285) | (0.00430) | (0.00333) | (0.00419) | (0.00401) | (0.00438) | (0.00308) |
| Dec DD | -0.0106* | -0.0152*** | -0.0319*** | -0.0399*** | -0.0331*** | -0.0302*** | 0.00260 | -0.00515 |
| | (0.00446) | (0.00341) | (0.00536) | (0.00381) | (0.00495) | (0.00474) | (0.00538) | (0.00377) |
| Constant | 0.241*** | 0.236*** | 0.162*** | 0.157*** | 0.221*** | 0.216*** | 0.264*** | 0.259*** |
| | (0.00172) | (0.00175) | (0.00287) | (0.00158) | (0.00272) | (0.00202) | (0.00209) | (0.00184) |
| Control Mean | 0.227 | 0.228 | 0.143 | 0.146 | 0.197 | 0.200 | 0.255 | 0.255 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 16677195 | 72,290,827 | 2,081,609 | 9,201,470 | 3,890,049 | 17,247,576 | 10,705,537 | 45,841,780 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in an area that experienced a worsening in environment air quality in urban areas in April - Aug, 2020 as measured by the Air Quality Index (AQI). Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in an area that experienced an improvement in environmental air quality in urban areas. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 8: Estimated Effect of Pandemic on Adherence: Variation By Average Income

| | Main | | 0–6 | | 6–17 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Low Income | High Income | Low Income | High Income | Low Income | High Income | Low Income | High Income |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0175*** | 0.0222*** | 0.0139*** | 0.0190*** | 0.0171*** | 0.0259*** | 0.0170*** | 0.0223*** |
| | (0.00138) | (0.00254) | (0.00185) | (0.00256) | (0.00205) | (0.00278) | (0.00130) | (0.00262) |
| Apr DD | 0.0151*** | 0.0217** | -0.00402 | 0.000480 | -0.000356 | 0.0105 | 0.0225*** | 0.0322*** |
| | (0.00342) | (0.00678) | (0.00347) | (0.00620) | (0.00345) | (0.00646) | (0.00334) | (0.00733) |
| May DD | 0.000211 | 0.00262 | -0.0219*** | -0.0219*** | -0.0184*** | -0.0164** | 0.0108*** | 0.0158** |
| | (0.00267) | (0.00519) | (0.00308) | (0.00498) | (0.00289) | (0.00518) | (0.00252) | (0.00555) |
| June DD | -0.00203 | -0.00180 | -0.0220*** | -0.0229*** | -0.0175*** | -0.0184*** | 0.00753*** | 0.00921* |
| | (0.00196) | (0.00360) | (0.00307) | (0.00375) | (0.00215) | (0.00371) | (0.00191) | (0.00386) |
| July DD | 0.00297 | 0.00157 | -0.0130*** | -0.0155*** | -0.00813*** | -0.0111** | 0.00978*** | 0.0103** |
| | (0.00197) | (0.00329) | (0.00339) | (0.00330) | (0.00206) | (0.00333) | (0.00199) | (0.00354) |
| Aug DD | 0.00140 | -0.000546 | -0.0150*** | -0.0173*** | -0.0155*** | -0.0179*** | 0.0106*** | 0.00954** |
| | (0.00179) | (0.00330) | (0.00286) | (0.00329) | (0.00235) | (0.00341) | (0.00200) | (0.00342) |
| Sept DD | -0.00551** | -0.00609 | -0.0274*** | -0.0284*** | -0.0276*** | -0.0286*** | 0.00744** | 0.00674 |
| | (0.00206) | (0.00338) | (0.00243) | (0.00316) | (0.00240) | (0.00363) | (0.00215) | (0.00355) |
| Oct DD | -0.00711*** | -0.00817* | -0.0316*** | -0.0327*** | -0.0244*** | -0.0256*** | 0.00435* | 0.00313 |
| | (0.00171) | (0.00332) | (0.00290) | (0.00306) | (0.00252) | (0.00350) | (0.00190) | (0.00356) |
| Nov DD | -0.00876*** | -0.0109** | -0.0374*** | -0.0415*** | -0.0263*** | -0.0288*** | 0.00324 | 0.00166 |
| | (0.00200) | (0.00376) | (0.00245) | (0.00343) | (0.00203) | (0.00389) | (0.00193) | (0.00403) |
| Dec DD | -0.00745** | -0.0121* | -0.0373*** | -0.0450*** | -0.0258*** | -0.0314*** | 0.00439 | 0.00140 |
| | (0.00270) | (0.00480) | (0.00309) | (0.00416) | (0.00254) | (0.00482) | (0.00267) | (0.00514) |
| Constant | 0.251*** | 0.266*** | 0.151*** | 0.181*** | 0.219*** | 0.242*** | 0.288*** | 0.289*** |
| | (0.00196) | (0.00198) | (0.00133) | (0.00195) | (0.00150) | (0.00241) | (0.00245) | (0.00204) |
| Control Mean | 0.217 | 0.229 | 0.127 | 0.152 | 0.183 | 0.202 | 0.254 | 0.253 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 24,307,208 | 51,843,226 | 3,594,716 | 5,780,538 | 5,929,533 | 11,994,495 | 14,782,959 | 34,068,192 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a low income zip code. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in a high income zip code. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 9: Estimated Effect of Pandemic on Adherence: Variation By Education

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Low Education (1) | High Education (2) | Low Education (3) | High Education (4) | Low Education (5) | High Education (6) | Low Education (7) | High Education (8) |
| March DD | 0.0237*** | 0.0165*** | 0.0210*** | 0.0154*** | 0.0269*** | 0.0185*** | 0.0228*** | 0.0160*** |
| | (0.00187) | (0.00103) | (0.00209) | (0.00153) | (0.00207) | (0.00136) | (0.00215) | (0.00110) |
| Apr DD | 0.0245*** | 0.0121** | 0.00333 | -0.00600 | 0.0127* | 0.00575 | 0.0321*** | 0.0191*** |
| | (0.00575) | (0.00424) | (0.00472) | (0.00516) | (0.00501) | (0.00469) | (0.00658) | (0.00415) |
| May DD | 0.00551 | -0.00239 | -0.0174*** | -0.0269*** | -0.0124** | -0.0165*** | 0.0159** | 0.00829** |
| | (0.00448) | (0.00328) | (0.00363) | (0.00471) | (0.00393) | (0.00370) | (0.00512) | (0.00301) |
| June DD | 0.0000162 | -0.00351 | -0.0199*** | -0.0255*** | -0.0158*** | -0.0156*** | 0.00921* | 0.00567* |
| | (0.00325) | (0.00236) | (0.00305) | (0.00368) | (0.00303) | (0.00291) | (0.00372) | (0.00217) |
| July DD | 0.00389 | 0.000628 | -0.0122*** | -0.0163*** | -0.00824** | -0.00807* | 0.0110** | 0.00757*** |
| | (0.00299) | (0.00228) | (0.00295) | (0.00348) | (0.00288) | (0.00303) | (0.00342) | (0.00203) |
| Aug DD | 0.00227 | -0.00101 | -0.0133*** | -0.0183*** | -0.0138*** | -0.0154*** | 0.0108** | 0.00777*** |
| | (0.00287) | (0.00220) | (0.00273) | (0.00296) | (0.00287) | (0.00283) | (0.00323) | (0.00203) |
| Sept DD | -0.00409 | -0.00634** | -0.0261*** | -0.0278*** | -0.0263*** | -0.0254*** | 0.00820* | 0.00489* |
| | (0.00311) | (0.00233) | (0.00249) | (0.00306) | (0.00297) | (0.00301) | (0.00343) | (0.00222) |
| Oct DD | -0.00608* | -0.00783*** | -0.0306*** | -0.0307*** | -0.0230*** | -0.0230*** | 0.00474 | 0.00209 |
| | (0.00262) | (0.00217) | (0.00222) | (0.00254) | (0.00266) | (0.00269) | (0.00321) | (0.00215) |
| Nov DD | -0.00842** | -0.00985*** | -0.0386*** | -0.0375*** | -0.0247*** | -0.0257*** | 0.00325 | 0.00104 |
| | (0.00300) | (0.00249) | (0.00231) | (0.00257) | (0.00290) | (0.00300) | (0.00360) | (0.00250) |
| Dec DD | -0.00886* | -0.00991** | -0.0402*** | -0.0380*** | -0.0265*** | -0.0258*** | 0.00350 | 0.000994 |
| | (0.00404) | (0.00322) | (0.00322) | (0.00341) | (0.00375) | (0.00367) | (0.00484) | (0.00329) |
| Constant | 0.253*** | 0.270*** | 0.166*** | 0.166*** | 0.227*** | 0.241*** | 0.279*** | 0.298*** |
| | (0.00192) | (0.00189) | (0.00167) | (0.00166) | (0.00179) | (0.00230) | (0.00227) | (0.00202) |
| Control Mean | 0.218 | 0.234 | 0.140 | 0.141 | 0.190 | 0.201 | 0.245 | 0.263 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 55,781,201 | 23,337,880 | 7,157,272 | 2,777,677 | 13,170,432 | 5,307,317 | 35,453,497 | 15,252,886 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a low education zip code based on the share of the population with at least some college education. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in a high education zip code. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 10: Estimated Effect of Pandemic on Adherence: Variation By Industry

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Blue Collar (1) | White Collar (2) | Blue Collar (3) | White Collar (4) | Blue Collar (5) | White Collar (6) | Blue Collar (7) | White Collar (8) |
| March DD | 0.0147*** | 0.0217*** | 0.0115*** | 0.0206*** | 0.0151*** | 0.0243*** | 0.0153*** | 0.0202*** |
| | (0.00121) | (0.00211) | (0.00223) | (0.00242) | (0.00235) | (0.00243) | (0.00123) | (0.00230) |
| Apr DD | 0.0155*** | 0.0194** | -0.00610 | 0.00351 | 0.00129 | 0.00849 | 0.0258*** | 0.0257*** |
| | (0.00264) | (0.00598) | (0.00570) | (0.00628) | (0.00611) | (0.00625) | (0.00270) | (0.00653) |
| May DD | 0.00137 | 0.00165 | -0.0258*** | -0.0186*** | -0.0160** | -0.0158** | 0.0135*** | 0.0116* |
| | (0.00206) | (0.00449) | (0.00476) | (0.00470) | (0.00504) | (0.00500) | (0.00189) | (0.00485) |
| June DD | -0.000542 | -0.00227 | -0.0216*** | -0.0207*** | -0.0136*** | -0.0173*** | 0.00857*** | 0.00668 |
| | (0.00156) | (0.00311) | (0.00350) | (0.00343) | (0.00376) | (0.00371) | (0.00133) | (0.00338) |
| July DD | 0.00350 | 0.00144 | -0.0126** | -0.0129*** | -0.00651 | -0.00960** | 0.0106*** | 0.00810** |
| | (0.00240) | (0.00277) | (0.00383) | (0.00320) | (0.00410) | (0.00335) | (0.00255) | (0.00300) |
| Aug DD | -0.000339 | -0.000303 | -0.0145*** | -0.0146*** | -0.0151** | -0.0161*** | 0.00791* | 0.00800** |
| | (0.00317) | (0.00248) | (0.00352) | (0.00293) | (0.00442) | (0.00316) | (0.00335) | (0.00249) |
| Sept DD | -0.00647 | -0.00703** | -0.0243*** | -0.0273*** | -0.0237*** | -0.0289*** | 0.00334 | 0.00491 |
| | (0.00354) | (0.00249) | (0.00437) | (0.00269) | (0.00483) | (0.00326) | (0.00373) | (0.00250) |
| Oct DD | -0.00646 | -0.00890*** | -0.0251*** | -0.0310*** | -0.0202*** | -0.0253*** | 0.00234 | 0.00123 |
| | (0.00379) | (0.00215) | (0.00403) | (0.00223) | (0.00466) | (0.00327) | (0.00406) | (0.00230) |
| Nov DD | -0.00936* | -0.0117*** | -0.0337*** | -0.0395*** | -0.0258*** | -0.0278*** | 0.00146 | -0.000749 |
| | (0.00426) | (0.00250) | (0.00366) | (0.00232) | (0.00506) | (0.00359) | (0.00457) | (0.00272) |
| Dec DD | -0.00977* | -0.0133*** | -0.0367*** | -0.0415*** | -0.0233*** | -0.0304*** | 0.000816 | -0.00200 |
| | (0.00457) | (0.00281) | (0.00427) | (0.00294) | (0.00574) | (0.00418) | (0.00496) | (0.00316) |
| Constant | 0.274*** | 0.262*** | 0.152*** | 0.173*** | 0.236*** | 0.238*** | 0.310*** | 0.288*** |
| | (0.00224) | (0.00184) | (0.00378) | (0.00131) | (0.00290) | (0.00182) | (0.00256) | (0.00210) |
| Control Mean | 0.237 | 0.228 | 0.125 | 0.147 | 0.196 | 0.200 | 0.273 | 0.255 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,904,904 | 86,461,812 | 615,357 | 10,803,163 | 1,070,221 | 20,441,547 | 3,219,326 | 55,217,102 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a zip code with few white collar jobs (blue collar). Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in a zip code with many white collar jobs (white collar). Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 11: Estimated Effect of Pandemic on Adherence: Variation By Race

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | White | Non-White | White | Non-White | White | Non-White | White | Non-White |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0181*** | 0.0207*** | 0.0149*** | 0.0193*** | 0.0184*** | 0.0235*** | 0.0180*** | 0.0205*** |
| | (0.00154) | (0.00220) | (0.00199) | (0.00224) | (0.00177) | (0.00235) | (0.00162) | (0.00242) |
| Apr DD | 0.0144** | 0.0220** | -0.00726 | 0.00289 | 0.00136 | 0.00931 | 0.0228*** | 0.0326*** |
| | (0.00535) | (0.00733) | (0.00637) | (0.00567) | (0.00533) | (0.00666) | (0.00566) | (0.00807) |
| May DD | -0.00134 | 0.00437 | -0.0264*** | -0.0191*** | -0.0182*** | -0.0153** | 0.00922* | 0.0178** |
| | (0.00413) | (0.00558) | (0.00500) | (0.00454) | (0.00415) | (0.00513) | (0.00434) | (0.00612) |
| June DD | -0.00340 | 0.0000875 | -0.0244*** | -0.0207*** | -0.0176*** | -0.0163*** | 0.00558 | 0.0113* |
| | (0.00291) | (0.00393) | (0.00353) | (0.00344) | (0.00292) | (0.00368) | (0.00310) | (0.00434) |
| July DD | 0.00122 | 0.00357 | -0.0147*** | -0.0128*** | -0.00827** | -0.00868* | 0.00754* | 0.0122** |
| | (0.00278) | (0.00346) | (0.00346) | (0.00298) | (0.00280) | (0.00326) | (0.00294) | (0.00380) |
| Aug DD | -0.000269 | 0.00129 | -0.0164*** | -0.0141*** | -0.0149*** | -0.0155*** | 0.00768** | 0.0114** |
| | (0.00244) | (0.00329) | (0.00292) | (0.00290) | (0.00244) | (0.00340) | (0.00261) | (0.00344) |
| Sept DD | -0.00611* | -0.00498 | -0.0270*** | -0.0272*** | -0.0252*** | -0.0275*** | 0.00444 | 0.00857* |
| | (0.00256) | (0.00336) | (0.00306) | (0.00287) | (0.00264) | (0.00356) | (0.00274) | (0.00350) |
| Oct DD | -0.00632** | -0.00734* | -0.0282*** | -0.0318*** | -0.0208*** | -0.0243*** | 0.00268 | 0.00456 |
| | (0.00235) | (0.00304) | (0.00282) | (0.00236) | (0.00236) | (0.00323) | (0.00263) | (0.00341) |
| Nov DD | -0.00812** | -0.0103** | -0.0348*** | -0.0404*** | -0.0243*** | -0.0269*** | 0.00208 | 0.00274 |
| | (0.00270) | (0.00350) | (0.00301) | (0.00261) | (0.00273) | (0.00346) | (0.00286) | (0.00393) |
| Dec DD | -0.00817* | -0.0113* | -0.0364*** | -0.0422*** | -0.0257*** | -0.0289*** | 0.00250 | 0.00242 |
| | (0.00347) | (0.00436) | (0.00362) | (0.00335) | (0.00315) | (0.00424) | (0.00388) | (0.00488) |
| Constant | 0.262*** | 0.265*** | 0.152*** | 0.178*** | 0.227*** | 0.243*** | 0.294*** | 0.289*** |
| | (0.00263) | (0.00227) | (0.00202) | (0.00174) | (0.00181) | (0.00229) | (0.00315) | (0.00249) |
| Control Mean | 0.227 | 0.228 | 0.130 | 0.150 | 0.189 | 0.203 | 0.259 | 0.253 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 18,458,788 | 53,454,211 | 2,257,783 | 6,535,609 | 4,111,843 | 12,765,101 | 12,089,160 | 34,153,501 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a mostly white zip code. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in a mostly non-white zip code. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 12: Estimated Effect of Pandemic on Adherence: Variation By Race in Urban Areas

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | White | Non-White | White | Non-White | White | Non-White | White | Non-White |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0205*** | 0.0209*** | 0.0196*** | 0.0193*** | 0.0236*** | 0.0245*** | 0.0189*** | 0.0206*** |
| | (0.00288) | (0.00247) | (0.00337) | (0.00235) | (0.00299) | (0.00251) | (0.00347) | (0.00281) |
| Apr DD | 0.0163 | 0.0221* | -0.00101 | 0.00230 | 0.0104 | 0.0113 | 0.0224* | 0.0325*** |
| | (0.00834) | (0.00825) | (0.00914) | (0.00600) | (0.00891) | (0.00731) | (0.00927) | (0.00920) |
| May DD | -0.000139 | 0.00431 | -0.0214** | -0.0196*** | -0.0113 | -0.0139* | 0.00919 | 0.0177* |
| | (0.00628) | (0.00627) | (0.00643) | (0.00476) | (0.00669) | (0.00561) | (0.00680) | (0.00695) |
| June DD | -0.00346 | -0.000134 | -0.0216*** | -0.0212*** | -0.0133** | -0.0158*** | 0.00480 | 0.0111* |
| | (0.00436) | (0.00438) | (0.00438) | (0.00357) | (0.00473) | (0.00401) | (0.00476) | (0.00488) |
| July DD | 0.00105 | 0.00341 | -0.0125** | -0.0134*** | -0.00440 | -0.00818* | 0.00661 | 0.0121** |
| | (0.00406) | (0.00381) | (0.00443) | (0.00305) | (0.00474) | (0.00352) | (0.00432) | (0.00421) |
| Aug DD | -0.000177 | 0.00119 | -0.0148*** | -0.0145*** | -0.0117** | -0.0149*** | 0.00752* | 0.0113** |
| | (0.00351) | (0.00360) | (0.00385) | (0.00301) | (0.00417) | (0.00360) | (0.00371) | (0.00382) |
| Sept DD | -0.00673 | -0.00501 | -0.0263*** | -0.0276*** | -0.0237*** | -0.0268*** | 0.00426 | 0.00863* |
| | (0.00350) | (0.00366) | (0.00395) | (0.00293) | (0.00400) | (0.00374) | (0.00384) | (0.00386) |
| Oct DD | -0.00726* | -0.00740* | -0.0272*** | -0.0321*** | -0.0196*** | -0.0237*** | 0.00179 | 0.00458 |
| | (0.00307) | (0.00332) | (0.00343) | (0.00238) | (0.00361) | (0.00335) | (0.00343) | (0.00380) |
| Nov DD | -0.00881* | -0.0104** | -0.0330*** | -0.0411*** | -0.0212*** | -0.0262*** | 0.000910 | 0.00283 |
| | (0.00362) | (0.00383) | (0.00394) | (0.00264) | (0.00396) | (0.00361) | (0.00392) | (0.00439) |
| Dec DD | -0.00892* | -0.0115* | -0.0337*** | -0.0430*** | -0.0213*** | -0.0282*** | 0.000631 | 0.00234 |
| | (0.00442) | (0.00476) | (0.00397) | (0.00339) | (0.00453) | (0.00440) | (0.00515) | (0.00545) |
| Constant | 0.252*** | 0.265*** | 0.153*** | 0.179*** | 0.223*** | 0.243*** | 0.284*** | 0.289*** |
| | (0.00297) | (0.00230) | (0.00277) | (0.00172) | (0.00236) | (0.00236) | (0.00361) | (0.00251) |
| Control Mean | 0.218 | 0.228 | 0.132 | 0.151 | 0.185 | 0.203 | 0.249 | 0.253 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,200,832 | 50,565,273 | 1,369,836 | 6,202,550 | 2,405,655 | 12,138,758 | 6,425,339 | 32,223,965 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a mostly white, urban zip code. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in a mostly non-white, urban zip code. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 13: Estimated Effect of Pandemic on Adherence: Variation By Payer

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Medicaid (1) | Third-Party (2) | Medicaid (3) | Third-Party (4) | Medicaid (5) | Third-Party (6) | Medicaid (7) | Third-Party (8) |
| March DD | 0.0125*** | 0.0227*** | 0.0110*** | 0.0194*** | 0.0148*** | 0.0237*** | 0.0127*** | 0.0222*** |
| | (0.00185) | (0.00145) | (0.00192) | (0.00178) | (0.00252) | (0.00174) | (0.00197) | (0.00157) |
| Apr DD | 0.00795 | 0.0240*** | -0.00371 | 0.00165 | 0.00714 | 0.00875 | 0.0265** | 0.0317*** |
| | (0.00778) | (0.00457) | (0.00441) | (0.00475) | (0.00665) | (0.00441) | (0.00922) | (0.00498) |
| May DD | -0.00595 | 0.00520 | -0.0260*** | -0.0194*** | -0.0134* | -0.0152*** | 0.0196** | 0.0157*** |
| | (0.00640) | (0.00349) | (0.00443) | (0.00369) | (0.00595) | (0.00346) | (0.00717) | (0.00380) |
| June DD | -0.00309 | 0.000372 | -0.0218*** | -0.0212*** | -0.0111** | -0.0167*** | 0.0195*** | 0.00954*** |
| | (0.00433) | (0.00240) | (0.00283) | (0.00274) | (0.00356) | (0.00256) | (0.00511) | (0.00269) |
| July DD | 0.00277 | 0.00427 | -0.0139*** | -0.0129*** | -0.00328 | -0.00895*** | 0.0219*** | 0.0112*** |
| | (0.00455) | (0.00230) | (0.00244) | (0.00260) | (0.00458) | (0.00241) | (0.00503) | (0.00263) |
| Aug DD | -0.00266 | 0.00244 | -0.0188*** | -0.0145*** | -0.0156** | -0.0153*** | 0.0207*** | 0.0111*** |
| | (0.00478) | (0.00219) | (0.00295) | (0.00227) | (0.00500) | (0.00220) | (0.00468) | (0.00255) |
| Sept DD | -0.0103* | -0.00371 | -0.0294*** | -0.0264*** | -0.0269*** | -0.0266*** | 0.0175*** | 0.00818** |
| | (0.00488) | (0.00239) | (0.00308) | (0.00228) | (0.00465) | (0.00239) | (0.00459) | (0.00276) |
| Oct DD | -0.00869 | -0.00556** | -0.0300*** | -0.0304*** | -0.0207*** | -0.0235*** | 0.0156*** | 0.00489 |
| | (0.00483) | (0.00204) | (0.00352) | (0.00199) | (0.00505) | (0.00222) | (0.00445) | (0.00259) |
| Nov DD | -0.0120* | -0.00758** | -0.0384*** | -0.0380*** | -0.0240*** | -0.0259*** | 0.0149** | 0.00383 |
| | (0.00574) | (0.00243) | (0.00395) | (0.00216) | (0.00605) | (0.00235) | (0.00552) | (0.00290) |
| Dec DD | -0.0126 | -0.00737* | -0.0423*** | -0.0393*** | -0.0229** | -0.0273*** | 0.0144* | 0.00465 |
| | (0.00653) | (0.00357) | (0.00390) | (0.00299) | (0.00720) | (0.00311) | (0.00652) | (0.00416) |
| Constant | 0.249*** | 0.255*** | 0.174*** | 0.167*** | 0.255*** | 0.232*** | 0.280*** | 0.279*** |
| | (0.00284) | (0.00176) | (0.00244) | (0.00106) | (0.00306) | (0.00147) | (0.00362) | (0.00202) |
| Control Mean | 0.214 | 0.221 | 0.147 | 0.142 | 0.215 | 0.195 | 0.244 | 0.246 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,662,611 | 125,234,312 | 2,144,598 | 15,458,521 | 3,982,962 | 2,951,0367 | 4,535,051 | 80,265,416 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose last prescription in the prior year was paid by Medicaid. Likewise, columns (2), (4), (6), and (8) are limited to those with private insurance. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 14: Estimated Effect of Pandemic on Adherence: Variation By Access to Medicaid

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Expansion | Non-Expansion | Expansion | Non-Expansion | Expansion | Non-Expansion | Expansion | Non-Expansion |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0182*** | 0.0240*** | 0.0153*** | 0.0203*** | 0.0201*** | 0.0247*** | 0.0169*** | 0.0237*** |
| | (0.00168) | (0.00211) | (0.00158) | (0.00264) | (0.00218) | (0.00263) | (0.00153) | (0.00200) |
| Apr DD | 0.0224*** | 0.0291*** | -0.00797 | 0.00721 | 0.0113* | 0.0117 | 0.0294*** | 0.0358*** |
| | (0.00439) | (0.00618) | (0.00593) | (0.00576) | (0.00496) | (0.00640) | (0.00447) | (0.00636) |
| May DD | 0.00622 | 0.00935 | -0.0262*** | -0.0157** | -0.00941* | -0.0143** | 0.0167*** | 0.0191*** |
| | (0.00388) | (0.00489) | (0.00474) | (0.00488) | (0.00424) | (0.00526) | (0.00402) | (0.00495) |
| June DD | 0.00219 | 0.00340 | -0.0241*** | -0.0190*** | -0.00995** | -0.0170*** | 0.0109*** | 0.0122*** |
| | (0.00273) | (0.00339) | (0.00369) | (0.00352) | (0.00290) | (0.00374) | (0.00297) | (0.00344) |
| July DD | 0.00658* | 0.00653* | -0.0158*** | -0.0117*** | -0.00174 | -0.00973** | 0.0126*** | 0.0134*** |
| | (0.00314) | (0.00305) | (0.00394) | (0.00306) | (0.00335) | (0.00324) | (0.00339) | (0.00314) |
| Aug DD | 0.00138 | 0.00539 | -0.0190*** | -0.0125*** | -0.0124*** | -0.0151*** | 0.0100** | 0.0137*** |
| | (0.00300) | (0.00293) | (0.00298) | (0.00290) | (0.00330) | (0.00317) | (0.00317) | (0.00311) |
| Sept DD | -0.00580* | -0.000242 | -0.0302*** | -0.0246*** | -0.0223*** | -0.0273*** | 0.00530 | 0.0115** |
| | (0.00258) | (0.00306) | (0.00278) | (0.00287) | (0.00269) | (0.00341) | (0.00302) | (0.00331) |
| Oct DD | -0.00692* | -0.00254 | -0.0309*** | -0.0304*** | -0.0176*** | -0.0250*** | 0.00186 | 0.00820* |
| | (0.00276) | (0.00268) | (0.00281) | (0.00252) | (0.00327) | (0.00278) | (0.00290) | (0.00306) |
| Nov DD | -0.0106** | -0.00351 | -0.0394*** | -0.0372*** | -0.0215*** | -0.0265*** | -0.000642 | 0.00806* |
| | (0.00315) | (0.00312) | (0.00280) | (0.00313) | (0.00405) | (0.00322) | (0.00325) | (0.00340) |
| Dec DD | -0.0119** | -0.00203 | -0.0397*** | -0.0399*** | -0.0232*** | -0.0271*** | -0.00226 | 0.0104 |
| | (0.00342) | (0.00499) | (0.00308) | (0.00433) | (0.00449) | (0.00490) | (0.00343) | (0.00528) |
| Constant | 0.261*** | 0.261*** | 0.166*** | 0.166*** | 0.241*** | 0.230*** | 0.290*** | 0.286*** |
| | (0.00223) | (0.00220) | (0.00221) | (0.00129) | (0.00197) | (0.00168) | (0.00308) | (0.00245) |
| Control Mean | 0.222 | 0.228 | 0.140 | 0.142 | 0.200 | 0.194 | 0.252 | 0.253 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 54,252,055 | 92,199,226 | 7,968,083 | 10,102,480 | 13,709,105 | 20,556,963 | 32,574,867 | 61,539,783 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a Medicaid Expansion state. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in a Non Medicaid Expansion state. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 15: Estimated Effect of Pandemic on Adherence: Variation By Prescription Delivery

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Mail Order | Non-Mail Order | Mail Order | Non-Mail Order | Mail Order | Non-Mail Order | Mail Order | Non-Mail Order |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0214*** | 0.00335 | 0.0182*** | 0.00143 | 0.0225*** | 0.00397 | 0.0211*** | 0.00225 |
| | (0.00148) | (0.00313) | (0.00164) | (0.0148) | (0.00175) | (0.00517) | (0.00156) | (0.00331) |
| Apr DD | 0.0228*** | -0.00824 | 0.00120 | -0.0200 | 0.00845 | -0.0242 | 0.0317*** | -0.00801 |
| | (0.00480) | (0.0132) | (0.00441) | (0.0394) | (0.00440) | (0.0175) | (0.00515) | (0.0141) |
| May DD | 0.00472 | -0.00636 | -0.0199*** | -0.0328 | -0.0151*** | -0.0271 | 0.0164*** | -0.00448 |
| | (0.00377) | (0.0104) | (0.00365) | (0.0328) | (0.00354) | (0.0140) | (0.00397) | (0.0111) |
| June DD | 0.000498 | -0.00668 | -0.0210*** | -0.0408 | -0.0160*** | -0.0315** | 0.0105*** | -0.00341 |
| | (0.00260) | (0.00790) | (0.00262) | (0.0241) | (0.00248) | (0.0116) | (0.00281) | (0.00830) |
| July DD | 0.00453 | -0.00777 | -0.0128*** | -0.0418 | -0.00805** | -0.0363** | 0.0122*** | -0.00391 |
| | (0.00254) | (0.00735) | (0.00248) | (0.0241) | (0.00242) | (0.0110) | (0.00277) | (0.00772) |
| Aug DD | 0.00235 | -0.00202 | -0.0148*** | -0.0445 | -0.0152*** | -0.0315** | 0.0118*** | 0.00221 |
| | (0.00245) | (0.00683) | (0.00229) | (0.0222) | (0.00232) | (0.00904) | (0.00269) | (0.00721) |
| Sept DD | -0.00397 | 0.00180 | -0.0264*** | -0.0452* | -0.0265*** | -0.0340*** | 0.00850** | 0.00717 |
| | (0.00261) | (0.00688) | (0.00223) | (0.0184) | (0.00247) | (0.00827) | (0.00291) | (0.00721) |
| Oct DD | -0.00561* | 0.00117 | -0.0300*** | -0.0582** | -0.0230*** | -0.0352*** | 0.00519 | 0.00679 |
| | (0.00229) | (0.00717) | (0.00197) | (0.0193) | (0.00228) | (0.00887) | (0.00269) | (0.00746) |
| Nov DD | -0.00770** | -0.000806 | -0.0375*** | -0.0779*** | -0.0255*** | -0.0393*** | 0.00412 | 0.00524 |
| | (0.00271) | (0.00839) | (0.00223) | (0.0216) | (0.00257) | (0.0106) | (0.00303) | (0.00881) |
| Dec DD | -0.00740 | -0.00143 | -0.0389*** | -0.103*** | -0.0265*** | -0.0436*** | 0.00500 | 0.00539 |
| | (0.00384) | (0.0109) | (0.00301) | (0.0222) | (0.00339) | (0.0121) | (0.00432) | (0.0116) |
| Constant | 0.249*** | 0.687*** | 0.164*** | 0.685*** | 0.228*** | 0.656*** | 0.273*** | 0.692*** |
| | (0.00187) | (0.00456) | (0.00104) | (0.0120) | (0.00147) | (0.00477) | (0.00218) | (0.00499) |
| Control Mean | 0.216 | 0.622 | 0.139 | 0.594 | 0.191 | 0.571 | 0.241 | 0.630 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 143,034,093 | 3,443,812 | 18,005,575 | 71,524 | 33,838,770 | 433,368 | 91,189,740 | 2,938,920 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose last prescription in the prior year was delivered by Mail. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescription was delivered by another mechanism (retail, for example). Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 16: Estimated Effect of Pandemic on Adherence: Variation By Population Density

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Rural | Urban | Rural | Urban | Rural | Urban | Rural | Urban |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0146*** | 0.0224*** | 0.0111*** | 0.0198*** | 0.0126*** | 0.0251*** | 0.0160*** | 0.0217*** |
| | (0.00117) | (0.00155) | (0.00260) | (0.00180) | (0.00225) | (0.00173) | (0.00133) | (0.00191) |
| Apr DD | 0.0148*** | 0.0240*** | -0.00994 | 0.00314 | 0.00185 | 0.0128** | 0.0242*** | 0.0320*** |
| | (0.00394) | (0.00555) | (0.00716) | (0.00477) | (0.00414) | (0.00470) | (0.00439) | (0.00649) |
| May DD | 0.000521 | 0.00571 | -0.0292*** | -0.0183*** | -0.0199*** | -0.0122** | 0.0117** | 0.0170** |
| | (0.00315) | (0.00432) | (0.00651) | (0.00370) | (0.00342) | (0.00370) | (0.00357) | (0.00493) |
| June DD | -0.000859 | 0.000858 | -0.0234*** | -0.0204*** | -0.0179*** | -0.0146*** | 0.00778** | 0.0107** |
| | (0.00224) | (0.00299) | (0.00521) | (0.00262) | (0.00320) | (0.00261) | (0.00256) | (0.00347) |
| July DD | 0.00305 | 0.00469 | -0.0128* | -0.0126*** | -0.00859* | -0.00704** | 0.00935*** | 0.0123*** |
| | (0.00235) | (0.00285) | (0.00537) | (0.00244) | (0.00321) | (0.00248) | (0.00266) | (0.00332) |
| Aug DD | 0.00117 | 0.00270 | -0.0149** | -0.0145*** | -0.0173*** | -0.0140*** | 0.00899** | 0.0121*** |
| | (0.00255) | (0.00268) | (0.00453) | (0.00227) | (0.00324) | (0.00236) | (0.00288) | (0.00313) |
| Sept DD | -0.00325 | -0.00358 | -0.0244*** | -0.0265*** | -0.0234*** | -0.0259*** | 0.00552 | 0.00917** |
| | (0.00252) | (0.00288) | (0.00532) | (0.00220) | (0.00302) | (0.00254) | (0.00285) | (0.00335) |
| Oct DD | -0.00349 | -0.00543* | -0.0281*** | -0.0303*** | -0.0202*** | -0.0226*** | 0.00466 | 0.00564 |
| | (0.00312) | (0.00248) | (0.00515) | (0.00183) | (0.00394) | (0.00222) | (0.00348) | (0.00312) |
| Nov DD | -0.00512 | -0.00747* | -0.0350*** | -0.0379*** | -0.0233*** | -0.0246*** | 0.00414 | 0.00457 |
| | (0.00334) | (0.00292) | (0.00515) | (0.00219) | (0.00372) | (0.00252) | (0.00366) | (0.00351) |
| Dec DD | -0.00526 | -0.00721 | -0.0371*** | -0.0393*** | -0.0251*** | -0.0251*** | 0.00495 | 0.00529 |
| | (0.00357) | (0.00415) | (0.00594) | (0.00289) | (0.00432) | (0.00343) | (0.00388) | (0.00496) |
| Constant | 0.281*** | 0.258*** | 0.153*** | 0.168*** | 0.232*** | 0.234*** | 0.310*** | 0.284*** |
| | (0.00273) | (0.00191) | (0.00533) | (0.00112) | (0.00274) | (0.00154) | (0.00272) | (0.00226) |
| Control Mean | 0.245 | 0.223 | 0.126 | 0.143 | 0.189 | 0.196 | 0.273 | 0.250 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,690,971 | 121,671,058 | 393,010 | 15,238,896 | 889,466 | 29,000,826 | 3,408,495 | 77,431,329 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients whose prescriber is located in a Rural zip code. Likewise, columns (2), (4), (6), and (8) are limited to those whose prescriber is located in an urban zip code. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 17: Estimated Effect of Pandemic on Adherence: Variation By Telehealth-Readiness

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | No | Yes | No | Yes | No | Yes | No | Yes |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0186*** | 0.0222*** | 0.0182*** | 0.0183*** | 0.0189*** | 0.0238*** | 0.0178*** | 0.0220*** |
| | (0.00220) | (0.00167) | (0.00292) | (0.00198) | (0.00327) | (0.00205) | (0.00180) | (0.00181) |
| Apr DD | 0.0136 | 0.0271*** | -0.00320 | 0.00399 | 0.00168 | 0.0124* | 0.0210* | 0.0360*** |
| | (0.00847) | (0.00474) | (0.00948) | (0.00497) | (0.00890) | (0.00464) | (0.00726) | (0.00542) |
| May DD | -0.00239 | 0.00838* | -0.0261** | -0.0162*** | -0.0202* | -0.0116** | 0.00876 | 0.0198*** |
| | (0.00673) | (0.00373) | (0.00828) | (0.00402) | (0.00763) | (0.00368) | (0.00562) | (0.00422) |
| June DD | -0.00552 | 0.00376 | -0.0276*** | -0.0171*** | -0.0208** | -0.0128*** | 0.00450 | 0.0133*** |
| | (0.00460) | (0.00251) | (0.00555) | (0.00290) | (0.00540) | (0.00265) | (0.00383) | (0.00297) |
| July DD | -0.00219 | 0.00775** | -0.0196** | -0.00887** | -0.0129* | -0.00531* | 0.00536 | 0.0151*** |
| | (0.00435) | (0.00241) | (0.00503) | (0.00263) | (0.00525) | (0.00250) | (0.00361) | (0.00292) |
| Aug DD | -0.00388 | 0.00535* | -0.0205*** | -0.0114*** | -0.0193** | -0.0128*** | 0.00507 | 0.0147*** |
| | (0.00424) | (0.00237) | (0.00472) | (0.00240) | (0.00539) | (0.00224) | (0.00347) | (0.00288) |
| Sept DD | -0.0109* | -0.000472 | -0.0322*** | -0.0229*** | -0.0313*** | -0.0237*** | 0.001000 | 0.0120*** |
| | (0.00423) | (0.00269) | (0.00460) | (0.00252) | (0.00609) | (0.00242) | (0.00345) | (0.00317) |
| Oct DD | -0.0131** | -0.00212 | -0.0362*** | -0.0263*** | -0.0292*** | -0.0200*** | -0.00255 | 0.00863** |
| | (0.00428) | (0.00210) | (0.00422) | (0.00198) | (0.00596) | (0.00222) | (0.00369) | (0.00278) |
| Nov DD | -0.0175** | -0.00402 | -0.0438*** | -0.0340*** | -0.0340*** | -0.0220*** | -0.00603 | 0.00779* |
| | (0.00517) | (0.00239) | (0.00508) | (0.00232) | (0.00699) | (0.00223) | (0.00451) | (0.00288) |
| Dec DD | -0.0216** | -0.00286 | -0.0467*** | -0.0352*** | -0.0390*** | -0.0221*** | -0.00954 | 0.00959* |
| | (0.00598) | (0.00375) | (0.00631) | (0.00353) | (0.00815) | (0.00306) | (0.00524) | (0.00436) |
| Constant | 0.267*** | 0.257*** | 0.171*** | 0.164*** | 0.239*** | 0.232*** | 0.294*** | 0.284*** |
| | (0.00257) | (0.00192) | (0.00206) | (0.00107) | (0.00324) | (0.00134) | (0.00269) | (0.00240) |
| Control Mean | 0.233 | 0.222 | 0.146 | 0.139 | 0.200 | 0.194 | 0.261 | 0.249 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 47,275,683 | 99,185,436 | 5,631,164 | 12,444,301 | 10,862,299 | 2,3406,654 | 3,0781,596 | 63,333,980 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients who live in states that did not require insurers to cover telemedicine services prior to the pandemic. Likewise, columns (2), (4), (6), and (8) are limited to those who live in states that required insurers to cover telemedicine services. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 18: Estimated Effect of Pandemic on Adherence: Variation Based on School Closure

| | Main | | 0–6 | | 6–7 | | 18–59 | |
|---|---|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High | Low | High |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| March DD | 0.0153*** | 0.0252*** | 0.0132*** | 0.0217*** | 0.0154*** | 0.0277*** | 0.0160*** | 0.0245*** |
| | (0.00115) | (0.00177) | (0.00136) | (0.00229) | (0.00150) | (0.00221) | (0.00147) | (0.00179) |
| Apr DD | 0.0208*** | 0.0283*** | -0.00363 | 0.00762 | 0.00724 | 0.0160** | 0.0331*** | 0.0367*** |
| | (0.00369) | (0.00584) | (0.00580) | (0.00531) | (0.00523) | (0.00550) | (0.00403) | (0.00653) |
| May DD | 0.00370 | 0.00893 | -0.0250*** | -0.0143** | -0.0134** | -0.00992* | 0.0173*** | 0.0204*** |
| | (0.00295) | (0.00458) | (0.00469) | (0.00422) | (0.00409) | (0.00432) | (0.00312) | (0.00505) |
| June DD | 0.000492 | 0.00277 | -0.0218*** | -0.0180*** | -0.0117*** | -0.0142*** | 0.0105*** | 0.0131*** |
| | (0.00218) | (0.00322) | (0.00355) | (0.00317) | (0.00276) | (0.00319) | (0.00222) | (0.00361) |
| July DD | 0.00340 | 0.00648* | -0.0123*** | -0.0104*** | -0.00426 | -0.00679* | 0.0103*** | 0.0146*** |
| | (0.00242) | (0.00298) | (0.00335) | (0.00293) | (0.00332) | (0.00291) | (0.00250) | (0.00344) |
| Aug DD | -0.000772 | 0.00471 | -0.0155*** | -0.0123*** | -0.0113** | -0.0136*** | 0.00673* | 0.0147*** |
| | (0.00305) | (0.00278) | (0.00325) | (0.00266) | (0.00394) | (0.00280) | (0.00292) | (0.00321) |
| Sept DD | -0.00551 | -0.00203 | -0.0211*** | -0.0258*** | -0.0161*** | -0.0275*** | 0.00217 | 0.0120** |
| | (0.00342) | (0.00320) | (0.00414) | (0.00275) | (0.00410) | (0.00316) | (0.00324) | (0.00351) |
| Oct DD | -0.00591 | -0.00408 | -0.0222*** | -0.0308*** | -0.0155*** | -0.0236*** | 0.00147 | 0.00819* |
| | (0.00352) | (0.00259) | (0.00385) | (0.00227) | (0.00379) | (0.00252) | (0.00358) | (0.00317) |
| Nov DD | -0.00909* | -0.00536 | -0.0322*** | -0.0378*** | -0.0192*** | -0.0238*** | -0.000144 | 0.00743* |
| | (0.00378) | (0.00290) | (0.00391) | (0.00275) | (0.00463) | (0.00264) | (0.00379) | (0.00339) |
| Dec DD | -0.00948* | -0.00453 | -0.0333*** | -0.0394*** | -0.0190*** | -0.0239*** | -0.000513 | 0.00888 |
| | (0.00389) | (0.00429) | (0.00376) | (0.00346) | (0.00418) | (0.00377) | (0.00406) | (0.00499) |
| Constant | 0.276*** | 0.251*** | 0.161*** | 0.164*** | 0.247*** | 0.224*** | 0.309*** | 0.278*** |
| | (0.00236) | (0.00236) | (0.00283) | (0.00150) | (0.00300) | (0.00161) | (0.00254) | (0.00281) |
| Control Mean | 0.235 | 0.218 | 0.131 | 0.140 | 0.202 | 0.189 | 0.268 | 0.245 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Individual FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 8,863,139 | 90,017,243 | 1,163,127 | 11,204,808 | 1,955,081 | 21,556,818 | 5,744,931 | 57,255,617 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), (5), and (7) are limited to the subsample of patients who live in areas with low school closure rates in the Fall of 2020. Likewise, columns (2), (4), (6), and (8) are limited to those who live in counties with high school closure rates in the fall of 2020. Controls include state x month unemployment rates, monthly COVID case counts, monthly mobility and individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 19: MEPS Analysis

Panel A: Differential Response

| | Log(Rx)<br>(1) | Log(Q)<br>(2) | Log(Rx)<br>(3) | Log(Q)<br>(4) | Log(Rx)<br>(5) | Log(Q)<br>(6) |
|---|---|---|---|---|---|---|
| Under 5 × 2020 | -0.207 | -1.288** | | | | |
| | (0.139) | (0.424) | | | | |
| Under 12 × 2020 | | | -0.277** | -1.142*** | | |
| | | | (0.0881) | (0.270) | | |
| Under 18 × 2020 | | | | | -0.282*** | -1.013*** |
| | | | | | (0.0761) | (0.226) |
| Person FE | x | x | x | x | x | x |
| Year FE | x | x | x | x | x | x |
| No. Individuals | | | | 1,692 | | |

Panel B: Differences within Children Under 18

| | Asthma<br>(1) | All Rx<br>(2) | ΔMental<br>(3) | Log(Q)<br>Lost Job<br>(4) | Lost Ins<br>(5) | Education<br>(6) | Log Wage<br>(7) |
|---|---|---|---|---|---|---|---|
| 2020 | -2.125*** | -2.143*** | -2.136*** | -2.135*** | -2.139*** | -2.115*** | -2.119*** |
| | (0.195) | (0.199) | (0.202) | (0.201) | (0.203) | (0.201) | (0.199) |
| 2020 × | 0.937* | 0.352* | -0.149 | -0.319 | -0.00343 | -0.0723 | -0.136 |
| Parental Measure | (0.425) | (0.137) | (0.395) | (0.508) | (1.015) | (0.0829) | (0.126) |
| Person FE | x | x | x | x | x | x | x |
| No. Individuals | | | | 330 | | | |

Notes: All log outcomes refer to log(1+variable). "Rx" refers to the number of distinct scripts recorded in MEPS and "Q" refers to the today number of days supplied. In Panel B, the columns denote the parental measure we are using in the interaction term. All measures are demeaned to preserve interpretation of the overall effect. "Asthma" is an indicator for whether an adult in the family also has asthma scripts in 2020. "All Rx" refers to log of the total adult scripts in 2020. $\Delta$Mental refers to the average change in self-reported mental health status across all adults in the family, with higher values representing worse status. Education refers to the higher number of years of education of any adult in the family. "Lost Ins" and "Lost Job" indicate whether any adult in the family lost insurance coverage or lost employment across the three rounds of the survey in 2020, respectively. "Log Wage" refers to the log of the sum of hourly wage across all adults in the family during the first round in 2020.

# Appendix to "All Children Left Behind: Drug Adherence and the COVID-19 Pandemic"

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## A MEPS – Data Construction and Additional Results

We discuss how we construct our MEPS asthma medication user panel, which we use to arrive at the estimates in Table 19, and provide additional results.

To identify asthma-related scripts in MEPS, we rely on product names and national drug codes (NDCs) present in the IQVIA data. First, we take all product names and NDCs present in the IQVIA database on asthma scripts. Next, we match information on scripts in MEPS (Prescription Medicines files) to these two lists, keeping any scripts that match either the product name or the NDC. We then aggregate the data to a person-by-year level. Finally, we use the Full-Year Population Characteristics files to identify asthma medication users who continue to be surveyed in 2020, in order to assign zeros to individuals who are surveyed but do not report any asthma scripts. The data also record the age of the individual, allowing us to classify each individual by age. We use age in 2019 to classify individuals into groups, in order to keep the variable fixed over time.

Next, we use the Prescription Medicines files and Full-Year Population Characteristics files to construct parental measures. The Prescription Medicines files allow us to identify the total scripts of any kind filled by parents of kids taking asthma medication. The Population Characteristics file records education, and also tracks self-reported mental health, insurance status, employment status, and hourly wage across the three survey rounds in a given year. This allows us to measure changes in insurance and employment status across rounds, and also use 2019 self-reported mental health as a reference point for understanding an individual's 2020 mental health status.

Column 1 of Table A5 provides additional context to the results reported in the main text. Here, we put all the parental measures in a horse race, in order to check whether individual measures are just proxying for other factors. We find evidence that some factors (parental scripts) are still precisely predictive of the size of the 2020 response, with other factors such as parental job loss and mental health status (higher is worse) also exhibiting negative, albeit imprecisely estimated effects on a child's adherence to asthma medication.

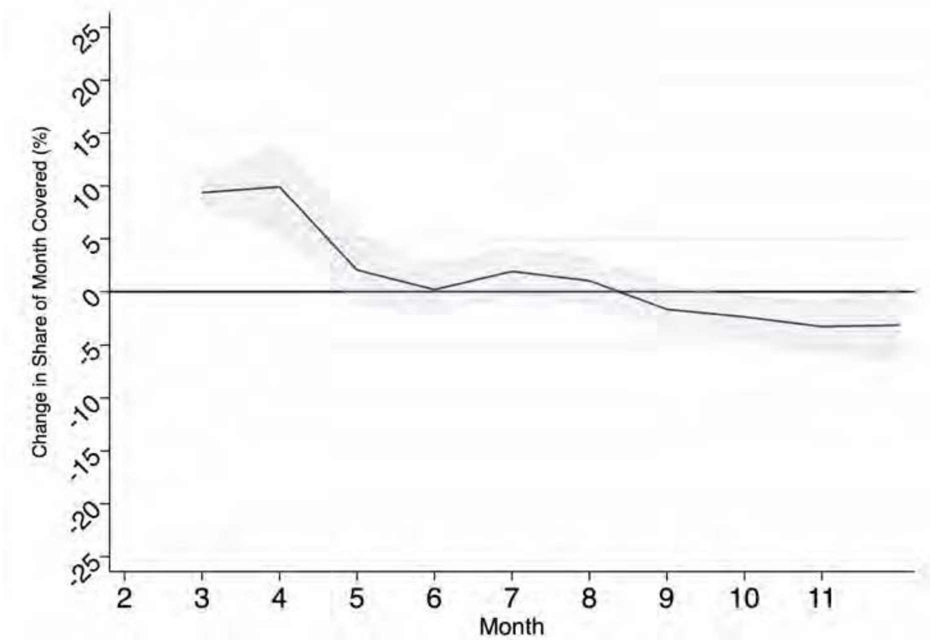
We also repeat the analysis for non-asthma chronic medication commonly taken by children under the age of 18. Specifically, we take all under 18 scripts in MEPS, and select drugs that are taken by more than 10 children and have an average of three or more scripts per child. This set of drugs primarily contains allergy medication (e.g., Zyrtec) and stimulants (e.g., Adderall). We then repeat the same horserace analysis for the set of kids taking one of these non-asthma chronic medications in 2019. Column 2 of Table A5 provides the estimates. We generally find very similar results to those for asthma medication. Having parents that also take medication and having parents who lost their job in 2020 serve as the strongest mediators of the overall drop in pediatric adherence. This evidence suggests that the mechanisms that we find generalize to other disease areas for which we do not have IQVIA data.

# B IQVIA: Robustness Checks and Additional Results

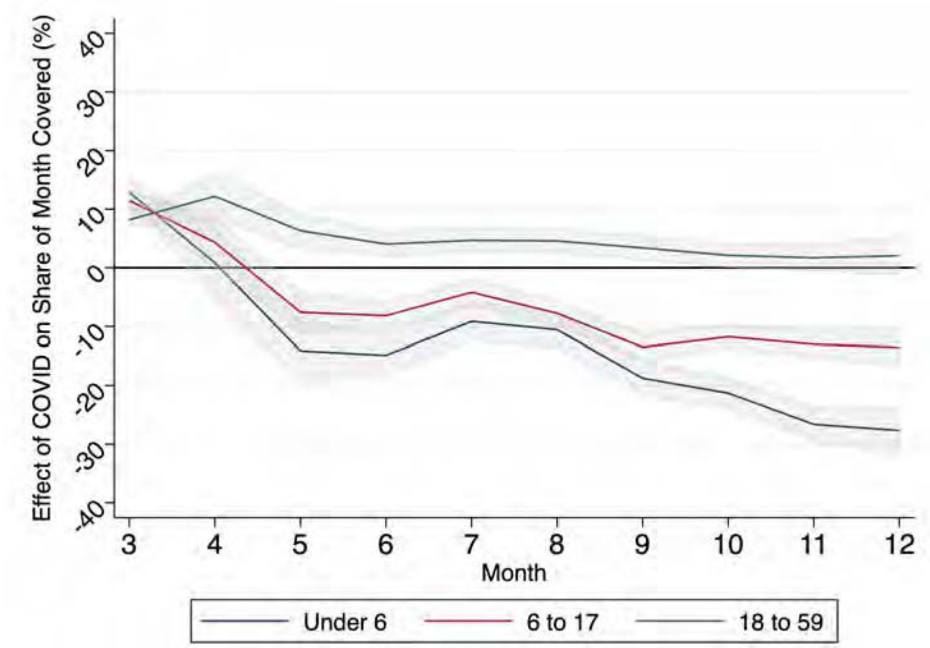
We provide robustness checks and additional results, using the IQVIA dataset.

Figure A1: Change in Monthly Drug Adherence During Pandemic using Individual Fixed Effects: Variation by Age

(a) 0– 59 Years Old



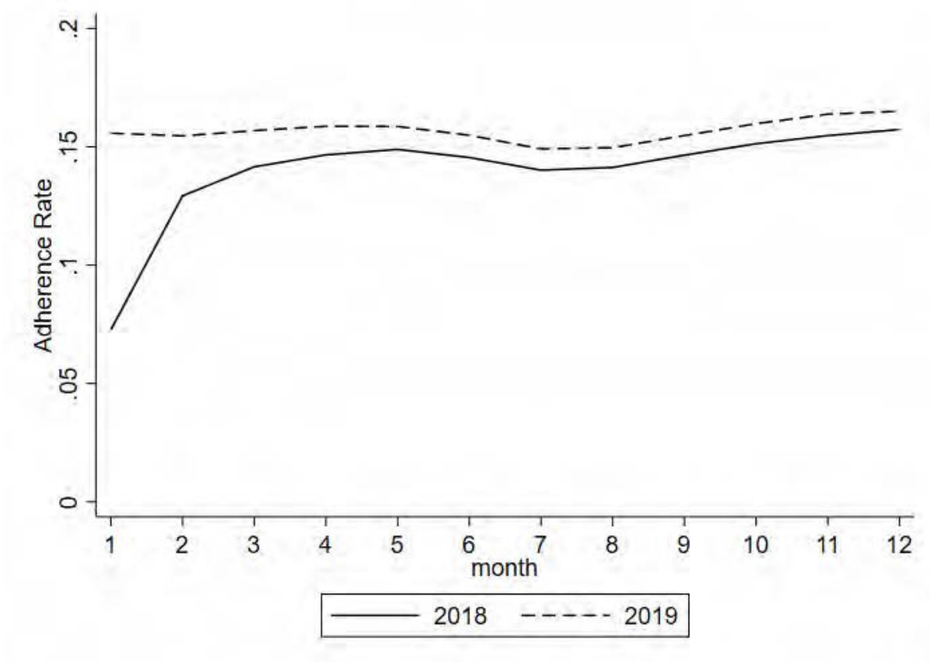

(b) Heterogeneity by Age




*Notes:* These figures plot the monthly raw adherence rates in 2019 and 2020 for a 1 in 20 sample of the population of continuing users. Continuing users are defined as those having had a prescription for asthma medication in the prior year.

Figure A2: Pre-Pandemic Seasonal Trends in Drug Adherence: 2018 and 2019

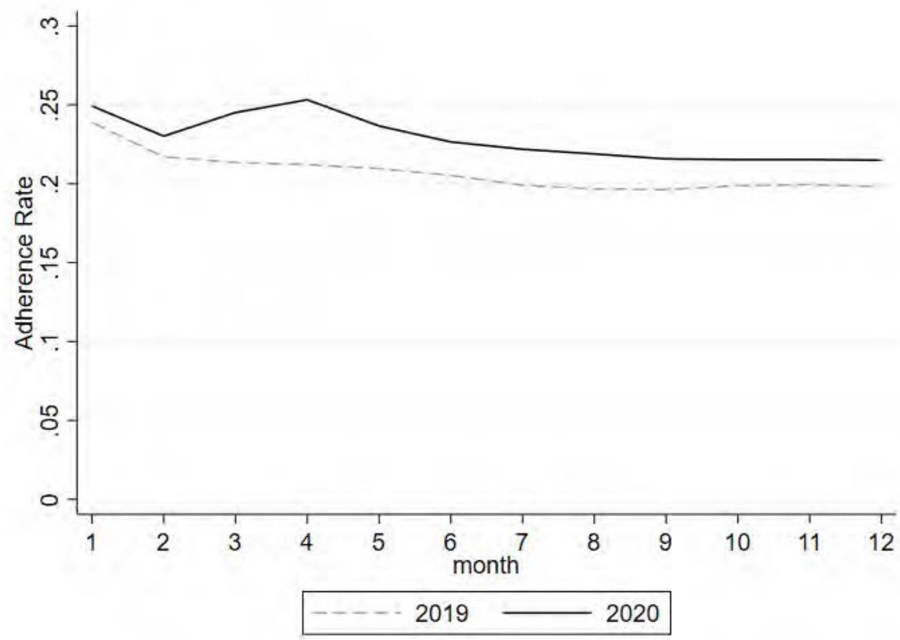
(a) 1 in 20 Sample of Full LrX Population



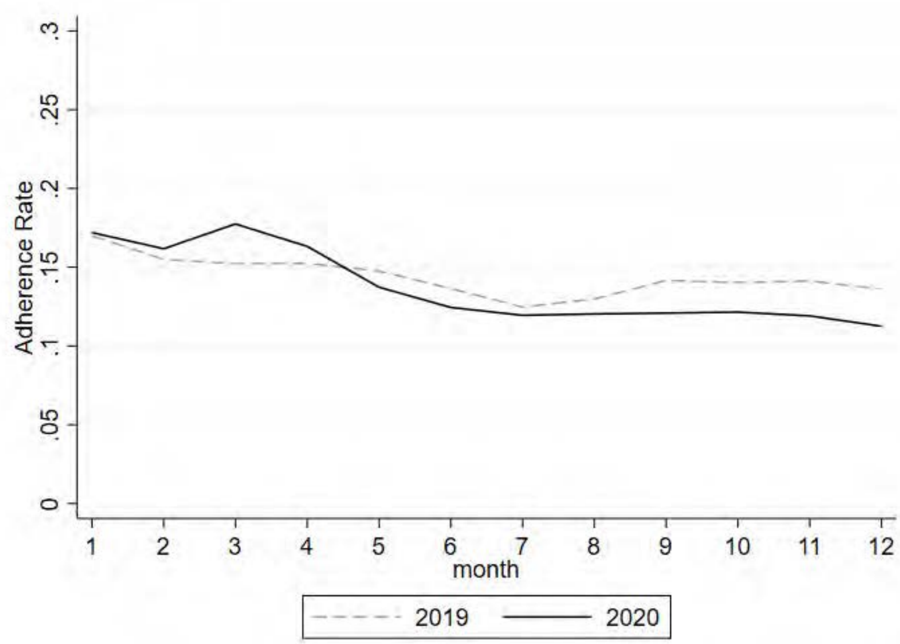

*Notes:* These figures plot the monthly raw adherence rates in 2018 and 2019 for a 1 in 20 sample of the population of asthma prescription claims, regardless of age.

Figure A3: Raw Trends in Adherence Rates: 2019 and 2020

(a) Adults Aged 18–59



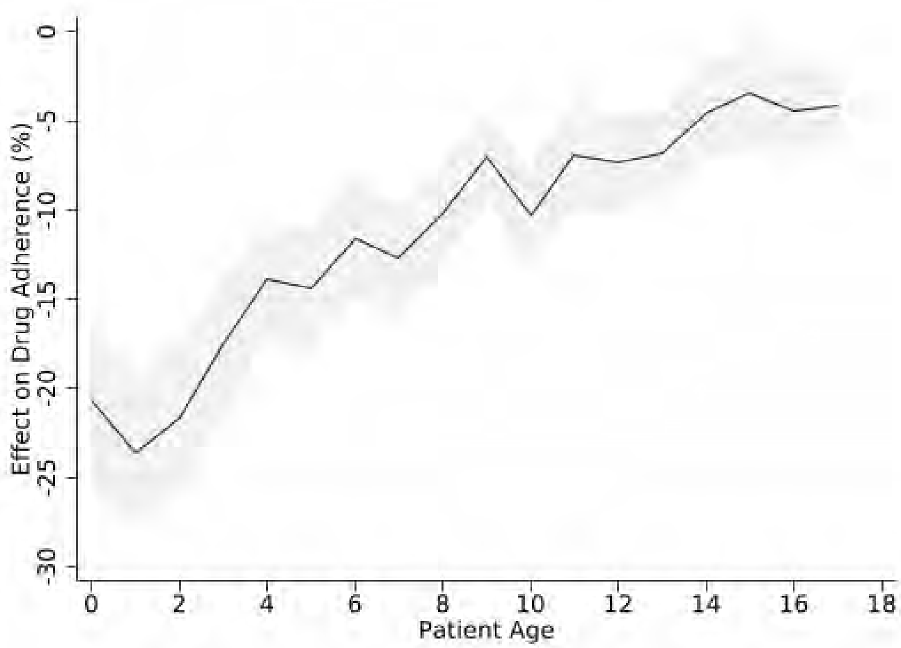

(b) Children Aged 0–17




*Notes:* These figures plot the monthly raw adherence rates in 2019 and 2020 for a 1 in 20 sample of the population of continuing users. Continuing users are defined as those having had a prescription for asthma medication in the prior year.

Figure A4: Estimated Effect of COVID: Variation by Age

(a) Non-Parametric Estimates




*Notes:* This figure plots the effect of the pandemic on drug adherence rates based on equation 2 and estimated separately for each age between 0 and 17. Point estimates are scaled by sample-specific adherence rates in January and February 2019. Estimates based on a specification that controls for state x month unemployment rates, monthly COVID case counts, monthly mobility and includes state fixed effects.

Table A1: Variable Definitions: Supplemental Data Sources

| **Variable** | **Definition** |
|---|---|
| High Asthma Prevalence | Dummy variable equal to one for patients with a provider located in a county that is in the top 25th percentile of the distribution of asthma prevalence rates *Source: Torch Insights, drawn from the Behavioral Risk Factor Surveillance System* |
| Medicaid Expansion | Dummy variable equal to one for patients with a provider located in a Medicaid Expansion State as of 12/31/2019 *Source: Kaiser Family Foundation* |
| High Minority Population | Dummy variable equal to one for patients with a provider located in a county in the top 25th percentile of the distribution of the share of the population that is non-white. *Source: Torch Insights, drawn from the American Community Survey* |
| High Education | Dummy variable equal to one for patients with a provider located in a county in the top 25th percentile of the distribution of the share of the population that has at least some college experience. *Source: Torch Insights, drawn from the American Community Survey* |
| High Income | Dummy variable equal to one for patients with a provider located in a county in the top 25th percentile of the distribution of per-capita income. *Source: Torch Insights, drawn from the American Community Survey* |
| Urban | Dummy variable equal to one for patients with a provider located in an zip code where more than 75% of the population is categorized as living in an urban area. *Source: U.S. Census* |
| High School Closure | Dummy variable equal to one for patients with a provider located in an a county that is in the top 25th percentile when ranked based on the share of schools with at least a 50% drop in school attendance in September, 2020 compared to September, 2019. *Source: U.S. School Closure and Distance Learning Database, Parolin and Lee (2021)* |
| AQI Drop | Dummy variable equal to one for patients with a provider located in an a county that experienced a drop in the average Air Quality Index (AQI) compared with 2018 to 2019 trends, which reflects an improvement in air quality *Source: Environmental Protection Agency* |
| Telehealth | Dummy variable equal to one for patients with a provider located in a state that required insurers to cover telemedicine services *Source: Commonwealth Fund Issue Brief* |
| Unemployment Rate | State-by-month unemployment rates from 2019–2020 *Source: Current Population Survey* |
| Mobility | County-level mobility data that track average weekly mobility levels for each county in the U.S. during the pandemic based on GPS data collected by Google. For our core analysis, we use the variable "time spent away from home" as a proxy for how much mobility there is in the county. *Source: (Chetty et al., 2020)* |
| Covid Case Counts | Number of new COVID cases, by state by month *Source: Centers for Disease Control* |

Table A2: Estimated Effect of Pandemic on Adherence: Robustness to Sample Size

| | Main (1) | 0–6 (2) | 6–17 (3) | 18–59 (4) |
|---|---|---|---|---|
| 5% Sample | 0.00324*** | -0.0201*** | -0.0103*** | 0.0126*** |
| | (0.000308) | (0.000745) | (0.000623) | (0.000396) |
| Observations | 30,163,176 | 3,744,228 | 7,077,048 | 19,341,900 |
| 25% Sample | 0.00348*** | -0.0202*** | -0.0103*** | 0.0130*** |
| | (0.000138) | (0.000335) | (0.000280) | (0.000177) |
| Observations | 150,677,436 | 18,739,284 | 35,267,832 | 96,670,320 |
| 50% Sample | 0.00347*** | -0.0201*** | -0.0102*** | 0.0129*** |
| | (0.0000975) | (0.000237) | (0.000198) | (0.000125) |
| Observations | 301,446,312 | 3,750,6720 | 70,546,620 | 193,392,972 |
| 100% Sample | 0.00355*** | -0.0200*** | -0.0101*** | 0.0130*** |
| | (0.0000689) | (0.000167) | (0.000140) | (0.0000886) |
| Observations | 603,082,560 | 74,999,076 | 141,138,876 | 386,944,608 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Estimates based on variation in age of patient, and report mean differences across a 5%, 25%, 50%, and 100% random sample of the population LRx data. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table A3: Variable Definitions: IQVIQ LRx Databse

| Variable | Definition |
|---|---|
| Drug Adherence | Share of days in a given month covered by the oldest, unused prescription. Constructed based on the following Rx specific information: the date the prescription was filled and the number of days that the prescription is intended to last, as instructed by the healthcare provider *Source: LRx, IQVIA*. |
| Age | The age of the patient at the time of the transaction using year of birth. *Source: LRx, IQVIA* |
| Gender | Gender of Patient (M,F) *Source: LRx, IQVIA* |
| Provider Zip Code | The zipcode for the provider's primary address. *Source: LRx, IQVIA*. |
| Chronic | Dummy variable equal to one for patients that were in the top 25th percentile of the distribution of days supplied in the prior year. *Source: LRx, IQVIA* |
| Payer | Primary Method of Payment: Cash, Medicaid, Third Party, Medicare, Medicare Part D *Source: LRx, IQVIA* |
| Mail Order | Dummy variable equal to one if the pharmacy distribution channel for the last prescription filled in the prior year was indicated to be "Mail" *Source: LRx, IQVIA* |

Table A4: Estimated Effect of Pandemic on Adherence: Divergent Medical Needs

| | Main | | 0–18 | | 18–59 | |
|---|---|---|---|---|---|---|
| | Diabetes (1) | Depression (2) | Diabetes (3) | Depression (4) | Diabetes (5) | Depression (6) |
| March DD | 0.0176*** | 0.00553 | -0.0101 | -0.0192*** | 0.0180*** | 0.00723* |
| | (0.00399) | (0.00338) | (0.00666) | (0.00407) | (0.00402) | (0.00339) |
| Apr DD | 0.0405*** | 0.00885 | -0.0404* | -0.0578*** | 0.0416*** | 0.0136 |
| | (0.00915) | (0.00744) | (0.0198) | (0.00945) | (0.00914) | (0.00747) |
| May DD | 0.0313*** | 0.00776 | -0.0259 | -0.0456*** | 0.0321*** | 0.0117* |
| | (0.00652) | (0.00537) | (0.0159) | (0.00697) | (0.00649) | (0.00541) |
| June DD | 0.0227*** | 0.00695 | -0.0127 | -0.0309*** | 0.0232*** | 0.00980** |
| | (0.00433) | (0.00363) | (0.0114) | (0.00532) | (0.00430) | (0.00364) |
| July DD | 0.0216*** | 0.00738* | -0.0145 | -0.0270*** | 0.0221*** | 0.00996** |
| | (0.00395) | (0.00354) | (0.0106) | (0.00563) | (0.00390) | (0.00350) |
| Aug DD | 0.0198*** | 0.00700* | -0.0144 | -0.0252*** | 0.0202*** | 0.00943** |
| | (0.00360) | (0.00335) | (0.00944) | (0.00509) | (0.00355) | (0.00331) |
| Sept DD | 0.0181*** | 0.00789* | -0.0149 | -0.0222*** | 0.0186*** | 0.0102** |
| | (0.00312) | (0.00309) | (0.00880) | (0.00465) | (0.00306) | (0.00305) |
| Oct DD | 0.0158*** | 0.00683 | -0.0202* | -0.0255*** | 0.0163*** | 0.00926** |
| | (0.00334) | (0.00341) | (0.00864) | (0.00447) | (0.00331) | (0.00338) |
| Nov DD | 0.0182*** | 0.00697 | -0.0279** | -0.0332*** | 0.0189*** | 0.00994* |
| | (0.00439) | (0.00427) | (0.00971) | (0.00515) | (0.00439) | (0.00425) |
| Dec DD | 0.0228*** | 0.00964 | -0.0330** | -0.0372*** | 0.0236*** | 0.0131* |
| | (0.00545) | (0.00527) | (0.0113) | (0.00625) | (0.00547) | (0.00525) |
| Constant | 0.590*** | 0.498*** | 0.559*** | 0.474*** | 0.590*** | 0.500*** |
| | (0.00283) | (0.00263) | (0.00590) | (0.00408) | (0.00279) | (0.00260) |
| Control Mean | 0.590 | 0.497 | 0.549 | 0.467 | 0.591 | 0.499 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 13,851,228 | 40,536,639 | 370,968 | 3,003,707 | 13,480,260 | 37,532,932 |

*Notes*: This table reports estimates based on a difference-in-different model described in equation (1). Columns (1), (3), and (5) present estimates for the effect of the pandemic on diabetes drug adherence based on continuing user patients with diabetes. Likewise, columns (2), (4), and (6) present estimates for the effect of the pandemic on diabetes depression adherence based on continuing user patients with depression. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table A5: MEPS Horserace (Under 18)

| | Asthma Log(Q) | Non-Asthma Log(Q) |
|---|---|---|
| 2020 | -2.096*** | -2.313*** |
| | (0.192) | (0.160) |
| Asthma × 2020 | 0.564 | – |
| | (0.460) | |
| All Rx × 2020 | 0.293* | 0.372*** |
| | (0.144) | (0.101) |
| ΔMental× 2020 | -0.131 | 0.026 |
| | (0.388) | (0.357) |
| Lost Job× 2020 | -0.374 | -0.975* |
| | (0.461) | (0.419) |
| Lost Ins × 2020 | 0.172 | 0.468 |
| | (0.860) | (0.581) |
| Education × 2020 | -0.0587 | -0.073 |
| | (0.0922) | (0.068) |
| Log Hourly Wage | -0.0967 | 0.019 |
| × 2020 | (0.133) | (0.122) |
| Person FE | x | x |
| No. Individuals | 330 | 585 |

Notes: Column 1 is a horserace version of Panel B of Table 19 and Column 2 is the corresponding analysis for non-asthma prescriptions. All measures are demeaned to preserve the interpretation of the overall effect. "Asthma" is an indicator for whether an adult in the family also has asthma scripts in 2020. "All Rx" refers to log of the total adult scripts in 2020. ΔMental refers to the average change in self-reported mental health status across all adults in the family, with higher values representing worse status. Education refers to the higher number of years of education of any adult in the family. "Lost Ins" and "Lost Job" indicate whether any adult in the family lost insurance coverage or lost employment across the three rounds of the survey in 2020, respectively. "Log Hourly Wage" refers to the log of the total hourly wage across all adults in the family at the start of 2020.