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PEDIATRIC DRUG ADHERENCE AND PARENTAL ATTENTION: EVIDENCE FROM COMPREHENSIVE CLAIMS DATA

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ABSTRACT

We study how pediatric drug adherence responds to macroeconomic shocks, leveraging comprehensive U.S. claims data and the COVID-19 pandemic. For the youngest asthmatic children, adherence to prescriptions fell by 30 percent by the end of 2020, with smaller negative effects for older children. The effect is not driven by factors distinctive to COVID, including school closures and air quality. Rather, we find evidence consistent with parental attention playing a large quantitative role. Our findings speak to the role of non-monetary factors in determining an important pediatric health behavior and to the evolution of the pediatric health-parental income gradient.

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1 Introduction

Parents wield significant influence over their children's health behaviors and outcomes (Case and Paxson, 2002). Previous studies have revealed two key findings regarding the association between parental economic circumstances and the health of their offspring. First, young children who grow up during a macroeconomic downturn experience worse health throughout their life (Van Den Berg et al., 2006). Second, there is a strong cross-sectional relationship between parental income and children's health — one that gets stronger as children age (Case et al., 2002; Currie and Stabile, 2003; Conti et al., 2010). However, the precise contribution of monetary and non-monetary mechanisms to these patterns remains uncertain. Resolving this ambiguity is crucial for assessing the effectiveness of cash transfer policies in improving children's well-being.

One key behavior that could contribute to both empirical observations is the management of chronic health conditions through prescription drug regimens. In particular, poor drug adherence increases the likelihood of negative clinical outcomes and increases the total cost of healthcare (Milgrom et al., 1996; Ordoñez et al., 1998; McCarthy, 1998; Chandra et al., 2010; Osterberg and Blaschke, 2015). Existing studies of nonadherence have identified several drivers in the adult population, including insurance coverage and socioeconomic factors. Systematic evidence on the drivers of *pediatric* adherence, however, is scarce — particularly the exploration of monetary and non-monetary mechanisms.

In this paper, we use comprehensive prescription claims data and the COVID-19 pandemic to shed light on mechanisms that drive pediatric adherence to prescription drug regimens. First, we establish that pediatric adherence to asthma medication fell significantly during the pandemic. Second, we show that factors that distinguish COVID from other macroeconomic downturns, such as school closings, restricted access to healthcare, and reduced environmental triggers, do not drive our results. Finally, we provide additional analyses that suggest parental attention plays a large role in driving the observed patterns. Together, the findings speak to how pediatric adherence responds to downturns and the broader role parental attention plays in the management of chronic disease.

We focus on the usage of asthma treatments because asthma is the single most prevalent chronic disease among children.[1] One-in-five children (8.6 million) reported having been diagnosed with asthma in the United States according to the 2018 National Health Interview Survey. Management of asthma symptoms almost always requires prescription drugs, delivered in either an aerosolized form (inhaler) or orally (pills). Poor drug adherence among pediatric asthma patients has been shown to negatively affect long-term health, educational attainment, and income (Ordoñez et al., 1998; Miller et al., 2009; Currie, 2009).

Our primary analysis relies on IQVIA's Longitudinal Prescription Claims (LRx) dataset, which is a transactions database that captures near-population level prescription drug claims from the U.S. market. These data contain individual identifiers, individual age and gender, prescription characteristics, and the geographic location of prescribers. The richness of this database conveys several advantages over previous studies, which are typically based on small sample surveys and self-reported information. First, these data are large enough to permit fine-grained subsample analysis to investigate the mechanisms underlying our result. Second, these data are comprehensive enough to track individuals over time, regardless of insurer. Alternative national databases, such as MarketScan, typically only track individuals to the extent that they remain covered by a subset of insurers. Finally, these data allow us to measure health behavior in a non-survey context by recording prescription fills and refills.

With this data, we build a patient-by-month panel that measures monthly medication coverage rates for roughly 12.8 million pediatric 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. This analysis compares monthly coverage rates in pre- and post-COVID months for patients in 2019 and 2020.

We find a sustained decrease in pediatric drug adherence during the pandemic. Overall,

[1]We also use data from diabetes and other non-asthma medication to provide additional evidence on pediatric adherence.

we estimate that adherence fell by 8.4 percent from March through December 2020. However, the dynamics of this effect are more sharply negative later in the year and for the youngest children in our sample. By December 2020, preschool-aged children experience a 30 percent decrease in adherence rates. During the same time period, adherence among school-aged children and teenagers fell by 14 percent and 7 percent, respectively.

Given the unique nature of the COVID pandemic as compared to other recessionary periods, we test whether these effects are driven by distinctive COVID factors or COVID-impacted measures. These include school closures, changes in air quality, changes in access to doctors and pharmacies, mobility, and COVID case counts. We study the potential mediating effect of these and other county and state-level socioeconomic measures. We find that these factors play a minimal quantitative role in driving the observed effect. Consistent with this, we show that the decrease in pediatric adherence is similar across all geographic areas, despite large geographic variation in the intensity of the pandemic.

Finally, we provide several pieces of evidence consistent with parental attention playing a major role in driving the observed effect. Our conjecture is that parental attention on chronic disease management fell during 2020. This would have the largest impact in cases where: (1) children cannot communicate; (2) feedback from not taking medication is not immediate; and, (3) there is a lack of built-in routines such as parents picking up their own prescriptions at the same time. Within the asthma data, we find that age and usage intensity in the previous year are the only quantitatively significant predictors of individuals' adherence responses. Beyond asthma, we find that pediatric adherence does not decrease for diabetes treatments, as would be expected for a more acute disease. Finally, we show using data from the Medical Expenditure Panel Survey (MEPS) that the pediatric adherence response in asthma and other chronic disease areas is much less negative when parents pick up prescriptions for themselves.

We contribute to the significant literature on the determinants and consequences of drug adherence. This 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, this 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; 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).[2] Our evidence speaks to an understudied and influential factor related to pediatric adherence: parental attention.[3] 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.[4]

We also contribute to the large body of work documenting the effects of macroeconomic conditions on health behaviors and outcomes. 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). In contrast to the general trends within adults, Burgard and Hawkins (2014) document decreases in healthcare use during the Great Recession, especially

[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, which we also see in our results, 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] Our findings on the importance of parental attention are consistent with survey evidence discussed in Matsui (2007).

[4] 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. (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.

among African Americans and Hispanics and among those individuals with less education. Our results add to this literature by studying the adherence behavior of children using comprehensive transaction data, and showing evidence that the negative response is not driven by factors special to COVID. They also suggest that fiscal stimulus is unlikely to mitigate the impact.

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 (SES), one that strengthens as children grow older (Case et al., 2002; Currie and Stabile, 2003; Conti et al., 2010). Yi et al. (2015) provides evidence of the reallocation of resources by parents in response to children's health shocks. 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 as children age.

2 Background

2.1 Asthma Prevalence, Management, and Measurement

In our core analysis, we focus on adherence to asthma medication. Asthma is one of the most prevalent conditions affecting children, and poor adherence to medication can lead to a number of adverse outcomes. 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. In 2018, 8.5 million (11.6 percent) children under 18 reported ever having been diagnosed with asthma, and 5.5 million (7.5 percent) children reported still having asthma. These and all subsequent summary statistics in this section are based on the author's calculations using the 2018 National Health Interview Survey (NHIS).

Drug adherence is a fundamental part of disease management, especially for chronic conditions like asthma. Asthma can be managed by taking short-term medications to help relieve symptoms during an asthma attack and long-term medications to help prevent attacks and control symptoms by reducing airway inflammation and preventing the narrowing of airways. In 2018, 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.

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). Drug adherence, or compliance, refers to the behavior of the patient in following a prescribed medication regimen. Non-adherence to drug therapy is a common problem, both in the general chronic population and specifically among asthmatic individuals. Poor adherence has been shown to have direct consequences for disease management, including increased risk of hospitalization and death (see, for example, Osterberg and Blaschke, 2015). Among asthma patients, average adherence rates have been shown to be below 50 percent (Bender et al., 1997; Yawn et al., 2016).

The costs and health consequences of mismanaged asthma can be large and myriad. When well controlled, asthma rarely leads to hospitalization, but non-adherence increases the odds of experiencing an asthma attack and emergency room visits, increasing healthcare spending (Weiss et al., 1992). Nurmagambetov et al. (2018) document significant costs during the 2008–2013 period using MEPS data. They find that asthma was responsible for \$9.7 billion in emergency room visits and hospitalizations.[5] Furthermore, they estimate that asthma led to 5.1 million days of missed schooling and 8.7 million days of missed work.

[5]They do not provide a breakdown by age, but the earlier work by Weiss et al. (1992) using the NHIS estimates that children account for 27% of this number.

Beyond these immediate costs, the medical literature has documented long-run health risks such as reduced lung function and the onset of other comorbidities that increase the risk of mortality (Milgrom et al., 1996; Ordoñez et al., 1998).

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 monthly medication coverage rates 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. We interpret individual-level year-over-year changes in monthly medication coverage rates as changes in adherence. These measures necessarily assume that refill adherence corresponds to drug-taking behavior, as is common in the drug adherence literature. Importantly, objective measures of drug adherence for asthmatic patients have been shown to be more accurate than subjective measures (Bender et al., 1997).

2.2 Timeline of Key COVID-19 Events in 2020

Finally, we discuss key dates in 2020 to provide context for our subsequent estimates. 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. 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 response. 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. In addition, Federal officials encouraged states and insurers to provide similar flexibility under private insurance, which many did (Volk et al., 2021).[6]

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 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.[7]

[6] 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).

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

3 Data and Summary Statistics

3.1 Data Sources

Our primary data source is the IQVIA Longitudinal Prescription Claims (LRx) 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), and primary payer (third party and managed Medicaid, fee-for-service Medicaid, Medicare, and cash). We provide detailed variable descriptions for these supplemental data, including sources, in Appendix Table A1. These data cover the vast majority of prescription drug claims in the U.S. market.

We study an extract of these data that captures all prescriptions associated with the treatment of asthma. The detail in these data permits us to generate a continuous, monthly 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.

We supplement these data with detailed geographic information describing the local population, including race, income, education, occupation, population density, asthma prevalence, and access to health insurance. All geographic information is matched to individuals based on their prescriber's zip code. In addition, we capture the development of the COVID pandemic using measures of case counts, changes in average weekly mobility levels, school closure rates, changes in air quality, and telehealth services prior to the pandemic using several external sources. We provide detailed variable descriptions for these supplemental data, including sources, in Appendix Table A2.

3.2 Constructing a Measure of Drug Adherence

Using the LRx database, we construct a monthly patient-level panel data set to study drug adherence in 2019 and 2020. We compute the share of days covered by a prescription in each month for each patient based on the prescription fill date and days of medication supplied. This process determines the stock of medication available based on the flow of prescription fills and refills.

To create our measure, we first identify the earliest claim in the LRx database for each patient and then track their stock of medication across subsequent prescription claims. We decrease the stock by one each day between prescription fills and refills, and we add additional medication to the stock with each new prescription observed. If a patient stock hits zero, all subsequent days are marked as uncovered until the next prescription is filled. We aggregate this measure to describe the proportion of days covered by a drug for a given patient within each month. We interpret year-over-year changes in monthly coverage rates as changes in drug adherence. Our measure is similar to other continuous measures such as the "Proportion of Days Covered", which is commonly used 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 monthly coverage rates before the pandemic and to avoid the confounding comparison of impacts on coverage rates for those that may have newly developed respiratory symptoms as a result of a COVID infection. In particular, the only patients included in our sample in year y are those who filled at least one asthma prescription in year $y-1$. We refer to these individuals as continuing users of asthma medication. Our final analysis sample contains roughly 13 million children under the age of 18 in 2019 and 2020.[8]

[8]Based on the 2018 NHIS, there were roughly 8 million children under 18 who report ever having been diagnosed with asthma and 6 million children who report currently having asthma. Our final sample contains roughly 4 million continuing users with an active prescription in 2019, 4 million continuing users with an

We characterize each patient and year based on the prescription characteristics that correspond to the final prescription filled in the previous year. First, we capture variation in 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 identify the payer associated with the last claim in the previous year (i.e., private insurance, Medicaid, Medicare, or cash). We fix these measures in the prior year to characterize any heterogeneity in medication adherence rates that are not influenced by other effects of the pandemic.

3.3 Characterizing Pre-COVID Pediatric Drug Coverage

Given the importance of drug coverage in the construction of our measure of drug adherence, we want to characterize and describe pre-COVID drug coverage. This analysis reveals several novel, descriptive facts.

First, Figure 1, Panel (A) depicts the coverage rate for all continuing users younger than 60 years old, averaged across all months in 2019. Average coverage rates range from 7 to 30 percent of days per month covered by a prescription. However, the relationship between age and coverage rates is different among adults than among children. For adults, coverage rates increase monotonically with age. This is consistent with the fact that the risk of severe asthma increases with age (Zein et al., 2015). Among children under 18, however, there is a non-monotonic relationship between coverage rates and age. In particular, coverage increases sharply with age up until age 8, plateaus, and then begins to fall for children aged 12 to 18. This shape cannot be fully reconciled by patterns in the onset of pediatric disease, which typically *decrease* with age (Zhang and Zheng, 2022) through age 18. Instead, these patterns likely combine changing disease severity and frictions that are unique to the pediatric population and affect coverage rates.

In Panel (B), we unpack monthly patterns in medication coverage for the pediatric pop-

active prescription in 2020, and 4 million users with an active prescription in 2019 and 2020.

ulation. This figure exposes underlying seasonality, where coverage is lowest in the summer months and highest in the early winter. These seasonal patterns mirror seasonal trends in environmental triggers that affect the severity of asthma symptoms. In Panel (C), we decompose pediatric coverage rates by income. While children living in low-income areas are more likely to be asthmatic, income is also a negative predictor of pediatric adherence (Matsui, 2007). We show that coverage rates are lower for patients who live in low-income geographies as compared to high-income geographies across all ages. Finally, Panel (D) depicts the average pediatric coverage rate by county in 2019, revealing the scope of geographic variation that exists across the United States.

In Table 1, we describe our analysis sample of continuing users in 2019 (Model 1), and then separately across three age subgroups (Models 2 to 4). The first subgroup roughly corresponds to children who are preschool-aged, the second children in elementary and middle school, and the third children in high school.[9] We observe 8.6 million unique users, of which 32, 42, and 26 percent are under 6, aged 6 to 12, and aged 13 to 17, respectively. Panel (A) describes individual characteristics of patients while Panel (B) describes geographic characteristics based on their providers.

Pediatric patients in our analysis sample are, on average, 8.26 years old. Their baseline consumption of medication is enough to supply 16 percent of the days within a month. Our sample is more likely to be male than female, consistent with external evidence that the risk of onset for pediatric asthma is higher for boys than girls. 12 percent of children were covered by fee-for-service Medicaid, and 85 percent were covered by a third-party payer, either private insurance or managed Medicaid. Finally, the average patient had enough medication to cover 71 days in 2018.

Next, we show that providers were located in relatively low-income counties, with an average per-capita income of roughly $32,000, a minority share of roughly 27 percent, and where roughly 21 percent of the population has completed at least some post-secondary

[9] We identify patient age at the start of the year to avoid within-year attrition.

education. These patients are overwhelmingly likely to come from urban areas, and they are roughly evenly divided among Medicaid expansion and non-expansion states.

4 The Impact of COVID on Pediatric Adherence

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

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

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

Here, y_{imt} measures the monthly drug coverage rate for individual i in month m in year t. μ_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 $m = 3, ..., 12$. λ_{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, γ_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. We are focused on ϕ_m, which identifies the change in monthly coverage rates from March through December 2020 compared to these same months in 2019 and relative to January and February as control months. All estimates are clustered based on the state of the last known provider in the prior year.

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), ϕ_m, into one post period:

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

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

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

For example, suppose π_i is a dummy variable equal to one for chronic patients and zero for non-chronic patients. Then ψ captures the estimate of the pandemic on monthly coverage rates for chronic patients relative to non-chronic patients, or the relative difference-in-differences.

We report summary statistics from 2019 and 2020, measured in our control months (January and February) in Table 2. Panel (A) describes the characteristics of patients and Panel (B) describes the geographic characteristics associated with the zip code of their provider. Broadly, these statistics underscore the similarity of patients in control months across the two years.

4.2 Core Estimates: Effect of Pandemic on Drug Adherence

We begin by documenting the average adherence response to the pandemic using our difference-in-differences model. Figure 2, Panel (A) reports mean changes in monthly coverage rates, scaled by the average coverage rate in January and February 2019. Results are presented separately for preschool-aged kids (aged 1 to 5), school-aged children (aged 6 to 12), and teenagers (aged 13 to 17).

For the March through December 2020 period, we estimate that adherence fell by 8.4 percent.[10] At the start of the pandemic, we find that adherence rates increased by 11 percent across all pediatric age groups. This abnormally large increase in adherence rates likely reflects stock-piling behavior that was seen across a wide variety of consumption goods at the start of the pandemic. However, this behavior was short-lived: pediatric adherence rates fell sharply in April and May. While adherence rates recovered somewhat during the late summer months, they fell even further beginning in the fall and through the end of 2020, with the youngest group exhibiting the largest effects. Focusing on December 2020, we find that preschool-aged children experience a 30 percent decrease from their expected coverage rate, while school-aged children and teenagers experienced decreases of 14 percent and 7 percent, respectively. Overall, these results describe a large and persistent negative response in pediatric adherence rates due to the onset of the pandemic. Moreover, the dynamics of this effect are more sharply negative for the youngest children in our sample.

In Figure 2, Panels (B) and (C) we enrich our specification by including state and individual fixed effects, respectively. State fixed effects control for all time-invariant unobservable determinants of pediatric adherence at the state level (e.g., policies that affect access to health insurance). Individual fixed effects subsume state fixed effects and additionally control for all time-invariant unobservable determinants of pediatric adherence at the individual level (e.g., disease severity). We find similar quantitative and qualitative estimates of the

[10] Drug coverage fell by 1.3 percentage points from March – December of 2020 (Table 3, col 1). We scale this by average drug coverage during January and February of 2019 (16%), reported in column 1 of Table 1. 1.3 pp / 16% = 8.4%

effect of the pandemic based on estimates that include either state or individual fixed effects. We report the corresponding month-by-month estimates for all three specifications in Appendix Table A3.[11]

In all cases, our negative estimates persist throughout the year, despite several events specific to the evolution of the pandemic and associated macroeconomic environment. First, stimulus payments were made in two waves during 2020. The first wave of payments began in mid-April, a time when pediatric adherence was falling. The second wave began at the end of December. These payments, however, do not correspond to an aggregate increase in pediatric adherence rates.

Second, the onset of the pandemic forced many schools and daycare centers to close for in-person learning, forcing young children and students into a remote learning environment. For example, by March 25, 2020, all U.S. public schools were temporarily closed to in-person learning. By mid-April, half of all public schools announced that remote-only learning would continue through the end of the academic year.[12] This time period corresponds with the sharp initial decline in pediatric adherence. By fall, adherence, especially among the youngest children, continued to plummet at a time when the majority of school districts had moved to a hybrid-learning model.

Finally, we report the within-county effect of the pandemic in Panel (D). As before, all estimates are scaled by average coverage rates in January and February 2019. This map underscores both the severity and the scope of the COVID response. Nearly all counties saw a decrease in pediatric coverage rates, regardless of underlying differences in population, political landscape, access to health care and health insurance, localized evolution of the pandemic, and many other factors. We revisit these and other COVID-specific factors in

[11] Appendix Table A4 provides additional estimates limited to the subsample of continuing users who have had an active prescription since 2018. These users contribute the most causal variation to the individual fixed effects specification because we observe their monthly coverage rates in each month from January 2019 through December 2020. Results are both qualitatively and quantitatively similar for this subsample of users.

[12] See https://www.edweek.org/leadership/a-year-of-covid-19-what-it-looked-like-for-schools/2021/03 (retrieved July 27, 2023).

greater detail in Section 5.

Appendix B.2 provides additional evidence that there are large, persistent decreases for some children. Using a random effects approach, we break down the year-on-year changes by individual and month. We find that the distribution of individual effects has a very large standard deviation relative to the average effect. The estimates suggest that our results are not driven by random negative shocks affecting all children, but by some children consistently having the same response relative to the (negative) mean response.

To summarize, our core results establish that pediatric adherence decreased significantly during the pandemic. The effects persist throughout 2020 and are the largest for the youngest children. We are able to precisely estimate this response to the pandemic thanks to the richness of our data, which includes the near-universe of transactions.

4.3 Identification and Data Validation

As previously discussed, our estimates are based on a difference-in-differences comparison of the change in monthly coverage rates before and after the onset of the pandemic in 2020 compared to the same months in 2019. Identification within this model requires that within-year seasonal variation in drug coverage rates would have been similar in 2020 and 2019 if not for the onset of the pandemic. We showed that there is seasonality in monthly coverage rates during 2019, with lower coverage in the summer months and higher coverage rates in the winter months (Figure 1, Panel B). This seasonality matches known seasonal variation in environmental triggers and highlights the necessity of our difference-in-differences control group. A simple comparison of the change in coverage rates after the onset of the pandemic (March to December) compared to before the pandemic (January and February) that was based only on changes in 2020 behavior before and after the onset of the pandemic would inappropriately attribute counterfactual seasonal changes in adherence.

To this end, we illustrate the dynamics of our difference-in-differences analysis by plotting raw trends in monthly coverage rates for children in 2019 and 2020 (Figure 3, Panel

A). During January and February in both 2019 and 2020, children experience very similar monthly coverage rates, supporting our assumption of counterfactual parallel trends across 2019 and 2020, if not for the onset of the pandemic. In March 2020, coverage rates rise relative to 2019 and fall sharply before leveling out at abnormally low rates in July 2020. Thereafter, coverage rates remain abnormally low, failing to follow typical seasonal patterns that would predict an increase in coverage rates during the fall. This leads to a negative estimate of the effect of the pandemic on pediatric adherence beginning in May 2020 and lasting throughout the year.

Abnormally low adherence rates in 2020 raise concerns about whether data quality issues arose during the pandemic. In particular, if the IQVIA database simply has worse or lower coverage due to data quality issues that arose during the pandemic, this would be consistent with the negative effects that we find for children. We provide two pieces of evidence to assuage these concerns. First, there were no known data quality issues during this time period. These data do not require any of the kind of in-person hand collection that led to data quality issues seen during the onset of the pandemic in other data sources, such as the Current Population Survey. Second, we implement a parallel difference-in-differences analysis to estimate the response of adult adherence rates. In the case of pandemic-related data-quality issues, we should see similarly abnormal, low adherence rates arise for the adult population. Instead, we find that adult adherence rates are *elevated* (Figure 3, Panel B) compared to what we observed across the pediatric population (Figure 2, Panel A). While adults constitute a different population with known variation in the presentation of symptoms, severity, and the maintenance of care compared with children (Trivedi and Denton, 2019), the analysis nonetheless provides additional evidence in support of our data quality during the pandemic.

5 Mechanisms: COVID Specific Factors and Parental Attention

In this section, we refine and extend our core results to derive implications for children's health behavior during macroeconomic events and in the cross-section.

5.1 Overview of Heterogeneity Results

We start by providing an overview of our heterogeneity analysis. For this, we enrich our core analysis in two ways. First, we add controls for COVID case counts, state unemployment, and mobility at the county-by-month level to partly control for channels specific to COVID. Second, we add a host of interactions with the core treatment effect to create a "horserace" regression following Equation (3). These include COVID-specific factors (e.g., school closings and air quality), individual-level factors (e.g., age, intensity of usage, insurance status, and use of mail order), and regional factors (e.g., demographics, economic indicators, and health policies).

Table 3 provides estimates from the basic difference-in-difference regression with controls and the "horserace" regressions that incorporate multiple interactions. In Model (1), we estimate that the average adherence rate fell by 1.33 percentage points for children. This average estimate serves as context for the subsequent discussion.[13] In Model (2), we control for COVID-specific facts; in Model (3), we control for user-specific disease intensity; and in Model (4), we combine these latter two control groups with a rich set of demographic and other provider-based characteristics.

Across all four models, we find that the only predictive factors in the horserace regression are age and disease intensity. The rest, including COVID-specific factors, are fairly unpredictive of the average effect, which suggests that despite the unique nature of the pandemic, COVID-specific factors do not drive our core estimates. In light of this, we interpret changes

[13]The average incorporates the stockpiling behavior that we observe in March, so it will understate the negative response observed during the later months of 2020.

in monthly coverage rates after the onset of the pandemic as a non-adherence response. In the remainder of this section, we discuss these additional analyses in greater detail.

5.2 Accounting for COVID-Specific Factors

We start by focusing on COVID-specific factors. If our core estimates are driven by elements of the pandemic, then these estimates likely have little to say about pediatric health behavior during other macroeconomic downturns. Table 3, Model (2) jointly estimates the effects of all COVID-specific factors, while Appendix Table A7 reports separate estimates exploring the effect of each COVID-specific factor.[14]

5.2.1 School Closures

The onset of the COVID-19 pandemic led to an historic, nationwide lockdown that resulted in the sudden closure of schools to in-person learning. In-person schooling can affect pediatric adherence in several ways. For example, many school policies had been put in place prior to the pandemic to increase pediatric medication adherence. For example, schools provide reminders to students to take their medication and reminders to parents to refill expiring or fully consumed prescriptions (McClure et al., 2020). This mechanism would tend to reduce drug consumption adherence in a remote-learning environment, all else equal.

To investigate how the remote-learning environment may have affected medication adherence, 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 high (low) school closure counties if they fall in the top (bottom) 25th percentile of this distribution

[14] In addition, Appendix Table A8 reports estimates for the subset of users who had an active prescription in 2018, 2019, and 2020. Results are qualitatively and quantitatively similar to the full sample of continuing users.

(*High School Closure*).

Figure 4, Panel (A) reports scaled estimates, and Appendix Table A7, Models (1) and (2) report responses for these two groups. In short, we find little difference in responses between the two groups throughout the year, including in the fall when there is more variation in in-person school attendance. Consistent with this, the estimated coefficient in the horserace regression (Table 3) is also quantitatively small (-0.00304, Model 2), statistically insignificant, and explains only 23 percent of the overall response.

5.2.2 Changes in Environmental Triggers

Next, we explore whether our results are driven by changes in medical need through reduced environmental triggers. In particular, stay-at-home orders imposed during the early months of the pandemic effectively shut down commercial air travel and severely reduced road travel (Berman and Ebisu, 2020; Slezakova and Pereira, 2021; Venter et al., 2020). Both are major contributors to local air pollutant levels. Because air pollution is an environmental trigger for the onset of asthmatic episodes, any associated improvements in air quality would serve to reduce medical need. Moreover, this change is atypical of macroeconomic downturns, which are not usually associated with such a severe reduction in travel.

Figure 4, Panel (B) reports scaled estimates and Appendix Table A7, Models (3) and (4) report point estimates based on whether local air quality was unexpectedly better during the April to August 2020 period (*AQI Drop*).[15] We find minimal differences in patterns across children facing different changes in air quality.[16] In other words, it does not appear that improvements in air quality had a large impact on pediatric adherence rates. Our horserace regression (Table 3, Model 2) shows that air quality improvement is associated with a reduction in drug coverage rates (increase in non-adherence). This is consistent

[15]Changes in air quality are measured by calculating the county-level change in air quality, as measured by the AQI, from April to August 2019 to 2020 relative to the change in air quality that occurred from 2018 to 2019. Lower AQI corresponds to better air quality. The binary variable "AQI Drop" captures whether a county had a negative difference (better air quality relative to trend).

[16]In additional analyses, we see similar patterns when we focus solely on urban counties.

with the hypothesis that better air quality reduced environmental triggers and, therefore, drug consumption. However, we urge caution in interpreting this effect because air quality improvements were most commonly associated with reduced mobility, which we also control for directly in this horserace regression.

5.2.3 Access

Another distinct aspect of COVID is the reduction in person-to-person interaction. It is plausible, therefore, that this reduced access to in-person health care and, as a result, reduced access to prescriptions. For example, a patient may be less able to visit doctors to obtain prescriptions or to pick up prescriptions at a pharmacy. However, previous research has documented that there was increased use of both telehealth services and mail-order delivery of prescriptions during the pandemic (Volk et al., 2021). We test whether access plays a significant role by measuring the preparedness of individuals to switch to telehealth and mail-order delivery.

Using data from the Commonwealth Fund Issue Brief, we identify those states that had policies in place that required insurers to cover telehealth services (*Telehealth*) prior to 2020. The subset of patients using these services prior to the pandemic should have been the least affected by disruptions due to the closures of physician offices. Figure 4, Panel (C) reports scaled estimates and Appendix Table A7, Models (5) and (6) report point estimates based on patients in states with and without pre-pandemic telehealth policies in place. As with other COVID-specific factors, we find that responses are similar throughout the year, regardless of differential access to telehealth. The horserace estimate (Table 3) provides confirmation. We find a quantitatively negligible moderating effect (-0.00044/-0.0133, Models 1 and 2) or less than 5 percent of the average effect.

In additional tests, we analyze the role played by mail-order prescription fills and refills. Patients who were using mail-order prescription delivery prior to the pandemic may have been better able to handle any disruptions to retail pharmacy services. 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. Figure 4, Panel (D) reports scaled estimates and Appendix Table A7, Models (9) and (10) report point estimates based on patients who filled prescriptions by mail as compared to other delivery channels. Consistent with our hypothesis, we find imprecise evidence that the mail-order group exhibits a smaller decrease in adherence rates. However, all users exhibit a decrease in pediatric adherence, regardless of delivery channel. Moreover, once we control for chronic use in the horserace regression (Table 3 Model (4)), which is strongly associated with mail-order usage, the differences become much smaller, around 25 percent of the average effect (0.00334/-0.0133), and statistically insignificant.

5.2.4 Additional factors

To conclude our discussion of COVID-specific factors, we briefly discuss the remaining factors included in Table 3, except for age (*Age*) and disease intensity (*Chronic*), which we discuss in more detail later. First, we note that variation in insurance plays a minor role in driving our results. Although prior literature has documented the importance of insurance coverage for adult adherence (Chandra et al., 2010; Finkelstein et al., 2012; Brot-Goldberg et al., 2017), children in the U.S. are much more likely to be insured due to public insurance programs like Medicaid and the Children's Health Insurance Program. We compare the response of patients with fee-for-service Medicaid (*FFS Medicaid*) to all other payers. Consistent with this, we find that the mediating effect of Medicaid coverage was qualitatively small (0.00233/-0.0133, Models 1 and 4) and statistically insignificant.[17]

In addition to variation in insurer, our regression includes a host of interactions with other county and state-level demographics, economic indicators, and population health statistics. The pandemic may have interacted with factors related to these measures in ways that a typical macroeconomic downturn does not. For example, changes in remote work, as proxied

[17]We also find minimal differences between children in Medicaid expansion states versus other states.

by the composition of occupations in a county, may change people's routines and, in turn, affect children's adherence. Another example is that minority communities may have been disrupted by COVID to an extent not captured by case counts because mortality rates were significantly higher. However, we generally do not find quantitatively large estimates due to these other factors. We want to stress that our results do not mean that these factors (e.g., parental income) do not matter in the cross-section. Instead, our research design likely nets out these factors by including individual fixed effects.

5.3 Evidence on Parental Attention

Finally, we provide evidence that our results are most consistent with parental attention as a key driver. The importance of this channel has implications for children's health beyond the scope of macroeconomic downturns.

5.3.1 Responses by Age

A distinguishing factor for pediatric drug adherence is the role that parents and caregivers play in filling and administering prescriptions (e.g., Conn et al., 2005). Moreover, the role of adult intervention is inversely related to age; the youngest children rely the most on adult caretakers to manage and maintain prescription drug regimes.

Consistent with this, our horserace results suggest that age plays a major role. As reported in Table 3, Model (3) a ten-year increase in *Age* offsets the average effect by 94 percent (0.00125 percentage point estimate per year). The full variation in pediatric age (a seventeen-year increase in age) *fully offsets the entire observed negative response.* To show that linearity assumptions are not driving our results, we report non-parametric estimates of the effect of the pandemic by age in Appendix Figure A1.

Further underscoring the role of parental attention, we show that the mediating effect of age is limited to children. In particular, Appendix Table A9 reports the same horserace results for adults. In this case, age does not interact with the effect of the pandemic in either a statistically or economically significant way (-0.0000424/0.0129, Models 1 and 4).

5.3.2 Response by Previous Usage Intensity

Next, we consider the differential response between low- and high-intensity users of asthma medication. High-intensity users likely have a stronger and more consistent need for medication. This may mitigate any decreases in parental attention during the pandemic.

To test this, we compare the response of high- and low-intensity users (*Chronic*). We measure usage intensity based on individual adherence rates in 2019. 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 monthly coverage rate of 5.1 percent in January and February 2019, whereas high-intensity users had an average coverage rate of 66.1 percent over the same time period.

Appendix Table A7, Models (7) and (8) report estimates for low-intensity and high-intensity users, respectively. While we estimate similar effects, these estimates are relative to very different levels of control means. However, even scaled by control means, we find large decreases in drug adherence across both low- and high-intensity pediatric users. In the horserace regression (Table 3), we see that high-intensity use offsets roughly 70 percent of the estimated pediatric effect (0.00968/-0.0133, Models 1 and 3).

5.3.3 Response of Diabetes Patients

As an additional piece of evidence, we analyze pediatric adherence to diabetes medication during the pandemic. Diabetes is a disease that provides more immediate negative feedback when not well managed, especially for children who rely on insulin to manage Type-I diabetes. In addition, there is less scope for the pandemic environment to directly affect the presentation of diabetes symptoms through a reduction of environmental triggers such as air pollutants and physical activity. In light of this, we hypothesize that relative to families managing pediatric asthma, parental attention likely increases in families managing pediatric diabetes, reducing the scope for any interaction between the pandemic-induced changes and pediatric adherence for this population.

For this analysis, we study the population of pediatric diabetes patients. We assemble a data set of monthly adherence rates using a methodology similar to that which was described in Section 3.1. Appendix Table A5 provides summary statistics about this population in 2019. To study the effect of the pandemic, we estimate the same difference-in-differences model, comparing monthly adherence rates during the pandemic to pre-pandemic months in 2020, holding fixed typical monthly patterns based on observed coverage rates in 2019.

Figure 3, Panel (C) plots both the scaled effect of the pandemic on medication adherence for pediatric diabetes patients together with the effect for pediatric asthma patients for reference. We find that the response of pediatric adherence to diabetes medication during COVID was a precise zero into Fall 2020, in stark contrast to our persistent negative estimate for pediatric asthma patients. We suggest that this attenuation is consistent with differential disease management intensity across these two conditions, which leaves less scope for the pandemic to reduce parental attention in families with diabetic children as compared to families with asthmatic children.

5.3.4 Evidence from Within Family Claims Data

Because our IQVIA evidence is 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 the MEPS database over IQVIA is that parents and children can be linked. This linkage allows us to directly measure parental socio-economic status and other family-specific contextual factors, such as the number of parental prescriptions. A major disadvantage of MEPS, however, is the sample size; this survey only tracks about fifteen thousand individuals over the 2019–2020 time period. As such, this survey captures comparatively few pediatric patients taking asthma medication (N=318 for individuals taking asthma medication in 2019 and surveyed in 2020) when compared to the IQVIA database (N=8,600,000 in 2019).

Notwithstanding this limitation, we proceed in two steps. First, we replicate our core finding that monthly coverage rates decrease for 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 by MEPS in 2020.[18]

We compute the total days supplied (Q) for each individual and year.[19] We then estimate the average change in adherence rates between 2019 and 2020 for children from different age groups using a Poisson regression $Y_{it} \sim Poisson(\lambda_{it})$:

$$\lambda_{it} = \alpha_i + \beta \cdot I_{t=2020} + \epsilon_{it} \tag{4}$$

where i indexes the individual and t the year (2019 or 2020). The primary outcome of interest is the total number of days of medication filled.

Table 4, Panel (A) reports these results. We find that the average quantity of medication decreased for all children, with larger effects for younger age groups. The effect sizes are much larger than in our IQVIA data, which could partly be driven by response issues associated with the survey methodology in MEPS during the pandemic. In contrast, adults exhibit no effect.[20]

Second, we construct data describing the parents of children who take asthma medication to study parent-level mediating factors. For each child taking asthma medication in 2019, we construct a set of parental measures based on MEPS data. These measures include (1) log of the total number of prescriptions for parents in 2020 (*Log Rx*), (2) the change in self-reported mental health state from 2019 to 2020 averaged across parents ($\Delta Mental$), (3)

[18] Although MEPS contains rounds of surveys within a given year, the dates of the scripts are not available. For this reason, we cannot implement a monthly analysis as we did using the IQVIA database.

[19] Appendix B.4 provides additional information about our data construction and empirical design. We also present summary statistics.

[20] Another potential issue is that MEPS does 5 survey rounds over two years. By selecting the sample based on usage in 2019, we are selecting a sample that is more likely to be surveyed three times in 2019 and two times in 2020.

whether any adult lost employment in 2020 (*Lost Job*), (4) whether any adult in the family lost health insurance coverage in 2020 (*Lost Ins*), (5) the highest education level of any parent (*Education*), and (6) hourly wages (*Log Wage*).[21]

Formally, we run the following Poisson specification within the set of children under the age of 18 in 2019:

$$\lambda_{it} = \alpha_i + \beta \cdot I_{t=2020} + \sum_j \gamma_j \cdot I_{t=2020} \cdot (X_i^j - \bar{X}^j) + \epsilon_{it} \tag{5}$$

where X^j are the factors discussed above and $\bar{X}^j$ are the population means. Results are reported for these factors in Table 4, Panel B.

We find that parental usage of medication is a significant predictor of the response size. The offsetting effect of log adult prescriptions is quantitatively large (0.205, Model 1) and statistically significant. An increase from zero to the median number of adult prescriptions (10) is associated with 58 percent of the baseline effect from Panel (A). We also find a large positive estimate for parental job loss, but this effect is not present in the subsequent non-asthma analysis. Other factors such as parental education and income have quantitatively smaller correlations with response size. Panel (B), Model 2 repeats the horserace analysis but for the most common non-asthma medication taken by children (primarily allergy medication and stimulants). We generally find qualitatively similar estimates for all factors except job loss and also find similar mediating effects for parental prescriptions.

Finally, we provide evidence on the plausibility of the parental attention channel by documenting the timing of prescription fills within families. To do so, we use claims data from MarketScan. Unlike the IQVIA and MEPS data, MarketScan provides family identifiers and dates associated with prescriptions.[22] In 2013, the last year of our sample, we find that a

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

[22] One disadvantage of MarketScan is that it only covers selected individuals on employer-sponsored insurance plans. We have access to data from 1996–2013. Appendix B.5 provides detailed methodology and results.

given pediatric asthma prescription is picked up on the same day as any parent prescription 13.2 percent of the time and that a given pediatric asthma prescription is picked up within nine days of a parent's prescription 50 percent of the time. Appendix Table A11 provides additional statistics.

The co-occurrence rates confirm the plausibility of the parental attention channel. As shown earlier, adult adherence rates increase in 2020. If the co-occurrence rates were close to 100 percent, this would make it implausible that the decrease in pediatric prescriptions is driven by adults forgetting. Furthermore, assuming that 13.2 percent of pediatric prescriptions are unaffected by changes in parental attention because of co-occurrence, the remaining 86.8 percent of prescriptions would only have to be missed 34 percent of the time to generate the negative 30 percent response we observe for the youngest children in December 2020; not an implausibly large number.

6 Conclusion

Using large-scale transaction data, we have documented a large decrease in pediatric adherence to asthma medication during the COVID-19 pandemic. Poor adherence has been shown to convey long-term negative health consequences and increased healthcare costs. We show that this change is not driven by factors that distinguish the COVID pandemic, such as school closures and reduced mobility, from other macroeconomic downturns. Moreover, we provide evidence that the response is unlikely to be driven by a decrease in need. Instead, we find that the results are likely driven by decreases in parental attention.

The parental attention mechanism that we study is most relevant for younger children. As we show, decreases in adherence during the pandemic were the largest for preschool-aged children. This mechanism raises important welfare concerns because drug adherence deficits accumulate over time. This is consistent with empirical evidence in the medical literature documenting the significant health differences across parental socioeconomic status among teenagers.

Our findings underscore the critical role that families play in managing chronic pediatric health conditions. Moreover, our results draw attention to heterogeneity in adherence across disease classes. Children with more acute conditions, such as diabetes, are less vulnerable to disease management risks imposed by macroeconomic turmoil. On the other hand, our work suggests that the management of pediatric asthma is intertwined with the demands on parental attention that are made by macroeconomic events. Our results also speak to the variation in the sensitivity of other pediatric health behaviors to parental attention.

Fortunately, this context provides a unique opportunity to focus on behavioral interventions that can help mitigate these effects. These include reminders, automatic mail delivery, and other forms of assistance to help parents of children who are prescribed chronic medication. Our findings suggest that the impact of these interventions might be especially impactful during times of individual and aggregate macroeconomic turmoil — for example, following a job loss or during recessions.

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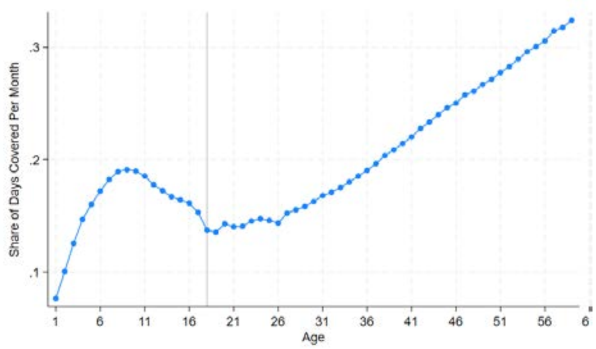
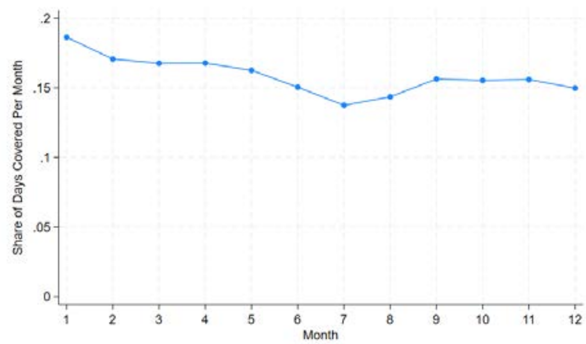
Figure 1: Pre-Pandemic Coverage Rates

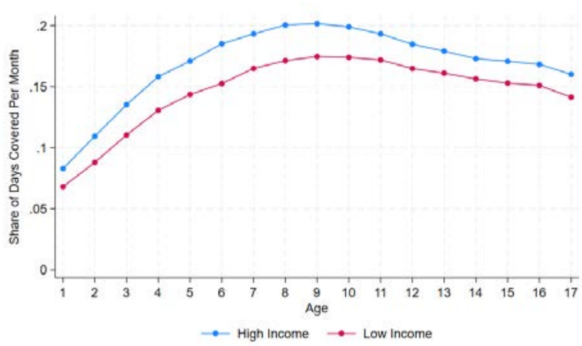
(a) Average Monthly Coverage Rate



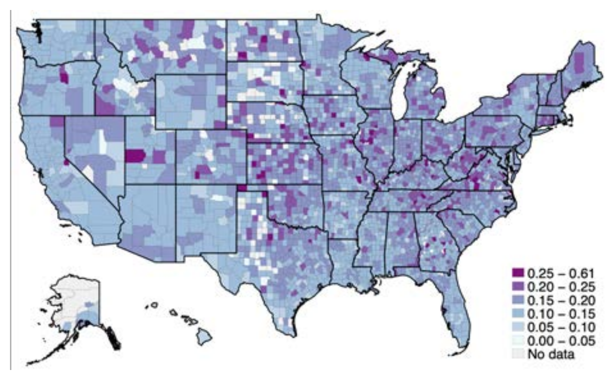
(b) Monthly Pediatric Coverage Rate



(c) Pediatric Coverage Rate, by Income

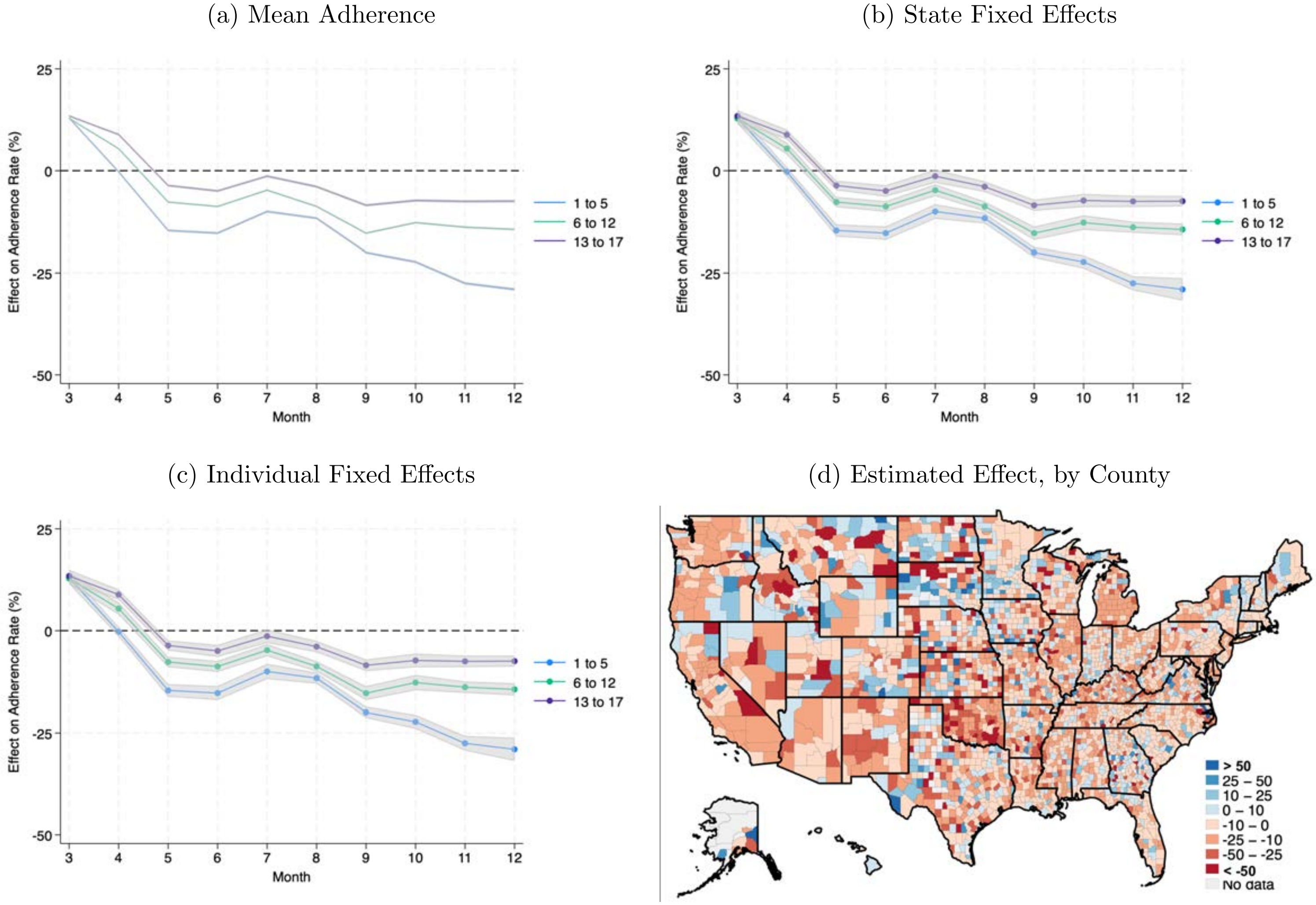


(d) Pediatric Coverage Rate, by Geography



Notes: The four panels in Figure 1 plot the average monthly coverage rates in 2019 for the population of continuing users. Panel (A) depicts average coverage rates by age. Panel (B) depicts monthly pediatric coverage rates, grouping children into preschool, school-aged, and teenage. Panel (C) depicts monthly pediatric coverage rates for children with a provider located in a high or low income zip code. Panel (D) depicts average pediatric coverage rates by county

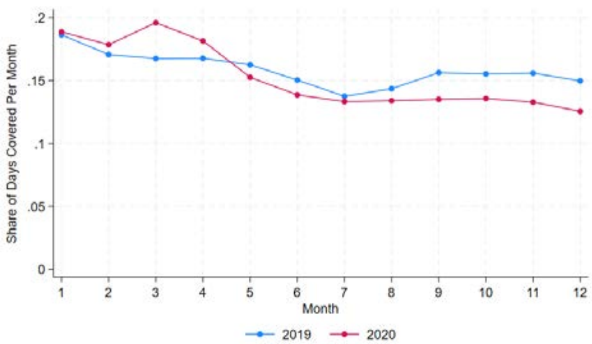
Figure 2: Drug Adherence During the COVID-19 Pandemic



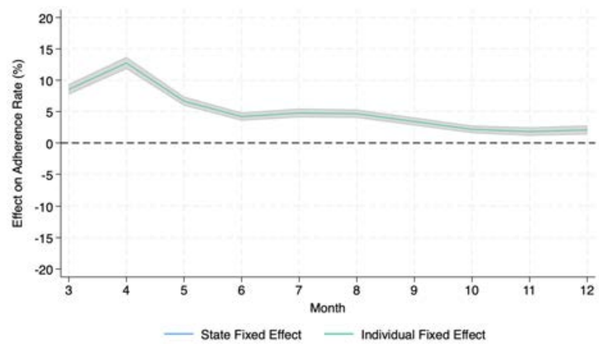
Notes: Figure 2, Panels (A) - (D) plot the effect of the pandemic on pediatric drug adherence using a difference-in-differences empirical model based on Equation 1. All results are scaled by the average pediatric adherence rate in January and February 2019. Panel (A) depicts mean changes in drug adherence. Panel (B) includes state fixed effects. Panel (C) includes individual fixed effects. Panel (D) plots the estimated mean effect of the pandemic within county based on Equation (2).

Figure 3: Identification and Data Validation

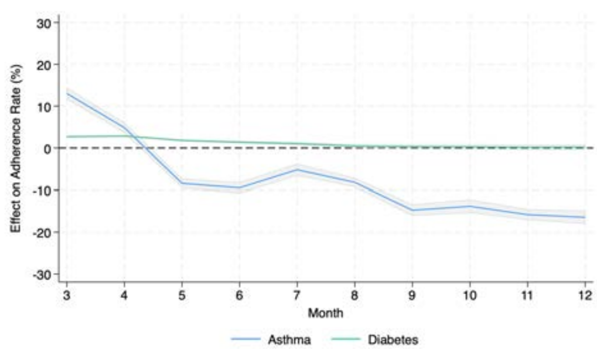
(a) 2019 and 2020 Coverage Rates



(b) Adherence Effect: Adults 18 to 59



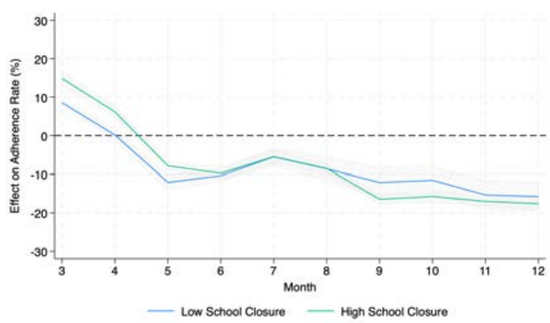
(c) Other Disease: Pediatric Diabetes



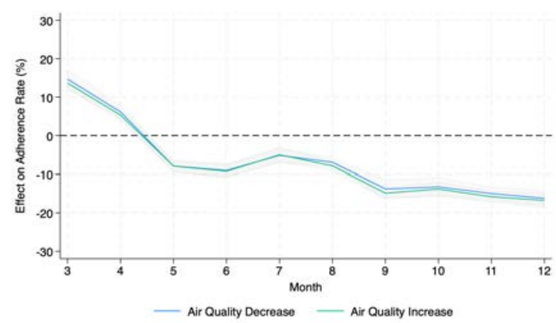
Notes: Panel (A) plots the average coverage rates for pediatric users in our analysis sample in 2019 and 2020. Panel (B) plots the effect of the pandemic on adult adherence using our difference-in-differences methodology, where results are scaled by the average pediatric adherence rate in January and February 2019. Panel (D) plots the effect of the pandemic on adherence rates for pediatric asthma patients together with pediatric diabetes patients.

Figure 4: COVID-Specific Mechanisms and Effect on Adherence

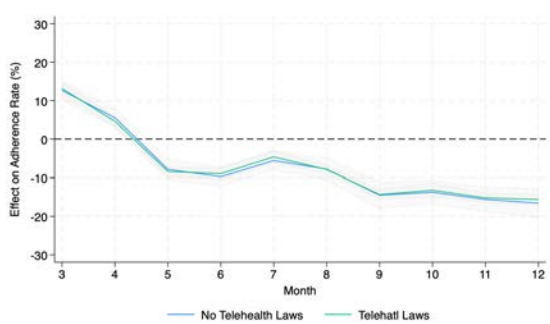
(a) School Closures



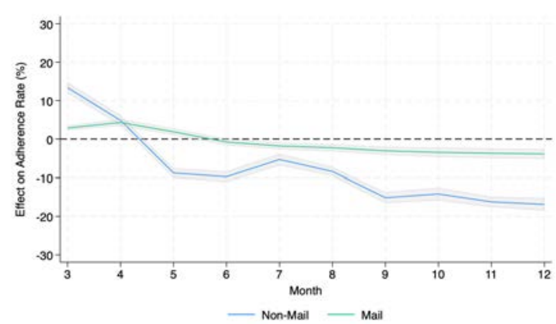
(b) Air Quality



(c) Telehealth



(d) Prescription Delivery Channel



Notes: Figure 4, Panels (A) - (D) plot the effect of the pandemic on pediatric adherence as related to several COVID-specific changes. Panel (A) compares the effect for patients in counties with low and high school closure rates in Fall 2020. Panel (B) compares the effect based on whether Air Quality improved or declined between April and August 2020. Panel (C) compares the effect based on whether states require that public health insurance provide access to telehealth. Panel (E) compares the effect based on the channel of delivery for prescriptions.

Table 1: Sample Statistics: Pediatric Asthma Patients, 2019

	Under 18 (1)	Under 6 (2)	6 to 12 (3)	13 to 18 (4)
Panel A: Individual Characteristics				
Monthly Coverage Rate	0.16	0.12	0.18	0.16
Patient Age	8.26	2.74	8.97	14.92
Share Female	0.44	0.42	0.43	0.49
Fee-For-Service Medicaid	0.12	0.12	0.12	0.11
Third Party Payer	0.85	0.85	0.85	0.86
Number Days Supplied, Prior Year	71.49	50.85	84.26	79.35
Panel B: 2018 Local Geographic Characteristics				
Per-Capita Income	32,293	32,027	32,339	32,588
Minority Population Share	0.27	0.27	0.27	0.26
Some College Population Share	0.21	0.21	0.21	0.21
Urban Population Share	0.94	0.94	0.94	0.93
Medicaid Expansion State	0.51	0.48	0.51	0.55
Observations	106,348,724	36,849,253	43,581,284	25,918,187

Notes: This table provides summary statistics describing the population of pediatric continuing asthma prescription users in 2019. Variable definitions provided in Appendix Table A1 and A2.

Table 2: Balance in Pre-COVID Statistics: Pediatric Asthma Patients

	2019	2020
Panel A: Individual Characteristics		
Monthly Coverage Rate	0.18	0.18
Patient Age	8.26	8.30
Share Female	0.44	0.44
Fee-for-Service Medicaid	0.12	0.11
Third Party Payer	0.85	0.87
Number Days Supplied, Prior Year	71.49	74.08
Panel B: 2018 Local Geographic Characteristics		
Per-Capita Income	32,293	32,262
Minority Population Share	0.27	0.27
Some College Population Share	0.21	0.21
Urban Population Share	0.94	0.94
Medicaid Expansion State	0.51	0.51
Observations	947,536	921,380

Notes: This table provides summary statistics describing the population of pediatric continuing asthma prescription users in January and February 2019 and 2020. Variable definitions provided in Appendix Table A1 and A2.

Table 3: Collective Impact of Mechanisms: Horse Race

	(1)	(2)	(3)	(4)
DD	-0.0133***	-0.0137***	-0.0248***	-0.0231***
	(0.000951)	(0.00248)	(0.00105)	(0.00260)
Telehealth x DD		-0.000440		-0.000543
		(0.00232)		(0.00203)
High School Closure x DD		-0.00304		-0.00286
		(0.00206)		(0.00161)
AQI Drop x DD		-0.00782***		-0.00542**
		(0.00201)		(0.00156)
Mail Order x DD		0.00660**		0.00334
		(0.00228)		(0.00217)
Age x DD			0.00125***	0.00128***
			(0.0000677)	(0.0000803)
Chronic x DD			0.00968***	0.00968***
			(0.00199)	(0.00201)
High Asthma Prevalence x DD				0.00238*
				(0.00106)
High Income x DD				-0.00666***
				(0.00115)
High Education x DD				-0.000527
				(0.000846)
White Collar x DD				0.00256
				(0.00195)
High Minority Population x DD				-0.00321*
				(0.00149)
FFS Medicaid x DD				0.00233
				(0.00143)
Medicaid Expansion x DD				0.000372
				(0.00212)
Urban x DD				-0.00132
				(0.00125)
Observations	204,028,360	204,028,360	204,028,360	204,028,360

Notes: This table reports estimates for the full population for pediatric asthma patients. Estimates are based on a difference-in-differences model that collapses the dynamic effect from March through December into one post period, reflected in the coefficient "DD." Variable definitions provided in Appendix Table A1 and A2. 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: Evidence on Adherence and Parents from MEPS

Panel A: Average Response by Age Group

	Total Number of Medication Days Covered (Q)				
	All	Under 5	6–12	13–17	Adults
	(1)	(2)	(3)	(4)	(5)
2020	-0.846***	-1.222***	-0.897***	-0.457	-0.101
	(0.162)	(0.343)	(0.237)	(0.248)	(0.0530)
Person FE	x	x	x	x	x
No. Individuals	318	91	124	103	1,353

Panel B: Horserace, All Kids

	Asthma Q	Non-Asthma Q
	(1)	(2)
2020	-1.005***	-0.462***
	(0.153)	(0.0845)
Log Rx × 2020	0.205*	0.157**
	(0.0992)	(0.0589)
Δ Mental × 2020	-0.110	-0.0312
	(0.386)	(0.137)
Lost Job × 2020	0.826**	-0.236
	(0.270)	(0.253)
Lost Ins × 2020	-0.391	-0.289
	(0.839)	(0.294)
Education × 2020	-0.103*	-0.0168
	(0.0439)	(0.0316)
Log Hourly Wage	0.0294	-0.0491
× 2020	(0.0987)	(0.0621)
Person FE	x	x
No. Individuals	318	566

Notes: Estimates from fixed-effects Poisson regressions for Equations (4) and (5). All log variables 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 models denote the parental measure we are using in the interaction term. All measures are demeaned to preserve the interpretation of the overall effect. "Rx" refers to 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 Wage" refers to the log of the sum of hourly wage across all adults in the family during the first round in 2020. Standard errors are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix to

"Pediatric Drug Adherence and Parental Attention: Evidence from Comprehensive Claims Data"

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Matthew Higgins, *University of Utah – David Eccles School of Business*

Elena Patel, *University of Utah – David Eccles School of Business*

July 2023

A Variable Definitions

Table A1: 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. Note: Managed Medicaid is categorized as a Third Party Payer *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 A2: 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 a 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 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 a county that experienced a decrease 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*

B Robustness Checks and Additional Results

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

B.1 Additional Core Results

In this part, we present the estimates associated with Figure 2 in table form. Appendix Table A3 contains estimates by age group, specification (means, state FE, individual FE), and by month.

Table A3: Effect of Pandemic on Adherence: Variation By Age

	1–5			6–12			13–17			18–59		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
March DD	0.0185***	0.0185***	0.0185***	0.0262***	0.0262***	0.0262***	0.0245***	0.0245***	0.0245***	0.0216***	0.0216***	0.0216***
	(0.000188)	(0.00105)	(0.00109)	(0.000191)	(0.00146)	(0.00150)	(0.000237)	(0.00137)	(0.00142)	(0.000170)	(0.00105)	(0.00110)
Apr DD	-0.000393	-0.000390	-0.000389	0.0111***	0.0111***	0.0111***	0.0161***	0.0161***	0.0161***	0.0323***	0.0323***	0.0323***
	(0.000210)	(0.000865)	(0.000891)	(0.000220)	(0.00153)	(0.00157)	(0.000274)	(0.00115)	(0.00119)	(0.000205)	(0.00125)	(0.00129)
May DD	-0.0210***	-0.0210***	-0.0210***	-0.0157***	-0.0157***	-0.0157***	-0.00661***	-0.00661***	-0.00661***	0.0169***	0.0169***	0.0169***
	(0.000212)	(0.00110)	(0.00115)	(0.000223)	(0.00133)	(0.00136)	(0.000278)	(0.00112)	(0.00117)	(0.000213)	(0.000922)	(0.000961)
June DD	-0.0219***	-0.0219***	-0.0219***	-0.0179***	-0.0179***	-0.0179***	-0.00905***	-0.00905***	-0.00905***	0.0106***	0.0106***	0.0106***
	(0.000215)	(0.00122)	(0.00127)	(0.000225)	(0.00137)	(0.00143)	(0.000283)	(0.00133)	(0.00139)	(0.000219)	(0.000840)	(0.000871)
July DD	-0.0143***	-0.0143***	-0.0143***	-0.00974***	-0.00974***	-0.00975***	-0.00244***	-0.00244	-0.00244	0.0121***	0.0121***	0.0121***
	(0.000217)	(0.00132)	(0.00138)	(0.000227)	(0.00153)	(0.00158)	(0.000287)	(0.00151)	(0.00158)	(0.000224)	(0.000881)	(0.000938)
Aug DD	-0.0167***	-0.0167***	-0.0167***	-0.0179***	-0.0179***	-0.0179***	-0.00713***	-0.00713***	-0.00712***	0.0118***	0.0118***	0.0118***
	(0.000222)	(0.000965)	(0.00101)	(0.000234)	(0.00129)	(0.00135)	(0.000297)	(0.00124)	(0.00131)	(0.000230)	(0.000841)	(0.000884)
Sept DD	-0.0286***	-0.0286***	-0.0286***	-0.0313***	-0.0313***	-0.0313***	-0.0155***	-0.0155***	-0.0155***	0.00863***	0.00864***	0.00863***
	(0.000232)	(0.000968)	(0.00100)	(0.000245)	(0.00172)	(0.00179)	(0.000306)	(0.00129)	(0.00134)	(0.000235)	(0.000817)	(0.000854)
Oct DD	-0.0319***	-0.0319***	-0.0319***	-0.0260***	-0.0260***	-0.0260***	-0.0133***	-0.0133***	-0.0133***	0.00548***	0.00548***	0.00548***
	(0.000239)	(0.00122)	(0.00127)	(0.000249)	(0.00188)	(0.00196)	(0.000310)	(0.00152)	(0.00159)	(0.000241)	(0.000769)	(0.000803)
Nov DD	-0.0394***	-0.0394***	-0.0394***	-0.0283***	-0.0283***	-0.0283***	-0.0137***	-0.0137***	-0.0137***	0.00455***	0.00455***	0.00456***
	(0.000247)	(0.00127)	(0.00133)	(0.000255)	(0.00143)	(0.00148)	(0.000316)	(0.00129)	(0.00134)	(0.000249)	(0.000873)	(0.000895)
Dec DD	-0.0415***	-0.0415***	-0.0415***	-0.0294***	-0.0294***	-0.0294***	-0.0136***	-0.0136***	-0.0136***	0.00524***	0.00524***	0.00524***
	(0.000254)	(0.00202)	(0.00210)	(0.000261)	(0.00151)	(0.00157)	(0.000324)	(0.00122)	(0.00127)	(0.000258)	(0.000921)	(0.000961)
Constant	0.143***	0.143***	0.168***	0.204***	0.204***	0.239***	0.182***	0.182***	0.219***	0.253***	0.253***	0.286***
	(0.000170)	(0.000971)	(0.000972)	(0.000179)	(0.00131)	(0.00149)	(0.000223)	(0.00119)	(0.00177)	(0.000193)	(0.00115)	(0.00159)
State FE		✓			✓			✓			✓	
Individual FE			✓			✓	No		✓			✓
Observations	66,871,050	66,871,050	66,871,001	85,595,128	85,595,128	85,595,097	51,562,245	51,562,245	51,562,230	94,128,713	94,128,713	94,128,660

Notes: This table reports estimates based on a difference-in-differences model described in Equation (2) and exploiting variation by age. Pediatric estimates (Models 1 to 9) are based on the full population. Adult estimates (Models 10 to 12) are based on a 25% sample to manage computing constraints. Models 2, 5, 8, and 11 include state fixed effects. Models 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 A4: Effect of Pandemic on Adherence for 2018 Continuing Users: Variation By Age

	1–5			6–12			13–17			18–59		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
March DD	0.0218***	0.0219***	0.0218***	0.0264***	0.0264***	0.0264***	0.0244***	0.0244***	0.0244***	0.0211***	0.0211***	0.0211***
	(0.000359)	(0.00207)	(0.00212)	(0.000310)	(0.00236)	(0.00242)	(0.000404)	(0.00209)	(0.00212)	(0.000301)	(0.00180)	(0.00186)
Apr DD	-0.000439	-0.000437	-0.000439	0.00672***	0.00672**	0.00672**	0.0141***	0.0141***	0.0141***	0.0335***	0.0335***	0.0335***
	(0.000407)	(0.00163)	(0.00165)	(0.000360)	(0.00229)	(0.00233)	(0.000472)	(0.00157)	(0.00159)	(0.000362)	(0.00205)	(0.00209)
May DD	-0.0251***	-0.0251***	-0.0251***	-0.0265***	-0.0265***	-0.0265***	-0.0143***	-0.0143***	-0.0143***	0.0147***	0.0147***	0.0147***
	(0.000414)	(0.00204)	(0.00211)	(0.000367)	(0.00227)	(0.00230)	(0.000484)	(0.00204)	(0.00213)	(0.000380)	(0.00144)	(0.00150)
June DD	-0.0184***	-0.0184***	-0.0184***	-0.0231***	-0.0231***	-0.0231***	-0.0133***	-0.0133***	-0.0133***	0.00910***	0.00910***	0.00910***
	(0.000419)	(0.00219)	(0.00230)	(0.000371)	(0.00274)	(0.00283)	(0.000492)	(0.00273)	(0.00286)	(0.000393)	(0.00131)	(0.00138)
July DD	0.00186***	0.00187	0.00186	-0.00514***	-0.00513	-0.00514	0.000388	0.000393	0.000388	0.0146***	0.0146***	0.0146***
	(0.000420)	(0.00229)	(0.00240)	(0.000374)	(0.00299)	(0.00308)	(0.000499)	(0.00310)	(0.00324)	(0.000402)	(0.00155)	(0.00165)
Aug DD	-0.00233***	-0.00233	-0.00233	-0.0209***	-0.0209***	-0.0209***	-0.0107***	-0.0107***	-0.0107***	0.0157***	0.0157***	0.0157***
	(0.000431)	(0.00176)	(0.00182)	(0.000386)	(0.00248)	(0.00259)	(0.000518)	(0.00244)	(0.00256)	(0.000414)	(0.00163)	(0.00170)
Sept DD	-0.0291***	-0.0291***	-0.0291***	-0.0470***	-0.0470***	-0.0470***	-0.0255***	-0.0255***	-0.0255***	0.0114***	0.0114***	0.0114***
	(0.000455)	(0.00198)	(0.00202)	(0.000405)	(0.00289)	(0.00300)	(0.000536)	(0.00250)	(0.00260)	(0.000426)	(0.00180)	(0.00186)
Oct DD	-0.0387***	-0.0387***	-0.0387***	-0.0381***	-0.0381***	-0.0381***	-0.0199***	-0.0199***	-0.0199***	0.00476***	0.00476**	0.00476**
	(0.000471)	(0.00188)	(0.00196)	(0.000413)	(0.00322)	(0.00334)	(0.000544)	(0.00282)	(0.00294)	(0.000438)	(0.00151)	(0.00158)
Nov DD	-0.0553***	-0.0553***	-0.0553***	-0.0402***	-0.0402***	-0.0402***	-0.0183***	-0.0183***	-0.0183***	0.00250***	0.00250	0.00250
	(0.000489)	(0.00217)	(0.00225)	(0.000424)	(0.00238)	(0.00246)	(0.000555)	(0.00235)	(0.00241)	(0.000453)	(0.00143)	(0.00146)
Dec DD	-0.0569***	-0.0570***	-0.0569***	-0.0373***	-0.0373***	-0.0373***	-0.0139***	-0.0139***	-0.0139***	0.00372***	0.00372*	0.00372*
	(0.000506)	(0.00349)	(0.00362)	(0.000437)	(0.00251)	(0.00258)	(0.000571)	(0.00238)	(0.00248)	(0.000473)	(0.00160)	(0.00163)
Constant	0.281***	0.281***	0.270***	0.349***	0.349***	0.348***	0.334***	0.334***	0.333***	0.474***	0.474***	0.470***
	(0.000312)	(0.00147)	(0.00164)	(0.000279)	(0.00228)	(0.00230)	(0.000374)	(0.00259)	(0.00270)	(0.000304)	(0.00196)	(0.00201)
State FE		✓			✓			✓			✓	
Individual FE			✓			✓			✓			✓
Observations	29,507,388	29,507,388	29,507,388	47,335,200	47,335,200	47,335,200	26,959,776	26,959,776	26,959,776	45,638,616	45,638,616	45,638,616

Notes: Estimates are based on the subsample of continuing users who had an active prescription in 2018. See also Appendix Table A3 notes.

B.2 Consistency of Response

We provide a further breakdown of the negative pediatric adherence response. There are two potential stylized scenarios. It could be that each individual misses a few scripts randomly, because of disruptions. Alternatively, some individuals may be missing many consecutive scripts while others are relatively unaffected.

We assess this using a simple methodology. We decompose the response in each month into an individual specific factor plus an idiosyncratic component:

$$\Delta y_{im} = \Delta \bar{y}_m + \alpha_i + \epsilon_{im}$$

where Δy_{im} is the difference in individuals' fill rates between 2019 and 2020 for each month between April and December, $\Delta \bar{y}_m = \frac{1}{|J|} \sum_{j \in J} \Delta y_{jm}$ is the average response in the population (J is the set of individuals), and α_i are persistent individual effects.

We can then compute the correlation across months $corr(\Delta y_{im} - \Delta \bar{y}_m, \Delta y_{i,m-1} - \Delta \bar{y}_{m-1})$, to arrive at the signal variance. This represents the variance of the distribution of individual effects. It would be close to zero if each individual were randomly missing scripts. It would be negative if individuals are "making up" missed scripts by filling more frequently. Finally, it would be very positive if some individuals are consistently not filling scripts while others are behaving more like they did in 2019.

Table A6 presents the estimates from this exercise. We provide results across all children and by age group. In each group, the average response is roughly a -8pp decrease in monthly rate. The standard deviation of the overall residual $\sqrt{Var(\alpha_i + \epsilon_{im})}$ is about 0.4. The signal standard deviation (square root of the signal variance) is about 0.3, which is sizeable relative to both the mean response and the overall residual. This suggests that some individuals are consistently filling medication at rates below their 2019 rates. We also repeat this at the quarterly level, by averaging across months first. This helps us assess consistency over a longer period. Again, we find a large signal standard deviation, although it is smaller in magnitude. The difference likely reflects some mean reversion within individuals over the medium term.

Table A5: Sample Statistics: Pediatric Diabetes Patients, 2019

	Under 18 (1)	Under 6 (2)	6 to 12 (3)	13 to 18 (4)
Panel A: Individual Characteristics				
Adherence Rate	0.59	0.67	0.64	0.56
Patient Age	12.60	3.80	9.73	15.28
Share Female	0.54	0.48	0.51	0.57
Medicaid Payer	0.12	0.06	0.11	0.13
Third Party Payer	0.75	0.62	0.73	0.78
Supply Days, Last Prescription	43.59	51.60	44.50	42.08
Panel B: 2018 Local Geographic Characteristics				
Per-Capita Income, 2018	32689.11	32323.70	32947.91	32596.63
Minority Share of Population, 2018	0.27	0.26	0.28	0.27
Share Population with Some College, 2018	0.20	0.21	0.20	0.21
Share of Population in Urban Area	0.92	0.89	0.93	0.93
Medicaid Expansion State	0.61	0.60	0.61	0.60
Observations	3,230,604	249,180	1,044,108	1,937,316

Notes: This table provides summary statistics describing the population of pediatric continuing diabetes prescription users in 2019. Variable definitions provided in Appendix Table A1 and A2.

Table A6: Consistency in Individuals' Response

	Month			Quarter		
	Average	Residual SD	Signal SD	Average	Residual SD	Signal SD
Under 17	-0.080	0.413	0.308	-0.080	0.334	0.215
1 to 5	-0.074	0.372	0.278	-0.074	0.303	0.198
6 to 12	-0.085	0.427	0.318	-0.085	0.345	0.220
13 to 17	-0.073	0.425	0.318	-0.073	0.344	0.221

B.3 Additional Mechanisms Results, IQVIA

Next, we present additional results related to our mechanisms exploration in Section 5. First, Appendix Table A7 presents point estimates associated with Figure 4. Next, we estimate non-parametric age responses at each age value and report estimates in Appendix Figure A1. Finally, we report the adult version of the IQVIA horse race regressions in Appendix Table A9.

Table A7: COVID Mechanisms

	School Closure		Air Quality		TeleHealth		Use Intensity		Delivery Channel	
	Low	High	Worsen	Improve	No	Yes	Low	High	Mail	Non-Mail
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
March DD	0.0150***	0.0258***	0.0265***	0.0249***	0.0233***	0.0232***	0.00927***	0.0352***	0.0233***	0.0165***
	(0.000472)	(0.000149)	(0.000325)	(0.000161)	(0.000212)	(0.000142)	(0.000138)	(0.000403)	(0.000118)	(0.00141)
Apr DD	0.000256	0.0107***	0.0111***	0.00968***	0.00996***	0.00804***	-0.00555***	0.0314***	0.00848***	0.0248***
	(0.000541)	(0.000170)	(0.000374)	(0.000184)	(0.000243)	(0.000162)	(0.000149)	(0.000484)	(0.000134)	(0.00183)
May DD	-0.0213***	-0.0136***	-0.0143***	-0.0145***	-0.0150***	-0.0151***	-0.0167***	0.00624***	-0.0153***	0.0108***
	(0.000553)	(0.000172)	(0.000380)	(0.000187)	(0.000246)	(0.000164)	(0.000147)	(0.000515)	(0.000136)	(0.00197)
June DD	-0.0182***	-0.0169***	-0.0163***	-0.0169***	-0.0186***	-0.0161***	-0.0149***	-0.00341***	-0.0170***	-0.00454*
	(0.000560)	(0.000173)	(0.000384)	(0.000189)	(0.000250)	(0.000166)	(0.000145)	(0.000537)	(0.000138)	(0.00203)
July DD	-0.00975***	-0.00950***	-0.00933***	-0.00912***	-0.0109***	-0.00854***	-0.00928***	0.00268***	-0.00929***	-0.0104***
	(0.000568)	(0.000174)	(0.000388)	(0.000192)	(0.000253)	(0.000168)	(0.000145)	(0.000554)	(0.000139)	(0.00210)
Aug DD	-0.0151***	-0.0148***	-0.0125***	-0.0143***	-0.0152***	-0.0144***	-0.0115***	-0.00591***	-0.0147***	-0.0131***
	(0.000590)	(0.000179)	(0.000399)	(0.000197)	(0.000261)	(0.000173)	(0.000149)	(0.000570)	(0.000143)	(0.00217)
Sept DD	-0.0213***	-0.0285***	-0.0249***	-0.0271***	-0.0276***	-0.0258***	-0.0177***	-0.0222***	-0.0264***	-0.0177***
	(0.000618)	(0.000186)	(0.000415)	(0.000205)	(0.000272)	(0.000180)	(0.000156)	(0.000588)	(0.000149)	(0.00224)
Oct DD	-0.0203***	-0.0273***	-0.0239***	-0.0251***	-0.0264***	-0.0239***	-0.0181***	-0.0222***	-0.0247***	-0.0199***
	(0.000628)	(0.000190)	(0.000424)	(0.000210)	(0.000278)	(0.000184)	(0.000159)	(0.000602)	(0.000153)	(0.00229)
Nov DD	-0.0270***	-0.0295***	-0.0270***	-0.0288***	-0.0300***	-0.0274***	-0.0220***	-0.0263***	-0.0283***	-0.0213***
	(0.000642)	(0.000196)	(0.000433)	(0.000215)	(0.000286)	(0.000189)	(0.000162)	(0.000618)	(0.000157)	(0.00235)
Dec DD	-0.0277***	-0.0305***	-0.0292***	-0.0305***	-0.0318***	-0.0282***	-0.0231***	-0.0258***	-0.0294***	-0.0223***
	(0.000653)	(0.000201)	(0.000443)	(0.000221)	(0.000294)	(0.000195)	(0.000162)	(0.000635)	(0.000161)	(0.00242)
Constant	0.176***	0.173***	0.180***	0.182***	0.183***	0.176***	0.0511***	0.661***	0.175***	0.576***
	(0.000449)	(0.000136)	(0.000305)	(0.000151)	(0.000197)	(0.000131)	(0.0000855)	(0.000368)	(0.000109)	(0.00154)
Control Mean	0.176	0.173	0.180	0.182	0.183	0.176	0.576	0.175	0.051	0.661
Observations	11,992,722	128,095,320	26,521,323	109,709,456	64,422,853	139,605,570	71,101,083	27,584,872	202,015,450	2,012,973

Notes: This table reports estimates of the response of pediatric monthly coverage to the pandemic across different subgroups based on a difference-in-differences comparison that includes individual fixed effects. Variable definitions provided in Appendix Table A1 and A2. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

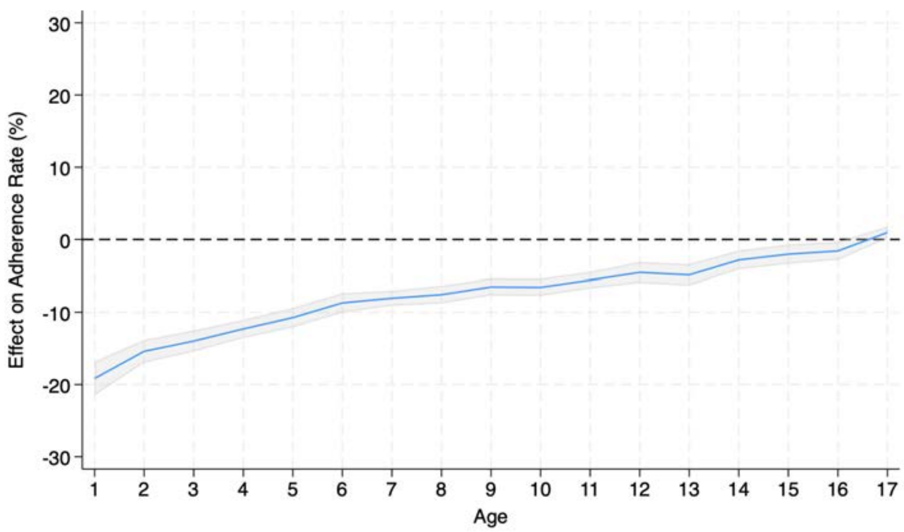
Table A8: COVID Mechanisms for 2018 Continuing Users

	School Closure		Air Quality		TeleHealth		Use Intensity		Delivery Channel	
	Low	High	Worsen	Improve	No	Yes	Low	High	Mail	Non-Mail
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
March DD	0.0147***	0.0285***	0.0297***	0.0272***	0.0244***	0.0252***	0.01000***	0.0263***	0.0254***	-0.00310
	(0.00176)	(0.00300)	(0.00393)	(0.00247)	(0.00366)	(0.00284)	(0.00187)	(0.00190)	(0.00227)	(0.00261)
Apr DD	-0.00439	0.0105***	0.0106***	0.00869***	0.00945*	0.00693**	-0.0115***	0.0203***	0.00753***	-0.00434
	(0.00240)	(0.00195)	(0.00262)	(0.00209)	(0.00327)	(0.00214)	(0.00103)	(0.00252)	(0.00182)	(0.00316)
May DD	-0.0313***	-0.0199***	-0.0223***	-0.0211***	-0.0202***	-0.0218***	-0.0264***	-0.00440	-0.0221***	-0.0212***
	(0.00285)	(0.00199)	(0.00261)	(0.00237)	(0.00425)	(0.00196)	(0.00197)	(0.00235)	(0.00192)	(0.00303)
June DD	-0.0180***	-0.0185***	-0.0185***	-0.0185***	-0.0193***	-0.0164***	-0.0155***	-0.0117***	-0.0180***	-0.0367***
	(0.00272)	(0.00283)	(0.00319)	(0.00328)	(0.00459)	(0.00277)	(0.00247)	(0.00194)	(0.00247)	(0.00290)
July DD	0.00163	-0.00104	-0.00165	-0.000841	-0.00196	0.00154	0.00188	-0.00206	0.0000526	-0.0398***
	(0.00354)	(0.00305)	(0.00359)	(0.00347)	(0.00476)	(0.00311)	(0.00239)	(0.00257)	(0.00267)	(0.00299)
Aug DD	-0.0120**	-0.0110***	-0.00873***	-0.0111***	-0.0104	-0.0103***	-0.00695**	-0.0101***	-0.0111***	-0.0417***
	(0.00366)	(0.00226)	(0.00247)	(0.00266)	(0.00508)	(0.00187)	(0.00207)	(0.00276)	(0.00206)	(0.00325)
Sept DD	-0.0284***	-0.0379***	-0.0339***	-0.0362***	-0.0346***	-0.0333***	-0.0290***	-0.0272***	-0.0350***	-0.0447***
	(0.00494)	(0.00251)	(0.00439)	(0.00287)	(0.00620)	(0.00187)	(0.00199)	(0.00310)	(0.00231)	(0.00384)
Oct DD	-0.0264***	-0.0366***	-0.0327***	-0.0336***	-0.0327***	-0.0306***	-0.0335***	-0.0262***	-0.0327***	-0.0446***
	(0.00472)	(0.00251)	(0.00446)	(0.00299)	(0.00571)	(0.00251)	(0.00192)	(0.00323)	(0.00249)	(0.00444)
Nov DD	-0.0370***	-0.0403***	-0.0373***	-0.0394***	-0.0379***	-0.0364***	-0.0456***	-0.0297***	-0.0385***	-0.0438***
	(0.00495)	(0.00193)	(0.00312)	(0.00237)	(0.00542)	(0.00139)	(0.00174)	(0.00307)	(0.00193)	(0.00469)
Dec DD	-0.0331***	-0.0388***	-0.0376***	-0.0384***	-0.0370***	-0.0340***	-0.0456***	-0.0274***	-0.0367***	-0.0410***
	(0.00497)	(0.00265)	(0.00374)	(0.00314)	(0.00630)	(0.00207)	(0.00256)	(0.00318)	(0.00246)	(0.00496)
Constant	0.332***	0.312***	0.326***	0.326***	0.330***	0.320***	0.0869***	0.780***	0.317***	0.732***
	(0.00261)	(0.00233)	(0.00234)	(0.00288)	(0.00440)	(0.00218)	(0.00201)	(0.00253)	(0.00217)	(0.00387)
Control Mean	0.335	0.314	0.326	0.327	0.331	0.322	0.122	0.720	0.319	0.702
Observations	5,842,308	65,436,588	13,609,968	56,899,860	33,259,047	70,532,338	22,418,316	24,384,046	102,277,260	1,525,104

Notes: Estimates are based on the subsample of continuing users who had an active prescription in 2018. See also Appendix Table A7 notes.

Figure A1: 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), using individual fixed effects, and estimated separately for each age between 1 and 17. Point estimates are scaled by sample-specific adherence rates in January and February 2019. 95% confidence intervals shown in shaded area.

Table A9: Collective Impact of Mechanisms for Adults: Horse Race

	(1)	(2)	(3)	(4)
DD	0.0129***	0.00186	0.0131***	0.00211
	(0.000754)	(0.00251)	(0.000747)	(0.00241)
Telehealth x DD		-0.000872		-0.00143
		(0.00209)		(0.00188)
High School Closure x DD		0.000619		0.000788
		(0.00136)		(0.00118)
AQI Drop x DD		-0.00363***		-0.00158
		(0.000781)		(0.000793)
Mail Order x DD		0.00573*		0.00178
		(0.00229)		(0.00229)
Age x DD			-0.0000579**	-0.0000424*
			(0.0000179)	(0.0000181)
Chronic x DD			0.0152***	0.0152***
			(0.00119)	(0.00123)
High Asthma Prevalence x DD				-0.000401
				(0.00151)
High Income x DD				-0.00392***
				(0.000772)
High Education x DD				0.00152
				(0.000762)
White Collar x DD				0.00324
				(0.00191)
High Minority Population x DD				-0.00144
				(0.000863)
FFS Medicaid x DD				0.00922***
				(0.00188)
Medicaid Expansion x DD				0.00174
				(0.00161)
Urban x DD				-0.00253*
				(0.00105)
Observations	94,128,660	94,128,660	94,128,660	94,128,660

Notes: This table reports estimates for the full population for a 25 percent sample of adult asthma patients aged 18 to 59. Estimates are based on a difference-in-differences model that collapses the dynamic effect from March through December into one post period, reflected in the coefficient "DD." Variable definitions provided in Appendix Table A1 and A2. 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.

B.4 MEPS Data Construction and Summary Statistics

We discuss how we construct our MEPS asthma medication user panel, which we use to arrive at the estimates in Table 4.

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.

We also repeat the analysis for non-asthma chronic medication commonly taken by children under the age of 18 (Table 4, Panel B, Model 2). 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 prescriptions per child. This set of drugs primarily contains allergy medication (e.g., Zyrtec) and stimulants (e.g., Adderall). We then repeat the same horse race analysis for the set of kids taking one of these non-asthma chronic medications in 2019.

Appendix Table A10 presents summary stats for asthma and non-asthma samples from 2020. The distribution of the outcome variable, days filled, motivates our usage of the Poisson regression. The summary statistics also motivate our usage of logs for parental prescriptions and hourly wage.

B.5 MarketScan Data Construction and Results

Here, we use data from MarketScan to provide context on the relationship between pediatric prescription filling and their parents' prescription filling. In the MEPS data, we find that parents filling prescriptions mitigates the negative response in children. However, MEPS does not have specific dates for prescription filling (and our IQVIA data does not contain links between parents and children).

To provide further context, we use data from MarketScan. MarketScan covers a large number of individuals who are insured by their employers. The data are not a random sample of the population but rather reflect the set of customers that use MarketScan services to better manage their health insurance. The advantage of the data is that it contains family identifiers and the dates on which scripts were filled. Our data covers the 1996 to 2013

Table A10: MEPS Summary Statistics, Kids 2020

Variable	Asthma			Non-Asthma		
	Median	Mean	S.D.	Median	Mean	S.D.
Days Filled (Q)	0	78.95	214.81	30	269.74	572.61
Parental Scripts	10	18.48	25.16	10	23.23	32.71
Mental Health	2.33	2.34	0.85	2.33	2.34	0.83
Lost Employment	0	0.19	0.40	0	0.18	0.39
Lost Insurance	0	0.03	0.18	0	0.05	0.22
Years Education	14	13.74	2.43	14	13.69	2.53
Hourly Wage	17	24.89	26.20	17.45	25.71	25.88
Individuals		318			566	

Notes: Summary statistics from 2020 for individuals under 18. "Days Filled" is the total days supplied across all prescriptions. The remaining variables are parental measures. "Parental Scripts" is the total prescriptions filled by parents. "Mental Health" is the average parental self-reported mental health status (1-5) across all rounds of the survey. Lost employment and lost insurance are measured based on changes across rounds in the survey, and equal one if there is any change to no employment or no insurance for one parent. "Years Education" is the maximum number of years of education across parents. Hourly wage is the total hourly wage across parents.

Table A11: Parental Prescriptions Around Children's Asthma Prescriptions

	Same Day	Within 9 days	Same Month	Same Quarter	Same Year
Rate	13.2%	50%	63.2%	79.8%	92.2%
N	920,551 individuals; 2,688,118 scripts				

Notes: This table reports statistics on the timing of parental prescriptions relative to each pediatric asthma prescription. Source: 2013 MarketScan drug claims data.

period.

Our sample is the set of asthma prescriptions filled for children in 2013, the last year of our sample. We use the same set of products in our IQVIA data and find associated claims in MarketScan for children aged 17 or younger at the start of 2013. Then, for each prescription, we create indicators for the closest parental prescription fill. This includes parents filling prescriptions on the same day, within eight days, and in the same month/quarter/year.

Appendix Table A11 presents the results. We observe 2,688,118 asthma prescriptions for 920,551 unique individuals under the age of 18. 14 percent of prescriptions are filled on the same day as a parent's prescription. Half of the children's asthma prescriptions come within 9 days of an adult prescription (19-day period). This co-occurrence rate increases to 62 percent, 79 percent, and 92 percent when counting prescriptions within the same month, quarter, and year, respectively. The results highlight the idea that pediatric prescriptions are sometimes but not always picked up at the same time as a parent picking up a prescription, leaving open the possibility that parental attention can have significant impacts on adherence rates.