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

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ABSTRACT

Using comprehensive U.S. drug claims data, we show that pediatric drug adherence declined during the COVID-19 pandemic. Focusing on asthma, we find that young children exhibited a 40 percent decrease in adherence by the end of 2020. The responses were less negative for older children and positive for adults. We provide evidence that parental attention played a key role in driving this decrease, even accounting for air quality changes, school closures, and other socioeconomic and COVID-related factors. Policy implications for future macroeconomic shocks are discussed.

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1 Introduction

Poor drug adherence increases the likelihood of negative clinical outcomes and increases the cost of healthcare (e.g., Osterberg and Blaschke, 2015). Although several studies have examined determinants of non-adherence for adults—highlighting factors such as insurance coverage and socioeconomic status—there is limited systematic evidence on the drivers of *pediatric* adherence. Yet, the need for such evidence is substantial because the mechanisms that influence adherence for children are likely to differ meaningfully from those that affect adults.

Our study sheds light on pediatric drug adherence mechanisms using comprehensive prescription claims data and the COVID-19 pandemic. First, we establish that pediatric adherence to asthma control medication declined significantly during the pandemic, with the largest impact on the youngest children.[1] Second, we find that age and pre-pandemic use of mail-order pharmacies significantly moderate the effect of the pandemic, even after accounting for socioeconomic factors and factors that distinguish COVID from other macroeconomic downturns. Finally, we provide evidence from a nationally representative survey to show that parental attention likely plays a significant role in driving the observed adherence patterns.

We focus on asthma because it is the most common chronic condition among children. According to the National Health Interview Survey (NHIS), one in five children in the U.S. has been diagnosed with asthma. Effective management of asthma typically requires prescription drugs, delivered either orally or in an aerosolized form. Critically, poor drug adherence among pediatric asthma patients has been shown to negatively affect long-term health, educational attainment, and income (e.g., Miller et al., 2009; Currie, 2009).

Our primary analysis relies on a proprietary transactions database that captures near-population-level prescription drug claims from the U.S. market. The richness of this database conveys several advantages over previous studies, which typically use small sample surveys, self-reported information, and track individuals only to the extent that they remain covered by the same employer. First, these data are large enough to permit a fine-grained subsample analysis to investigate the mechanisms underlying our result. Second, these data allow us to track individuals over time, regardless of insurer. Finally, the transactional nature of the

[1] Control medication is intended to be taken daily to manage asthma, as opposed to "as-needed" medication, which is used in the case of an acute asthma attack. We follow the classifications in Karaca-Mandic et al. (2012) and Sayed et al. (2022) to separate products in our data. Our primary measure of adherence is based on the proportion of days covered (PDC) in a given month. We find that adult drug adherence *increased* slightly during 2020, which rules out many alternative interpretations. Our results also stand in contrast to earlier analyses of the impact of COVID-19 on pediatric drug adherence (Kaye et al., 2020; Yang et al., 2022).

data makes it more reliable than self-reported survey evidence for measuring an important health behavior.

Using this dataset, we build a patient-by-month panel of monthly medication coverage rates for roughly 2 million pediatric asthma patients who filled prescriptions in the 2018 to 2020 period. Crucially, we focus on patients who take "control" medication, which is necessary for managing the disease and preventing asthma attacks.[2] We compare monthly adherence outcomes in 2020 to those from 2018 and 2019, both overall and within individuals, to estimate the response to the pandemic. Overall, we find a sustained decrease in pediatric drug adherence of 13 percent during the pandemic. However, the dynamics of this effect are more sharply negative later in 2020, especially for the youngest children in our sample. By December 2020, preschool-aged children experienced a 40 percent decrease in adherence rates while adherence among school-aged children and teenagers fell by 25 percent and 21 percent over the same period, respectively.

Given the unique nature of the COVID pandemic relative to other macroeconomic downturns, we test whether these effects are driven by COVID-specific factors or by broader underlying mechanisms. For this analysis, we estimate a horse-race regression that allows COVID-specific factors (including school closures, changes in air quality, and access), as well as other county and state-level socioeconomic measures, and individual-level factors to mediate the average effect. We find that age and pre-pandemic use of mail-order pharmacies are statistically and quantitatively significant predictors of adherence responses; each of these factors is associated with less negative responses.

We conjecture that parental attention plays a key role in pediatric adherence. Changes in parental attention would have the largest impact in cases where: (1) children are too young to communicate effectively; (2) feedback from non-adherence is not immediate; and (3) there is a lack of built-in routines, such as mail-order usage or parents picking up their own prescriptions alongside their child's. These predictions are consistent with our horse-race estimates and with our estimate that pediatric adherence to insulin regimes was unaffected by the pandemic. To further support this hypothesis, we use data from the Medical Expenditure Panel Survey (MEPS) to show that the negative adherence response is much smaller when parents also pick up their own prescriptions.[3]

Our results underscore the critical role that parents play in managing chronic health conditions. Our work suggests that the management of pediatric asthma is intertwined with the demands of parental attention, especially within the context of macroeconomic events.

[2]The remaining drugs in our data are "as needed" medications that patients take during asthma attacks. Our methodological restriction helps us avoid picking up on shortages in "as-needed" medication at the start of the pandemic (Hendeles and Prabhakaran, 2020). We discuss this and other issues in Section 2.

[3]Our IQVIA data do not link children to parents, which MEPS does.

As such, behavioral policy interventions may be warranted in response to macroeconomic shocks. For example, reminders, automatic mail delivery, and other forms of assistance directed toward parents may help mitigate the effects of these shocks on their children. These kinds of interventions are likely to be high-impact, given previous work showing high marginal value associated with public programs that primarily benefit children (Finkelstein and Hendren, 2020).

We contribute to the 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 (e.g., Chandra et al., 2010; Osterberg and Blaschke, 2015). Our evidence speaks to an understudied and influential factor related to pediatric adherence: parental attention. Our findings on the importance of parental attention are consistent with survey evidence (Matsui, 2007). 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 (Chandra et al., 2010; Finkelstein et al., 2012; Brot-Goldberg et al., 2017).

We also contribute to a nascent literature studying the impact of the pandemic on prescription drug adherence (Kaye et al., 2020; Ferraro et al., 2021; Yang et al., 2022; Haapanen et al., 2022; Clement et al., 2021). We are the first to document longer-run negative effects on pediatric drug adherence using large-scale administrative data and a measure of adherence that is based on coverage rates. By comparison, the existing literature generally finds a positive relation based on small sample studies and more subjective adherence measures.

Our findings also contribute to the literature on pediatric health and the role of parents. 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 pediatric health shocks. Focusing on adults, Fadlon and Nielsen (2019) provides quasi-experimental evidence of within-family spillovers, including drug adherence. Our results suggest that differences across children in their parents' attention to chronic disease management could be a driver of the increasingly steep health-SES gradient as children age.

Finally, we contribute to the large body of work documenting the effects of macroeconomic conditions on health behaviors and outcomes. Ruhm (2000) documents the procyclical nature of mortality; subsequent work has examined mortality differences by age (Dehejia and Lleras-Muney, 2004; Van Den Berg et al., 2006; Miller et al., 2009) and employment (Sullivan and Wachter, 2009). Burgard and Hawkins (2014) focuses specifically on the Great Recession, finding decreases in healthcare use, especially among African Americans and Hispanics, and among those individuals with less education. We expand this literature by studying pediatric adherence and showing that the negative response is not primarily driven by factors specific to COVID.

2 Background

2.1 Pediatric Asthma

Asthma is one of the most common chronic conditions affecting children. 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[4] Asthma can be managed by taking short-term "as-needed" medications to help relieve symptoms during an asthma attack and long-term "control" medications to help prevent attacks and control symptoms by reducing airway inflammation and preventing the narrowing of airways (Karaca-Mandic et al., 2012).[5] In 2018, 72 percent of young children with asthma reported using a prescription inhaler within the last three months, and 55 percent of young children with asthma reported taking preventative medication.

Adherence to prescriptions is a key issue, both for the management of chronic disease generally and specifically among asthmatic individuals. 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). Poor adherence has been shown to directly affect disease management, including increased risk of hospitalization and death (Osterberg and Blaschke, 2015; Asamoah-Boaheng et al., 2021). The costs and health consequences of mismanaged asthma can be significant. When well controlled, asthma rarely leads to hospitalization, but non-adherence increases the odds of experiencing an asthma attack and emergency room visits (Weiss et al., 1992). 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).

[4]Summary statistics are based on the author's calculations using the 2018 NHIS.

[5]Table A1 provides detailed classifications for asthma medication in our sample, based on the classifications in Karaca-Mandic et al. (2012) and Sayed et al. (2022).

As noted earlier, we focus on adherence to control medication for several reasons. First, adherence measures are less appropriate for as-needed medication, which is only used during an asthma attack. As a result, these prescriptions may be filled infrequently and used with significant lag relative to their fill date, making fill patterns difficult to interpret in the context of adherence measures. Moreover, declines in as-needed fills may also capture changes in the incidence of asthma attacks (e.g., from improved air quality) rather than from changes in adherence behavior. In contrast, control medications are intended for continuous use, making adherence measures derived from fill and refill data more appropriate and interpretable. Excluding as-needed medication also helps us avoid complications related to the Albuterol shortage in the first months of the pandemic (Hendeles and Prabhakaran, 2020).

2.2 Key COVID-19 Events

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, California became the first state to issue a stay-at-home order; other states quickly followed. In what follows, we outline several significant events that are likely to affect drug adherence.

Several significant pieces of federal legislation were passed in response to the onset of the pandemic. First, the Coronavirus Preparedness and Response Supplemental Appropriations Act, enacted on March 6, 2020, included a waiver allowing Medicare providers to offer telehealth services. 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, enacted on March 18, 2020, mandated that states could not disenroll 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 and Economic Security Act (CARES), enacted on March 27, 2020, provided $2 trillion worth of emergency assistance for individuals, families, and businesses. For example, CARES provisioned up to $1,200 in individual Economic Impact Payments beginning April 15, 2020. Collectively, these three pieces of legislation likely expanded access to care, increased quantities of drugs per claim, and made time between claims more irregular.

School closures and re-openings were also highly relevant events, especially in the context of pediatric adherence, because schools often play a key role in administering treatment routines for children. After the national emergency declaration, all public schools in the

[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).

U.S. were closed for in-person learning. These closures were recommended or mandated for the rest of the 2019-2020 academic year in most states. During the start of the 2020-2021 academic year, there was additional heterogeneity in mandated in-person learning.[7]

3 Data and Methodology

3.1 Data

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, and primary payer. We provide detailed variable descriptions for these supplemental data, including sources, in Appendix Table A2. These data cover the near-universe of prescription drug claims in the U.S.

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 not only allows us to derive representative results for the population but also allows us to precisely estimate sub-population effects.

We supplement these data with local population data based on the prescriber's zip code, including race, income, education, occupation, population density, and access to health insurance. We also characterize the development of the COVID pandemic using measures school closures, air quality, and access to telehealth using several external sources. These data and sources are described in Table A3.

3.2 Measuring Drug Adherence

We construct a monthly, patient-level panel data set for patient cohorts in 2018-2020. Each patient cohort consists of individuals who filled control medication in the first three months of a given year.[8] We compute the share of days covered in each month of the cohort-year for each patient based on the stock of medication available and the flow of prescription fills and refills. Specifically, we begin by identifying the earliest claim in the LRx database

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

[8]Patients appear in multiple cohorts if they have filled a control medication in January - March in multiple years.

for each patient, and then we track their stock of medication across subsequent 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. We aggregate this measure to describe the proportion of days covered (PDC) by control medication for a given patient-month. We interpret year-over-year changes in monthly coverage rates as changes in drug adherence. Our measure is similar to other continuous measures commonly used for assessing adherence in asthma pharmacy claims databases (Lam and Fresco, 2015; Asamoah-Boaheng et al., 2021). Our final analysis sample contains roughly 2 million children under the age of 18 per cohort.

We characterize each patient-year based on the characteristics of the first prescription filled during the first three months of the year. For example, we note the type of payer for a given individual and whether they fill scripts via mail order versus at a retail pharmacy.

3.3 Pre-COVID Pediatric Drug Adherence

Figure 1, Panel (a) depicts the average monthly coverage rate for users younger than 60 years old. The average PDC measure ranges from less than 0.3 for the youngest patients to over 0.5 for adults over 40.[9] These values are within the range of PDC values found in the literature (Asamoah-Boaheng et al., 2021).[10]

Panel (b) depicts monthly patterns in pediatric coverage for our sample. Because we require that at least one prescription be filled between January and March, PDC rates are highest in the first three months of the year. PDC rates gradually fall across the first six months of the year, stabilizing at roughly 35% by the end of the year. In Panel (c), we decompose pediatric coverage rates by income, showing that coverage rates are lower for patients who live in low-income geographies. This is consistent with the fact that children living in low-income areas are more likely to be asthmatic and that income is a negative predictor of pediatric adherence (Matsui, 2007). Finally, Panel (d) depicts the average pediatric coverage rate by county in 2019, revealing the scope of geographic variation that exists across the U.S.

Additionally, Table 1 reports baseline statistics describing our pediatric analysis sample in 2019 (Col 1), and then separately across three age subgroups (Cols 2 to 4). The first subgroup roughly corresponds to children who are preschool-aged, the second to children in elementary and middle school, and the third to children in high school.[11] We observe 1.9

[9] We exclude patients described as 0 years old when filling their first control medication prescription in January - March of a given year. For this reason, the youngest patient in our sample is 1 year old.

[10] Table S9 of Asamoah-Boaheng et al. (2021) summarizes studies in the literature that measure PDC. The studies range from 0.32 to 0.41 in average PDC, with lower average PDC values for children than for adults.

[11] We characterize patient age based on the age associated with the first prescription filled in the calendar

million unique users, of which 24, 50, 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.

3.4 Methodology

We estimate the effect of the COVID pandemic on drug consumption by comparing coverage rates in each month of 2020 to coverage rates the same month in 2019:

$$y_{imt} = \beta_0 + \beta_1 Y2020 + \beta_2 Y2018 + \gamma_z + u_{imt} \tag{1}$$

Here, y_{imt} measures the monthly drug coverage (PDC) for individual i in month m in year t, and β_1 estimates any change in drug consumption in 2020 compared to 2019. In addition, β_2 estimates any change in drug consumption from 2018 to 2019. We interpret $\hat{\beta}_1$ as a test of the effect of the pandemic on drug consumption. $\hat{beta}_2$ provides a placebo test related to whether trends in year-over-year drug consumption existed prior to the pandemic. In some specifications, we include a provider zip-code fixed effect, γ_z, based on the prescriber of the first prescription filled for a given cohort, and in other specifications, we include individual fixed effects. All estimates are clustered at the state level.

In addition to the above model, we also estimate specifications that drop the $Y2018$ variable, so that estimates of $\hat{\beta}_1$ reflect the difference in any given month of 2020 compared to average consumption in 2019 and 2018. We take advantage of this simplification to conduct empirical tests of the relative importance of patient and geographic characteristics, π_i, in explaining $\hat{\beta}_1$:

$$y_{imt} = \beta_0 + \beta_1 Y2020 + \pi_i + \psi \cdot \pi_i \times Y2020 + \gamma_z + u_{imt} \tag{2}$$

For example, suppose π_i is a dummy variable equal to one for patients who filled their first prescription of the year by mail. Then ψ captures the estimate of the pandemic on monthly coverage rates for patients who fill their prescriptions by mail relative to those who use alternative delivery channels, or the relative effect of the pandemic.

Table 2 reports summary statistics from 2018, 2019, and 2020, measured based on prescriptions filled in the first three months of each year. Panel (A) describes the characteristics of patients and patient consumption, and Panel (B) describes the geographic characteristics associated with the zip code of their provider. Patient characteristics appear to be balanced

year to avoid within-year attrition.

across all three cohorts included in our analysis. [12]

Table 3 presents statistics related to the mechanics of prescriptions in each year in our sample. The average number of scripts per year at the patient level is about 5, and the average days supplied is about 35 days. About half of the scripts are marked as refills. The fractions of scripts that involve cash payments (1-2 percent) and mail delivery (2 percent) are very low in the pediatric sample. All statistics are similar across years, except the number of scripts filled (lower) and days supplied per script (higher) in 2020.

The key identification assumption behind our study design is that year-over-year variation in monthly drug consumption would have been similar in 2020 compared to 2019 if not for the onset of the pandemic. We revisit this assumption and present evidence in support of this identification strategy after presenting our core results in Section 4.

4 Empirical Findings

4.1 Impact of COVID on Adherence

Figure 2, Panel (a) depicts the estimated mean monthly change in pediatric adherence using our core specification without any fixed effects. Estimates, scaled by average monthly consumption in 2019, are reported separately for preschool-aged children (aged 1 to 5), school-aged children (aged 6 to 12), and teenagers (aged 13 to 17).[13]

We find substantial heterogeneity in the effect of the pandemic from March through December. For March, we find that adherence rates increased by 5-8 percent across all pediatric age groups, likely reflecting stockpiling with the onset of the pandemic. Pediatric adherence responses became negative starting in June, and fell even further in the fall and through the end of 2020. Furthermore, these estimates show that the youngest group exhibited the largest effects. Overall, we find that preschool-aged children experienced a 20 percent decrease from their expected coverage rate in December 2020, whereas school-aged children and teenagers experienced decreases of 10 and 5 percent, respectively.

Figure 2, Panels (b) and (c), present results that incorporate zip code and individual fixed effects. We find similar qualitative patterns throughout, with larger quantitative effects when including individual fixed effects: preschool-aged children experienced a 40 percent decrease in December 2020, whereas school-aged children and teenagers experienced decreases of 25

[12]We interpret the imbalance in patient consumption in 2018 compared to 2019 and 2020 as mechanically due to the way we build our consumption data, which is calculated based on prescription fills and refills that we observe beginning in January 2018. This leads to a "burn-in" issue for 2018, because we do not observe scripts from late 2017.

[13]Table A4 reports corresponding unscaled coefficients.

and 22 percent, respectively.[14] Ultimately, we estimate that adherence fell by an average of 13 percent across all children from March through December when incorporating individual fixed effects.[15]

We also verify that response sizes are similar in percentage terms when we use other measures of adherence. As noted above, our main measure of adherence is PDC. Asamoah-Boaheng et al. (2021) note that evidence in the health literature suggests that having a PDC below 50 percent is associated with negative long-term health outcomes. Therefore, we re-estimate Equation(1) using indicators for whether an individual's PDC was above 50 percent and above 30 percent. Figure A1 shows that the percentage response is similar when using these alternate adherence measures.

We note that the drop in adherence persisted through at least December, despite events specific to the evolution of the pandemic that may have impacted pediatric adherence. For example, economic impact payments were made in April and December, which may have affected budget constraints and, therefore, adherence patterns. These payments, however, do not correspond to an aggregate increase in pediatric adherence rates. Second, schooling and childcare disruptions may have affected adherence patterns by disrupting routines, triggers, and access to care. All public schools and daycare centers were temporarily closed to in-person learning by March 25, 2020, and by mid-April, half of all public schools announced that remote-only learning would continue through the end of the academic year.[16] This period corresponds with a sharp initial decline in pediatric adherence. By fall, however, adherence continued to plummet, especially among the youngest children, even though the majority of school districts had moved to a hybrid learning model.

Next, we report the within-county scaled effects of the pandemic in Panel (d). 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, underscoring both the severity and the scope of the COVID response We revisit these and other COVID-specific factors in greater detail below.

Next, Figure 3 presents several results related to our identification assumption. First, Panel (a) shows that pediatric adherence rates were very similar for March through December in 2018 and 2019, providing evidence of a stable control sample.[17] Panel (b) provides detailed

[14] Table A5 reports corresponding unscaled coefficients for within-zip code and within-patient specifications.

[15] This number is based on column (1) of Table 4. Although control medication is intended for daily use, individuals may ration medication during the initial stockpiling period, so that usage differs from our PDC measure. Pooling across the whole year helps us reliably estimate an overall effect.

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

[17] The January and February adherence rates in 2018 are lower than in 2019, partly reflecting the "burn-in"

comparisons within pediatric age groups, again showing very similar rates in 2018 and 2019.

Figure 3 also provides additional contextual results. Panel (c) presents estimates of the effect of the pandemic on adult adherence under different fixed effects specifications, showing that adults *increased* adherence throughout 2020; this rules out mechanisms that would have similar effects on both adults and children. Panel (d) compares results for asthma to diabetes and finds that pediatric diabetes patients exhibited some stockpiling but no negative adherence response in 2020. We revisit this in our discussion below on mechanisms.

4.2 Horse-race Analysis

Next, we evaluate the relevant importance of COVID-specific factors (school closings and air quality), individual-level factors (age, insurance status, and use of mail order), and regional factors (demographics, economic indicators, and health policies) in mediating the estimated effect of the pandemic. To do so, we add a host of interactions with the core treatment effect to create a horse-race regression following Equation (2).

Table 4 reports estimates for individuals under 18, providing estimates for all months, March to July, and August to December. The first three columns focus on the average response, as captured by the "2020" variable. Differences in these estimates highlight the early stockpiling and subsequent negative effects (-10pp in the August to December period versus -5.78pp overall).

The next three columns of Table 4 repeat this analysis but include a large set of interaction terms to assess potential mediating factors. We find that the quantitatively large and statistically significant mediating factors for August to December are age and pre-pandemic usage of mail-order pharmacies.

Because we focus on factors other than COVID-specific ones, we relegate a detailed discussion of COVID-specific factors to Appendix C.[18] We note, however, that several COVID-specific factors are not associated with quantitatively large mediating effects. In particular, local school closure rates do not meaningfully mediate the average effect in the latter months 2020 (+1pp effect on a baseline of -10pp). This is consistent with the longitudinal pattern in our core estimates, namely that the negative pediatric response becomes stronger even as schools reopen in the fall. We also find quantitatively small effects for access variables, including telehealth laws (precise zero). Finally, we find that air quality has a limited mediating impact (precise zero).[19]

issue noted earlier.

[18] Figure A3 and Table A6 provide evidence that these factors are associated with minimal quantitative differences.

[19] This likely reflects our choice to focus on control medication rather than "as-needed" medication.

Our regression also includes interactions with other county and state-level demographics, socioeconomic measures, and population health statistics. Overall, we find minimal evidence that these factors had quantitatively large mediating effects.[20] We want to stress that our results do not mean these factors do not matter in the cross-section.[21] Instead, our research design nets out these factors by including individual fixed effects.

4.3 Evidence on Parental Attention

Given the evidence in Table 4, we conjecture that decreases in parental attention play a key role in driving the decrease in pediatric adherence. Key predictions under this conjecture are that the effect would be largest: i) for children too young to communicate; ii) for medication where non-adherence does not create immediate feedback; iii) for children whose parents face greater logistical barriers to filling medication. To support this, we discuss the existing evidence in greater detail and provide additional evidence from other data sources.

Our existing evidence provides support for each of the predictions. First, the estimates in Column 6 of Table 4 suggest that a sixteen-year increase in *Age* offsets half of the average effect for August through December (-10pp from Column 3). Figure A2 reports non-parametric estimates of the effect by age to show that linearity assumptions are not driving our results. In the August to December period, the estimates are monotonic by age, with minimal effects for 17-year-olds and a large negative response for the youngest children. Finally, we find quantitatively negligible age effects within the adult population (Table A7).

As evidence related to our second prediction, we analyze any changes in 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 1 diabetes. We assemble a data set of monthly adherence rates using a methodology similar to that which was described above and estimate the same regression model. Figure 3, Panel (d) plots both the scaled effect of the pandemic on adherence for pediatric diabetes and asthma patients.[22] We find that the response of pediatric adherence to diabetes medication during COVID was a precise zero, outside of some initial stockpiling, in stark contrast to our persistent negative estimate for pediatric asthma patients.

Finally, our results on mail-order pharmacy usage support the logistics-related prediction. Mail order has several advantages in terms of logistics relative to filling prescriptions at a retail pharmacy: i) although refills are not automatic, they can be ordered online; ii) the

[20] Surprisingly, traditional measures of high SES (high income and education) seem to be associated with negative point estimates, indicating a larger decrease in adherence in these areas.

[21] As noted earlier, we do find higher adherence in higher-income areas in the 2018 and 2019 data.

[22] Appendix Table A8 provides summary statistics for this population in 2019.

number of days covered is usually much larger due to differences in regulations.[23] As shown in Table 4, the mediating effect of already using mail order at the start of the pandemic is 40 percent of the average effect in the August to December period (3.94pp in column 6 versus -10pp average in column 3). We also provide graphical evidence in Figure 4, focusing just on differences between users of mail order before the pandemic and other individuals. Consistent with the horse-race estimates, we see less stockpiling for individuals using mail delivery, followed by less negative responses later in the year.

4.3.1 Evidence from Within Family Claims Data

Because our IQVIA data does not contain family identifiers, we complement our findings with an analysis based on a panel data set constructed from the nationally representative MEPS. MEPS also 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 and, as a result, captures very few pediatric patients taking asthma medication (N=318 for individuals taking asthma medication in 2019 compared to N=2 million in the IQVIA database).[24]

Notwithstanding this limitation, we proceed in two steps. First, we replicate our core finding that monthly coverage rates decrease for children. To do so, we create an individual-by-year panel for users of asthma medication in 2019 who continue to be surveyed by MEPS in 2020.[25] We compute the total days supplied for each individual and year.[26] We then estimate the average change in adherence rates between 2019 and 2020 for children from different age groups using a Poisson regression $Y_{it} \sim Poisson(\lambda_{it})$:

$$\lambda_{it} = \alpha_i + \beta \cdot I_{t=2020} + \epsilon_{it} \tag{3}$$

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 5, Panel (A) reports these results. We find that the average quantity of medication decreased for all children, with larger effects for younger age groups. In contrast, adults exhibit no effect.

Second, we construct data describing the parents of children who take asthma medication

[23]In our data, the average mail order script contains a 60-day supply of medication versus 30 days for scripts filled at retail pharmacies.

[24]Because of the limited sample size, we choose to focus on all asthma prescriptions rather than restricting to users of control medication. Table A9 presents summary stats related to our analysis sample.

[25]Although MEPS contains rounds of surveys within a given year, the dates of the scripts are not available, so a monthly analysis is not possible.

[26]Appendix D.1 provides information about data, empirical design, and summary statistics.

to study parent-level mediating factors. For each asthmatic child in 2019, we construct a set of parental measures based on MEPS. These measures include (1) log of one plus 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 (Δ*Mental*), (3) 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*).

Formally, we estimate the following Poisson specification:

$$\lambda_{it} = \alpha_i + \beta \cdot I_{t=2020} + \sum_j \gamma_j \cdot I_{t=2020} \cdot (X_i^j - \bar{X}^j) + \epsilon_{it} \tag{4}$$

where X^j are the factors discussed above and $\bar{X}^j$ are the population means. Results are reported in Table 5, Panel B, Model (1).

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 and statistically significant. An increase from zero to the median number of adult prescriptions 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. Importantly, other factors, such as parental education and income, have quantitatively smaller correlations with response size. Panel (B), Model 2 repeats the horse-race analysis for the most common non-asthma medication taken by children. We generally find similar mediating effects for parental prescriptions and qualitatively similar estimates for all other factors except job loss.

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 IQVIA and MEPS, MarketScan provides family identifiers and dates associated with prescriptions.[27] In the last year of our sample, we find that a 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. Table A10 provides additional statistics.

These co-occurrence rates confirm the plausibility of the parental attention channel. As shown earlier, adult adherence rates increased 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 prescrip-

[27]We have access to data from 1996–2013. Appendix D.2 provides detailed methodology and results.

tions 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, a reasonable rate.

4.4 Evidence on Health Impacts

As noted earlier, the medical literature suggests that reduced adherence to control medication will lead to worse long-run health outcomes. However, identifying such effects is difficult for several reasons. First, our IQVIA data is not linked to medical claims, which precludes a comparison of health outcomes across individuals with differing adherence responses. Second, Binney et al. (2024) find that asthma hospitalizations had been significantly decreasing leading up to the pandemic, with half as many hospitalizations in 2019 versus 2012. The authors attribute this to better management of asthma.

Despite these issues, we use MEPS data to provide some evidence on health trends among pediatric asthma patients.[28] For each age group (1–5, 6–12, 13–17, and adults) and year between 2013 and 2022, we calculate the average number of emergency room visits plus hospital stays among asthma patients.[29]

We find patterns that are generally consistent with non-adherence having subsequent negative health impacts. Consistent with Binney et al. (2024), Figure A4 shows a decreasing trend in the number of events leading up to 2020 and a sharp drop in 2020. In 2021 and 2022, we only find a consistent increase within the youngest age group, consistent with non-adherence being a key issue among the youngest asthma patients in the latter half of 2020. Table A11 provides formal estimates at the individual level that suggest a large relative increase in hospitalization rates for the youngest children after 2020. However, the pre-trends and limited sample size in MEPS make it difficult to address the issues with great precision.

5 Conclusion

Using large-scale transaction data, we have documented a large decrease in pediatric adherence to asthma control medication during the COVID-19 pandemic. Poor adherence has been shown to convey long-term negative health consequences and increased healthcare costs. We

[28] Appendix D.3 provides details on methodology.

[29] 2022 is the latest year for which MEPS has posted data. Other commonly used datasets like the one used in Binney et al. (2024) are also only available through 2022.

show that this change is not primarily driven by factors that distinguish the COVID pandemic, such as school closures, from other macroeconomic downturns. Moreover, we provide evidence that the response was not primarily 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. 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.

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, appear less vulnerable. On the other hand, our work suggests that the management of pediatric asthma is intertwined with the demands on parental attention that are increased 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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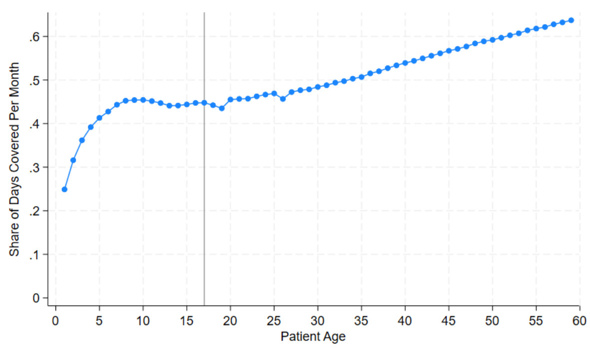
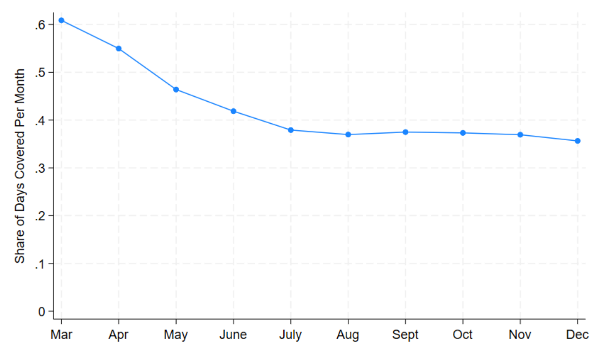
Figure 1: Pre-Pandemic Coverage Rates

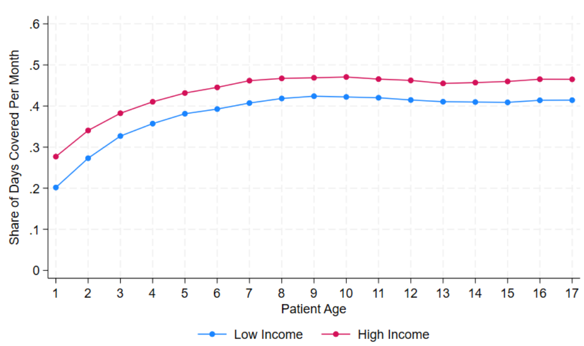
(a) Average Monthly Coverage Rate



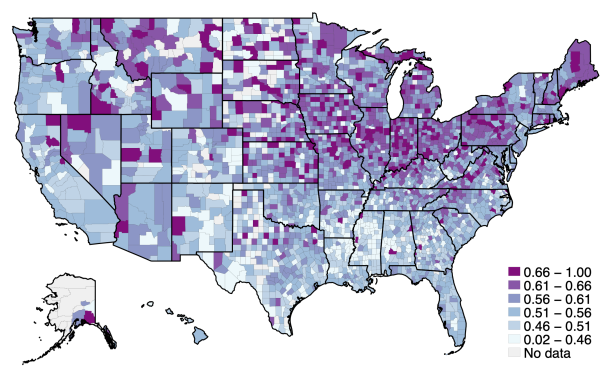
(b) Monthly Pediatric Coverage Rate



(c) Pediatric Coverage Rate, by Income

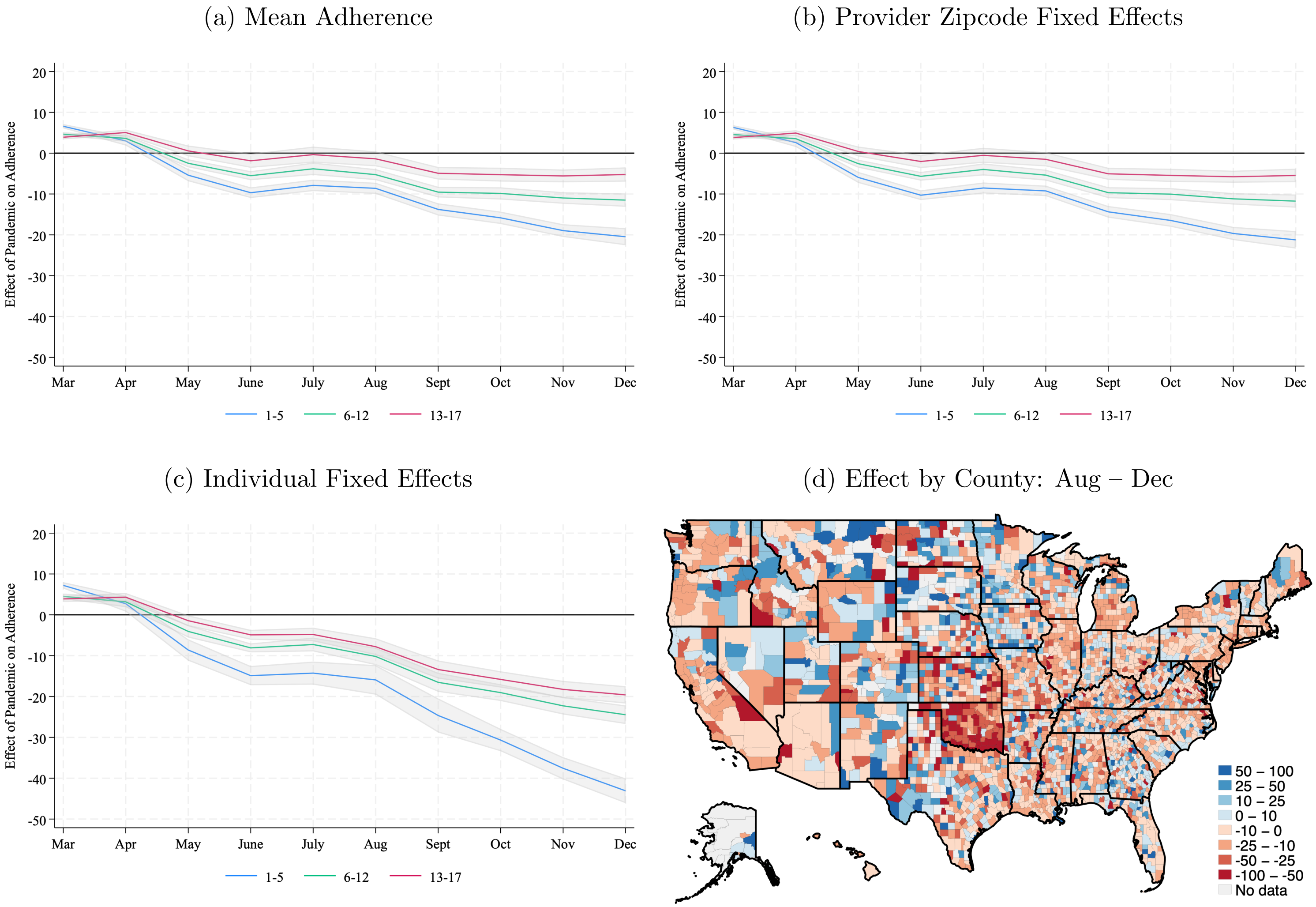


(d) Pediatric Coverage Rate



Notes: The four panels in Figure 1 plot the average monthly coverage rates in 2018 and 2019 for asthma patients taking control medication. All statistics reflect coverage rates between March and December, which defines our analysis window. Panel (A) depicts average coverage rates by age. Panel (B) depicts monthly pediatric coverage rates. Panel (C) depicts monthly pediatric coverage rates for children with a provider located in a high and low income zip code. Panel (D) depicts average pediatric coverage rates by county, based on the providers zip code

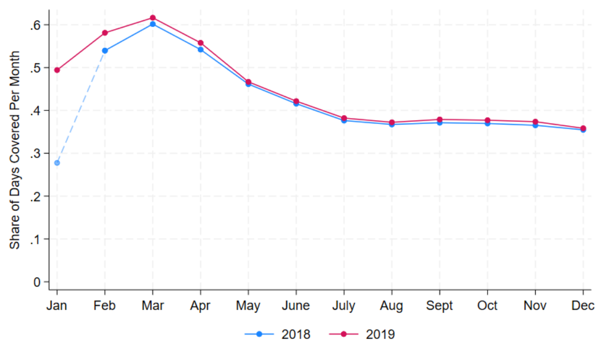
Figure 2: Effect of the Pandemic on Monthly Pediatric Drug Adherence



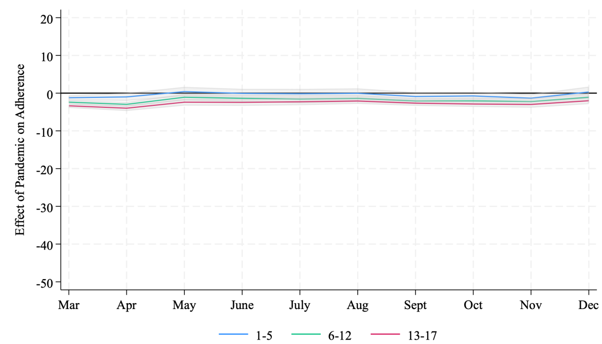
Notes: Figure 2, Panels (A) - (C) plot the monthly difference in pediatric drug adherence from 2019 to 2020 by age of the patient based on Equation 1. All results are scaled by the 2019 average pediatric adherence rate. Panel (A) depicts mean changes in drug adherence. Panel (B) includes state fixed effects. Panel (C) includes individual fixed effects. Panel (D) plots the estimated mean effect of the pandemic for patients aged 1 to 17 within county averaged across August - December; data ranges reflect the following parts of the distribution: 0-10,10-25,25-50,50-75,75-90,90-100

Figure 3: Identification and Data Validation

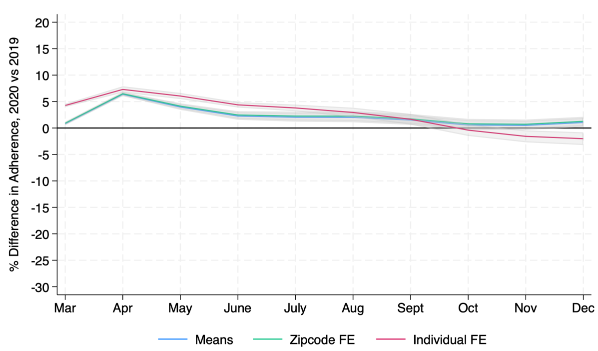
(a) 2018 and 2019 Coverage Rates



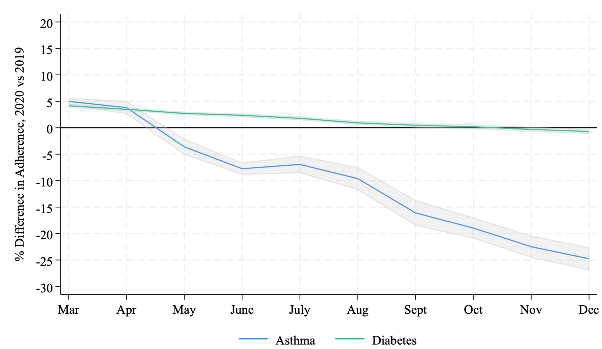
(b) 2018 and 2019 Differences



(c) Adherence Effect: Adults 18 to 59

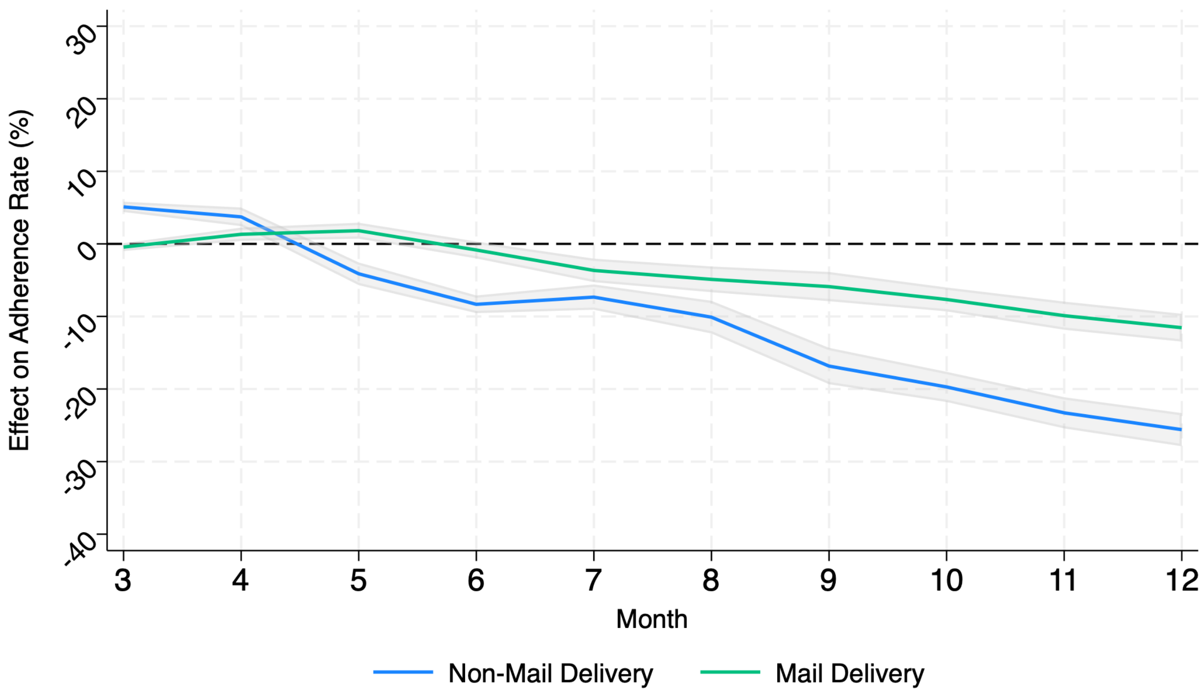


(d) Other Disease: Pediatric Diabetes



Notes: Panel (A) plots the average coverage rates for pediatric users in our analysis sample in 2018 and 2019. Panel (B) plots differences in coverage rates in 2018 compared to 2019 for pediatric patients. Panel (C) plots differences in coverage rates in 2020 compared to 2019—or the effect of the pandemic; results are scaled by the average pediatric adherence rate each month in 2019. Panel (D) plots the effect of the pandemic on adherence rates for pediatric asthma patients together with pediatric diabetes patients using an individual fixed effect specification.

Figure 4: Heterogeneity by Delivery Channel



Notes: Figure 4 plots the effect of the pandemic on pediatric adherence by the delivery channel used by the individual before the onset of the pandemic.

Table 1: Sample Statistics: Pediatric Asthma Patients, January - March 2019

	Under 18 (1)	Under 6 (2)	6 to 12 (3)	13 to 17 (4)
Panel A: Individual Characteristics				
Adherence Rate	0.56	0.51	0.58	0.58
>30% Days Covered	0.66	0.62	0.68	0.67
Patient Age	9.18	3.41	8.96	14.83
Share Female	0.42	0.40	0.41	0.45
Medicaid Payer	0.13	0.13	0.13	0.13
Third Party Payer	0.86	0.86	0.85	0.86
Panel B: 2018 Local Geographic Characteristics				
Per-Capita Income, 2018	31,905	31,755	31,897	32,057
Minority Share of Population, 2018	0.26	0.26	0.26	0.25
Share Population with Some College, 2018	0.21	0.21	0.21	0.21
Share of Population in Urban Area	0.89	0.90	0.89	0.89
Medicaid Expansion State	0.56	0.54	0.55	0.57
Observations	1,925,675	458,648	962,432	504,595

Notes: This table provides summary statistics describing the population of pediatric asthma prescription users in 2019. Adherence statistics reflect prescriptions filled between January and March, and individual characteristics reflect the first prescription filled in 2019. Local geographic characteristics are matched based on the zip code of the provider associated with the first prescription filled. Columns 2 – 4 report summary statistics for subpopulations based on age. Variable definitions provided in Appendix Table A2 and A3.

Table 2: Balance: Pediatric Asthma Patients, January – March

	2018	2019	2020
Panel A: Individual Characteristics			
Adherence Rate	0.47	0.56	0.56
>30% Days Covered	0.58	0.66	0.66
Patient Age	9.13	9.18	9.34
Share Female	0.42	0.42	0.42
Medicaid Payer	0.13	0.13	0.12
Third Party Payer	0.85	0.86	0.87
Panel B: 2018 Local Geographic Characteristics			
Per-Capita Income, 2018	32076.38	31904.98	32117.20
Minority Share of Population, 2018	0.26	0.26	0.26
Share Population with Some College, 2018	0.21	0.21	0.21
Share of Population in Urban Area	0.90	0.89	0.90
Medicaid Expansion State	0.56	0.56	0.56
Observations	2,092,890	1,925,675	2,039,886

Notes: This table provides summary statistics describing the population of pediatric continuing asthma prescription users based on their January - March 2018, 2019, and 2020 prescriptions. Variable definitions provided in Appendix Table A2 and A3.

Table 3: Annual Patient-Level Summary Statistics: Pediatric Asthma Prescriptions

	2018	2019	2020
Number Rx	5.51	5.35	4.92
Avg Days Supplied Per Rx	34.84	35.52	37.09
Share Rx, Refill	0.46	0.47	0.48
Share Rx, Medicaid	0.13	0.13	0.12
Share Rx, Third Party	0.85	0.86	0.87
Share Rx, Cash	0.02	0.01	0.01
Share Rx, Mail Delivery	0.02	0.02	0.02
Annual Days Supplied	185.99	182.39	174.52
Observations	2,092,890	1,925,675	2,039,886

Notes: This table provides summary statistics describing annual asthma prescriptions for pediatric users in our analysis in 2018, 2019, and 2020. Variable definitions provided in Appendix Table A2 and A3.

Table 4: Collective Impact of Mechanisms: Horse Race

	Mar - Dec (1)	Mar - July (2)	Aug - Dec (3)	Mar - Dec (4)	Mar - July (5)	Aug - Dec (6)
2020	-0.0578***	-0.0154***	-0.100***	-0.0292***	-0.0139*	-0.0445***
	(0.00236)	(0.00210)	(0.00306)	(0.00762)	(0.00609)	(0.0105)
Age x 2020				0.00219***	0.00128***	0.00311***
				(0.000144)	(0.000130)	(0.000192)
Mail x 2020				0.0362***	0.0331***	0.0394***
				(0.00254)	(0.00248)	(0.00352)
AQI Improvement x 2020				0.00111	0.00198	0.000232
				(0.00234)	(0.00255)	(0.00255)
High Income x 2020				-0.00530**	-0.00192	-0.00869***
				(0.00183)	(0.00166)	(0.00229)
High Education x 2020				-0.00785***	-0.00572***	-0.00997***
				(0.00169)	(0.00141)	(0.00255)
White Collar x 2020				-0.00795	-0.00237	-0.0135
				(0.00517)	(0.00367)	(0.00788)
High Minority x 2020				0.000556	-0.000886	0.00200
				(0.00177)	(0.00178)	(0.00221)
Medicaid Payer x 2020				0.0115**	0.0102**	0.0128
				(0.00428)	(0.00323)	(0.00660)
Medicaid Expansion x 2020				0.00680*	0.00667*	0.00693
				(0.00321)	(0.00307)	(0.00413)
Telehealth x 2020				-0.00127	-0.00270	0.000171
				(0.00400)	(0.00308)	(0.00590)
Urban x 2020				0.0125***	0.0126***	0.0125***
				(0.00267)	(0.00242)	(0.00345)
High School Closure x 2020				0.0113***	0.0120***	0.0105**
				(0.00268)	(0.00244)	(0.00345)
Control Mean	.431	.489	.372	.431	.489	.372
Individual FE	x	x	x	x	x	x
Observations	60,584,510	30,292,255	30,292,255	60,584,510	30292255	30,292,255

Notes: Estimates are based on a regression model that compares adherence in 2020 to adherence in 2019 and 2018, following Equation 1. Columns 1 and 3 report the average effect across all months, and columns 2, 3, 5, and 6 report estimates for a subset of months as indicated by column headers. Control means reflect average pediatric adherence in the designated months in 2019. Variable definitions provided in Appendix Table A2 and A3. All specifications include individual fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Table 5: 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 (3) and (4). 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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September 2023

A Variable Definitions

Table A1: Drug Classification Crosswalk: LRx Database

Marketed Product Name	**Total Pediatric Scripts**	**USC Code**	Classification
MONTELUKAST SODIUM	23,832,218	28500	maintenance
ALBUTEROL SULFATE	14,673,416	28112	acute
FLOVENT HFA	8,843,200	28410	maintenance
PROAIR HFA	8,784,009	28111	acute
ALBUTEROL SULFATE HFA	8,544,319	28111	acute
VENTOLIN HFA	6,068,265	28111	acute
BUDESONIDE	2,925,650	28410	maintenance
QVAR REDIHALER	2,050,127	28410	maintenance
SYMBICORT	1,437,621	28431	maintenance
ADVAIR HFA	885,086	28431	maintenance
PROVENTIL HFA	815,239	28111	acute
QVAR	653,260	28410	maintenance
DULERA	625,478	28431	maintenance
PROAIR RESPICLICK	457,569	28111	acute
PULMICORT	419,619	28410	maintenance
ADVAIR DISKUS	395,680	28431	maintenance
LEVALBUTEROL HCL	360,092	28112	acute
LEVALBUTEROL TARTRATE HFA	271,257	28111	acute
ASMANEX HFA	266,074	28410	maintenance
ARNUITY ELLIPTA	257,637	28410	maintenance
PULMICORT FLEXHALER	211,642	28410	maintenance
FLUTICASONE PROPIONATE/SA	177,138	28431	maintenance
BUDESONIDE/FORMOTEROL FUM	171,385	28431	maintenance
BREO ELLIPTA	164,509	28431	maintenance
ASMANEX TWISTHALER 30 MET	148,084	28410	maintenance
DUPIXENT	137,160	86230	maintenance
WIXELA INHUB	108,949	28431	maintenance
XOLAIR	107,488	28900	maintenance
FLOVENT DISKUS	101,412	28410	maintenance
SPIRIVA RESPIMAT	97,160	28121	maintenance
ALVESCO	46,356	28410	maintenance
ASMANEX TWISTHALER 60 MET	45,445	28410	maintenance
XOPENEX HFA	38,031	28111	acute
LEVALBUTEROL HYDROCHLORID	37,732	28112	acute
ASMANEX TWISTHALER 120 ME	14,622	28410	maintenance
SINGULAIR	13,621	28500	maintenance
TRELEGY ELLIPTA	12,810	28432	maintenance
ZAFIRLUKAST	12,431	28500	maintenance
NUCALA	10,494	28900	maintenance
THEOPHYLLINE ER	9,068	28131	maintenance
CROMOLYN SODIUM	8,040	28210	maintenance
SEREVENT DISKUS	5,299	28118	maintenance
XOPENEX	5,122	28112	acute
FASENRA	4,427	28900	maintenance
TERBUTALINE SULFATE	4,181	28113	maintenance
THEO-24	4,138	28131	maintenance
AEROSPAN	3,212	28410	maintenance
LEVALBUTEROL	3,142	28112	acute
THEOPHYLLINE	1,882	28131	maintenance
ZILEUTON ER	700	28500	maintenance
FASENRA PEN	656	28900	maintenance
ALBUTEROL SULFATE ER	556	28113	acute
ASMANEX TWISTHALER 14 MET	520	28410	maintenance
AIRDUO RESPICLICK 113/14	480	28431	maintenance
PROAIR DIGIHALER	389	28111	acute
AIRDUO RESPICLICK 232/14	214	28431	maintenance
AIRDUO RESPICLICK 55/14	174	28431	maintenance

Table A2: 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 based on the first prescription filled in a given calendar year. *Source: LRx, IQVIA*
Gender	Gender of Patient (M,F) *Source: LRx, IQVIA*
Provider Zip Code	The zipcode for the provider's primary address based on the first prescription filled in a given calendar year. *Source: LRx, IQVIA.*
Payer	Primary Method of Payment: Cash, Medicaid, Third Party, Medicare, Medicare Part D based on the first prescription filled in a given calendar year. 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 was indicated to be "Mail" based on the first prescription filled in a given calendar year. *Source: LRx, IQVIA*

Table A3: Variable Definitions: Supplemental Data Sources

Variable	**Definition**
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*

Table A4: Mean Effect of Pandemic on Adherence: Variation By Age

	Mar (1)	Apr (2)	May (3)	Jun (4)	July (5)	Aug (6)	Sept (7)	Oct (8)	Nov (9)	Dec (10)	Obs (11)
Panel A: 1–5 years old											
$Y2018$	-0.00684***	-0.00493	0.00161	-0.000236	-0.000514	-0.000127	-0.00269	-0.00231	-0.00423*	0.000958	
	(0.00188)	(0.00265)	(0.00253)	(0.00214)	(0.00201)	(0.00195)	(0.00176)	(0.00172)	(0.00176)	(0.00222)	
$Y2020$	0.0372***	0.0148***	-0.0214***	-0.0339***	-0.0242***	-0.0252***	-0.0417***	-0.0492***	-0.0601***	-0.0629***	
	(0.00154)	(0.00288)	(0.00302)	(0.00233)	(0.00220)	(0.00204)	(0.00230)	(0.00241)	(0.00254)	(0.00329)	
Control Mean / N	0.565	0.495	0.397	0.350	0.308	0.293	0.302	0.311	0.317	0.307	1,419,607
Panel B: 6–12 years old											
$Y2018$	-0.0151***	-0.0171***	-0.00531*	-0.00609**	-0.00637**	-0.00555**	-0.00845***	-0.00824***	-0.00885***	-0.00420*	
	(0.00184)	(0.00185)	(0.00220)	(0.00213)	(0.00223)	(0.00180)	(0.00162)	(0.00183)	(0.00180)	(0.00204)	
$Y2020$	0.0293***	0.0209***	-0.0121***	-0.0245***	-0.0154***	-0.0208***	-0.0385***	-0.0395***	-0.0434***	-0.0435***	
	(0.00150)	(0.00238)	(0.00247)	(0.00249)	(0.00315)	(0.00272)	(0.00271)	(0.00306)	(0.00286)	(0.00319)	
Control Mean / N	0.631	0.576	0.489	0.444	0.403	0.395	0.404	0.400	0.395	0.379	3,038,615
Panel C: 13–17 years old											
$Y2018$	-0.0213***	-0.0231***	-0.0117***	-0.0109***	-0.00939***	-0.00834***	-0.0106***	-0.0114***	-0.0115***	-0.00737***	
	(0.00183)	(0.00219)	(0.00227)	(0.00208)	(0.00189)	(0.00156)	(0.00147)	(0.00152)	(0.00167)	(0.00165)	
$Y2020$	0.0248***	0.0293***	0.00272	-0.00832*	-0.00146	-0.00558	-0.0197***	-0.0207***	-0.0214***	-0.0191***	
	(0.00169)	(0.00213)	(0.00329)	(0.00393)	(0.00411)	(0.00377)	(0.00315)	(0.00340)	(0.00306)	(0.00327)	
Control Mean / N	.636	.58	.488	.445	.41	.401	.401	.393	.384	.366	1,600,229

Notes: This table reports monthly estimates based on the regression model described by Equation (1) with no additional control variables across columns 1–10. Column 11 reports the monthly observation count for each subsample along side control means in each month. Panel A reports estimates for patients aged 1–5, panel B reports estimates for patients aged 6–12, and panel C reports estimates for patients aged 13–17. Scaled estimates for $Y2020$ are depicted in panel A of Figure 2. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

B Robustness Checks and Additional Results

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

B.1 Additional Core Results

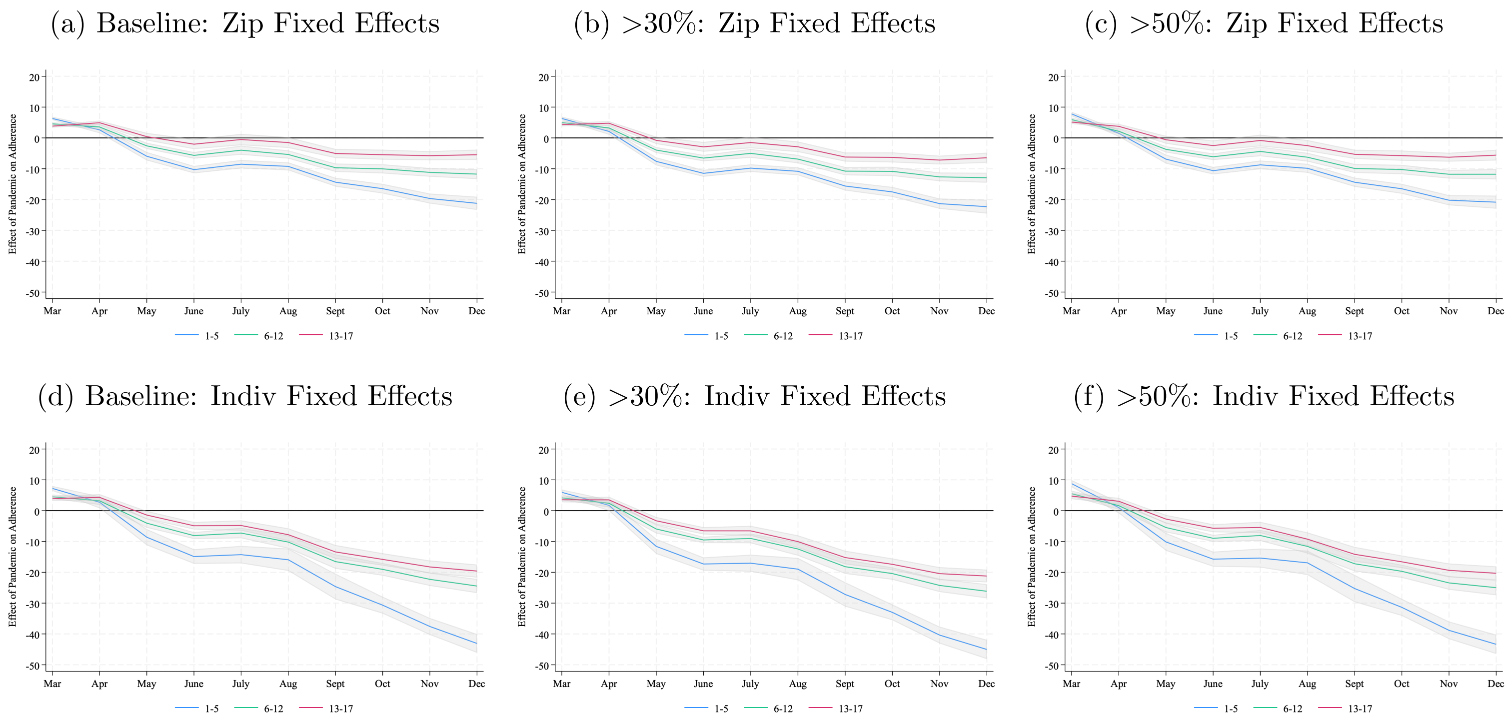
In this part, we present the estimates associated with Figure 2 in table form. Tables A4 and A5 contain estimates by age group, specification (means, state FE, individual FE), and by month.

Table A5: Effect of Pandemic on Adherence: Variation By Age

	Mar (1)	Apr (2)	May (3)	Jun (4)	July (5)	Aug (6)	Sept (7)	Oct (8)	Nov (9)	Dec (10)	Obs (11)
Panel A: Within-Zip Code Estimates											
1–5 years old	0.0441***	0.00774*	-0.0282***	-0.0386***	-0.0276***	-0.0295***	-0.0453***	-0.0527***	-0.0669***	-0.0655***	1,418,334
	(0.00204)	(0.00302)	(0.00301)	(0.00224)	(0.00225)	(0.00219)	(0.00239)	(0.00261)	(0.00278)	(0.00339)	
6–12 years old	0.0382***	0.0129***	-0.0188***	-0.0281***	-0.0182***	-0.0254***	-0.0415***	-0.0423***	-0.0484***	-0.0459***	3,037,746
	(0.00200)	(0.00277)	(0.00262)	(0.00249)	(0.00328)	(0.00291)	(0.00307)	(0.00318)	(0.00290)	(0.00331)	
13–17 years old	0.0331***	0.0227***	-0.00304	-0.0115**	-0.00351	-0.0103**	-0.0221***	-0.0233***	-0.0249***	-0.0210***	1,599,289
	(0.00191)	(0.00249)	(0.00325)	(0.00390)	(0.00405)	(0.00374)	(0.00313)	(0.00341)	(0.00289)	(0.00331)	
Panel B: Within-Individual Estimates											
1–5 years old	0.0496***	0.00518	-0.0416***	-0.0571***	-0.0486***	-0.0507***	-0.0795***	-0.100***	-0.128***	-0.136***	529,349
	(0.00333)	(0.00486)	(0.00604)	(0.00450)	(0.00496)	(0.00604)	(0.00708)	(0.00449)	(0.00482)	(0.00501)	
6–12 years old	0.0353***	0.00980*	-0.0277***	-0.0412***	-0.0334***	-0.0470***	-0.0722***	-0.0811***	-0.0963***	-0.0972***	1,609,688
	(0.00322)	(0.00396)	(0.00404)	(0.00259)	(0.00376)	(0.00480)	(0.00529)	(0.00446)	(0.00463)	(0.00491)	
13–17 years old	0.0304***	0.0185***	-0.0138***	-0.0263***	-0.0230***	-0.0380***	-0.0589***	-0.0671***	-0.0769***	-0.0763***	750,848
	(0.00322)	(0.00326)	(0.00349)	(0.00303)	(0.00389)	(0.00458)	(0.00507)	(0.00421)	(0.00450)	(0.00427)	

Notes: This table reports the monthly effect of the pandemic on pediatric adherence based on the regression model described by Equation (1) across columns 1–10. Panel A reports the 2020 estimated effect for patients based on a within zip code specification, and panel B reports the 2020 estimated effect for patients based on a within individual specification. Scaled estimates for $Y2020$ are depicted in panels B and C of Figure 2. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Figure A1: Effect of the Pandemic on Monthly Pediatric Drug Adherence



(a) Baseline: Zip Fixed Effects

(b) >30%: Zip Fixed Effects

(c) >50%: Zip Fixed Effects

(d) Baseline: Indiv Fixed Effects

(e) >30%: Indiv Fixed Effects

(f) >50%: Indiv Fixed Effects

Notes: Panels (a) and (d) are repeated from Figure 2, which is based on the raw proportion of days covered measure as the outcome. The remaining panels use an indicator for whether an individual had adherence above a given threshold in a given month (greater than 30 percent or greater than 50 percent) as the outcome. Although there are some differences across the three measures, we generally find quantitatively similar estimates.

B.2 Additional Mechanisms Results, IQVIA

Next, we present additional results related to our mechanisms exploration in Section 4. First, Table A6 presents point estimates associated with Figure A3. Next, we estimate non-parametric age responses at each age value and report estimates in Figure A2. Next, we report the adult version of the IQVIA horse race regressions in Table A7. Finally, we report summary stats for our pediatric diabetes sample in Table A8

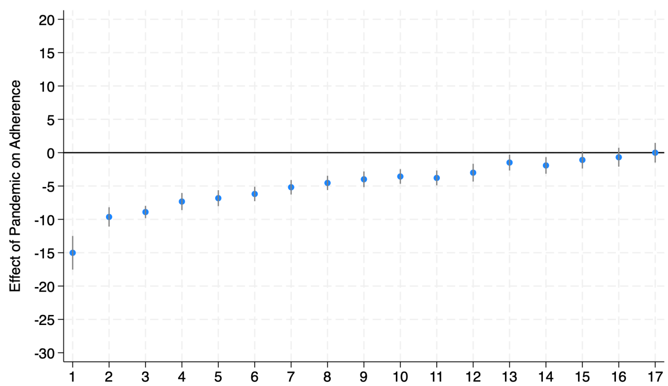
Table A6: COVID Mechanisms

	Mar (1)	Apr (2)	May (3)	Jun (4)	July (5)	Aug (6)	Sept (7)	Oct (8)	Nov (9)	Dec (10)	Obs (11)
Panel A: School Closure											
Low	0.0182***	-0.00977	-0.0492***	-0.0610***	-0.0540***	-0.0707***	-0.0905***	-0.100***	-0.115***	-0.117***	
	(0.00342)	(0.00486)	(0.00597)	(0.00465)	(0.00852)	(0.0127)	(0.0146)	(0.0149)	(0.0139)	(0.0140)	
Control Mean / N	.597	.543	.455	.405	.367	.363	.373	.367	.361	.343	171,963
High	0.0345***	0.0277***	-0.00907**	-0.0269***	-0.0203***	-0.0277***	-0.0557***	-0.0678***	-0.0797***	-0.0852***	
	(0.00239)	(0.00322)	(0.00297)	(0.00248)	(0.00356)	(0.00279)	(0.00407)	(0.00229)	(0.00251)	(0.00341)	
Control Mean / N	.611	.549	.455	.411	.371	.358	.365	.365	.363	.349	1,932,158
Panel B: Air Quality											
Low Improvement	0.0284***	0.0200***	-0.0194***	-0.0368***	-0.0334***	-0.0397***	-0.0629***	-0.0749***	-0.0877***	-0.0919***	
	(0.00436)	(0.00497)	(0.00508)	(0.00368)	(0.00359)	(0.00410)	(0.00535)	(0.00414)	(0.00340)	(0.00362)	
Control Mean / N	.621	.567	.477	.432	.391	.379	.385	.385	.381	.366	384,774
High Improvement	0.0313***	0.0219***	-0.0151***	-0.0317***	-0.0259***	-0.0349***	-0.0612***	-0.0719***	-0.0842***	-0.0908***	
	(0.00267)	(0.00346)	(0.00321)	(0.00268)	(0.00337)	(0.00376)	(0.00472)	(0.00379)	(0.00398)	(0.00360)	
Control Mean / N	.622	.564	.475	.431	.392	.381	.388	.387	.383	.368	1,758,283
Panel C: Telehealth											
No Telehealth	0.0304***	0.0245***	-0.0137*	-0.0326***	-0.0283***	-0.0375***	-0.0616***	-0.0721***	-0.0856***	-0.0915***	
	(0.00328)	(0.00510)	(0.00581)	(0.00438)	(0.00639)	(0.00902)	(0.00993)	(0.0102)	(0.0104)	(0.0101)	
Control Mean / N	.626	.567	.477	.435	.396	.385	.391	.389	.385	.37	1,084,591
Telehealth	0.0305***	0.0191***	-0.0190***	-0.0332***	-0.0260***	-0.0356***	-0.0612***	-0.0718***	-0.0840***	-0.0882***	
	(0.00280)	(0.00455)	(0.00455)	(0.00319)	(0.00388)	(0.00442)	(0.00534)	(0.00315)	(0.00331)	(0.00365)	
Control Mean / N	.612	.554	.462	.416	.376	.366	.373	.372	.368	.353	2,196,578
Panel D: Delivery Channel											
Non-Mail	0.0311***	0.0205***	-0.0189***	-0.0345***	-0.0275***	-0.0368***	-0.0627***	-0.0731***	-0.0856***	-0.0902***	
	(0.00220)	(0.00360)	(0.00366)	(0.00256)	(0.00333)	(0.00419)	(0.00476)	(0.00392)	(0.00402)	(0.00410)	
Control Mean / N	.609	.55	.458	.414	.375	.365	.372	.371	.368	.352	3,235,801
Mail	-0.00400	0.0121**	0.0151**	-0.00631	-0.0261***	-0.0338***	-0.0391***	-0.0497***	-0.0631***	-0.0718***	
	(0.00254)	(0.00427)	(0.00462)	(0.00447)	(0.00589)	(0.00626)	(0.00681)	(0.00545)	(0.00630)	(0.00608)	
Control Mean / N	.917	.91	.827	.754	.714	.692	.665	.65	.638	.622	69,514

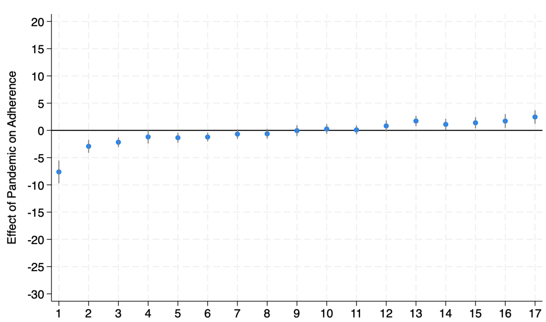
Notes: This table reports monthly estimates of the response of pediatric monthly coverage to the pandemic across different subgroups based on a regression specification that includes individual fixed effects. Variable definitions provided in Table A2 and A3. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

Figure A2: Estimated Effect of COVID: Variation by Age

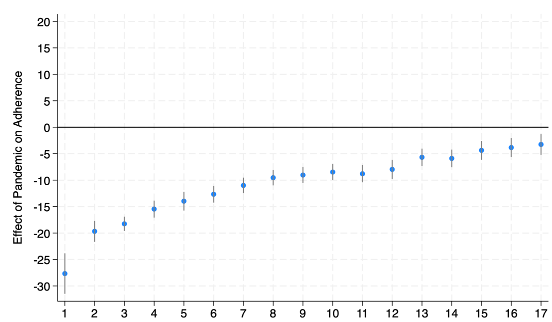
(a) March - December



(b) March - July



(c) August - December



Notes: This figure plots the effect of the pandemic on drug adherence rates based on Equation (1), using provider zipcode fixed effects, and estimated separately for each age between 1 and 17. Panel (a) aggregates the effect in all post-pandemic months (March - December) and panels (b) and (c) aggregate the effect in two time periods (March - July and August - December) Point estimates are scaled by age-specific adherence rates observed during this same time period in 2019. 95% confidence intervals shown in shaded area.

Table A7: Collective Impact of Mechanisms for Adults: Horse Race

	Mar - Dec (1)	Mar - July (2)	Aug - Dec (3)	Mar - Dec (4)	Mar - July (5)	Aug - Dec (6)
2020	0.0269***	0.0368***	0.0171***	0.0256***	0.0340***	0.0173*
	(0.00220)	(0.00194)	(0.00267)	(0.00599)	(0.00439)	(0.00808)
Age x 2020				0.000226***	0.000276***	0.000175***
				(0.0000242)	(0.0000236)	(0.0000291)
Mail x 2020				0.0124***	-0.00435*	0.0291***
				(0.00190)	(0.00169)	(0.00282)
AQI Improvement x 2020				0.00139	0.00162	0.00117
				(0.00148)	(0.00133)	(0.00182)
High Income x 2020				-0.00624***	-0.00346**	-0.00902***
				(0.00148)	(0.00119)	(0.00183)
High Education x 2020				0.00246	0.00217	0.00274
				(0.00144)	(0.00129)	(0.00171)
White Collar x 2020				-0.00395	-0.000408	-0.00750
				(0.00287)	(0.00204)	(0.00446)
High Minority x 2020				-0.00169	-0.00196	-0.00142
				(0.00138)	(0.00124)	(0.00168)
Medicaid Payer x 2020				0.0183***	0.00840*	0.0282***
				(0.00408)	(0.00356)	(0.00483)
Medicaid Expansion x 2020				-0.00530	-0.00691**	-0.00369
				(0.00322)	(0.00236)	(0.00446)
Telehealth x 2020				-0.00224	-0.00331	-0.00116
				(0.00365)	(0.00267)	(0.00508)
Urban x 2020				0.00201	0.00220	0.00182
				(0.00219)	(0.00153)	(0.00303)
High School Closure x 2020				-0.00481*	-0.00283	-0.00679**
				(0.00190)	(0.00175)	(0.00231)
Control Mean	.572	.629	.516	.572	.629	.516
Zip Code FE	x	x	x	x	x	x
Observations	128,001,280	64,000,640	64,000,640	128,001,280	64,000,640	64,000,640

Notes: Estimates are based on a regression model that compares adherence in 2020 to adherence in 2019 and 2018 for the adult population. Columns 1 and 3 report the average effect across all months, and columns 2, 3, 5, and 6 report estimates for a subset of months as indicated by column headers. Control means reflect the average pediatric adherence in the designated months in 2019. Variable definitions provided in Table A2 and A3. All specifications include zip code fixed effects. Standard errors are clustered at the state level. *,** and *** denote 5%, 1%, and 0.1% significance levels, respectively.

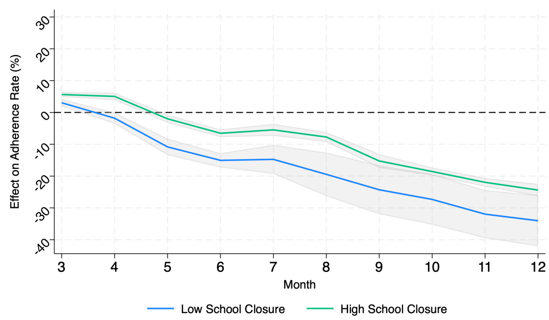
Table A8: Sample Statistics: Pediatric Diabetes Patients, January-March 2019

	Under 18 (1)	Under 6 (2)	6 to 12 (3)	13 to 18 (4)
Panel A: Individual Characteristics				
Adherence Rate	0.80	0.83	0.82	0.79
Patient Age	12.65	4.21	9.68	15.25
Share Female	0.52	0.47	0.50	0.54
Medicaid Payer	0.12	0.06	0.11	0.13
Third Party Payer	0.76	0.64	0.73	0.79
Panel B: 2018 Local Geographic Characteristics				
Per-Capita Income, 2018	32,764	32,190	32,901	32,7 48
Minority Share of Population, 2018	0.28	0.26	0.28	0.28
Share Population with Some College, 2018	0.20	0.21	0.20	0.20
Share of Population in Urban Area	0.93	0.89	0.93	0.93
Medicaid Expansion State	0.61	0.60	0.62	0.61
Observations	177,899	11,674	59,797	106,428

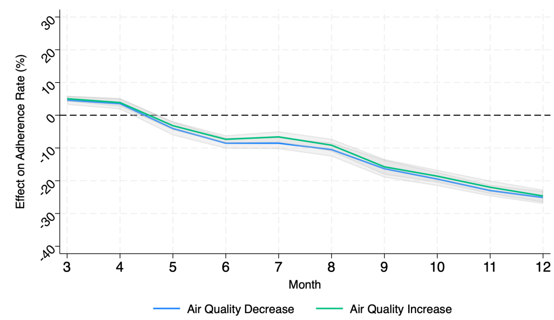
Notes: This table provides summary statistics describing the pediatric diabetes users in 2019. Adherence statistics reflect prescriptions filled between January and March, and individual characteristics reflect the first prescription filled in 2019. Local geographic characteristics are matched based on the zip code of the provider associated with the first prescription filled. Variable definitions provided in Table A2 and A3.

Figure A3: COVID-Specific Mechanisms and Effect on Adherence

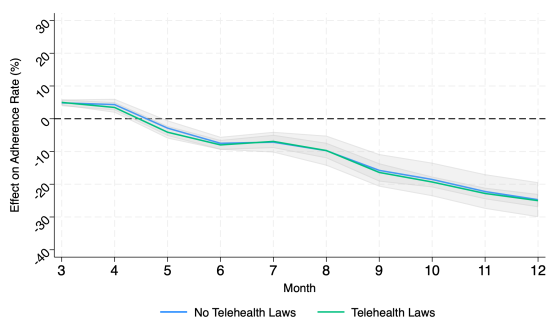
(a) School Closures



(b) Air Quality



(c) Telehealth



Notes: Figure 4, Panels (A) - (C) 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.

C Detailed Discussion of COVID-Specific Factors

If our core estimates are driven by mechanisms specific to the pandemic, then these estimates likely have little to say about pediatric health behavior during other macroeconomic downturns.

Table 4 jointly estimates the effects of all COVID-specific factors along with other factors, and Figure A3 provides graphical confirmation that these channels have minimal quantitative impacts.

C.1 School Closures

Nationwide lockdowns resulted in the sudden closure of schools to in-person learning. In-person schooling can affect pediatric adherence in several ways. For example, schools provide reminders to students to take their medication and reminders to parents to refill prescriptions (McClure et al., 2020). This mechanism would tend to reduce adherence in a remote learning environment, all else equal.

To investigate this conjecture, 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 (*High School Closure*). Figure A3, Panel (A) reports scaled estimates.

In short, we find a consistently small difference in responses between the two groups throughout the year. In particular, there is no additional difference in the fall, when there is more variation in in-person school attendance. Consistent with this, the estimated coefficient in the horse-race regression (Table 4) is quantitatively small (+1pp on a baseline of -10pp).

C.2 Environmental Triggers

Next, we explore whether our results are driven by changes in medical need through reduced environmental triggers. Previous research notes that air quality had a major impact on health outcomes, particularly for older individuals (Finkelstein et al., 2023). In the case of COVID, stay-at-home orders effectively shut down commercial air travel and severely reduced road travel (Berman and Ebisu, 2020; Slezakova and Pereira, 2021; Venter et al., 2020), which may have led to even larger changes in air pollutant levels relative to a typical macroeconomic downturn. Because air pollution is an environmental trigger for the onset of asthmatic episodes, any associated improvements in air quality should serve to reduce medical need.

Figure A3, Panel (B) reports scaled estimates based on whether local air quality was unexpectedly better during the April to August 2020 period (*AQI Drop*).[30] We find very small differences across areas in terms of adherence responses. Our horse-race regression (Table 4, Models 4 and 6) shows that air quality improvement has minimal quantitative impacts on adherence to control medication. In unreported results, we do find an effect of air quality on prescriptions for as-needed medication, consistent with a reduced need for rescue inhalers due to better air quality.

C.3 Access

The stay-at-home orders, along with reductions in person-to-person interactions, may have reduced access to in-person health care and, as a result, reduced access to prescriptions. However, previous research has documented that there was increased use of telehealth services during the pandemic (Volk et al., 2021). Thus, we test whether access plays a significant role by measuring the preparedness of individuals to switch to telehealth.

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 A3, Panel (C) reports scaled estimates. We find that responses are similar throughout the year, regardless

[30] 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).

of differential access to telehealth. The horse-race regression (Table 4) provides confirmation. We find a quantitatively negligible moderating effect.

C.4 Additional Factors

To conclude our discussion of COVID-specific factors, we briefly discuss the remaining factors included in Table 4. 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. 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 quantitatively small and statistically insignificant.[31]

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

D Additional Results from MEPS and Marketscan

D.1 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 5.

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 5, 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.

Table A9 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.

D.2 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

Table A9: 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 A10: 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.

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 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.

Table A10 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.

D.3 Trends in Hospitalizations and Emergency Room Visits

To provide evidence on trends in hospitalizations and emergency room visits, we again make use of MEPS data.

We proceed as follows:

1. For each year, we identify individuals with an asthma diagnosis in the "Medical Conditions" file. This corresponds to ICD-9 code 493 (before 2016) and ICD-10 code J45 (2016 and after).

2. We then sort users into the same age bins as for the main analysis (1–5, 6–12, 13–17, 18+).

3. We then count events from the "Hospital Inpatient Stays" and "Emergency Room Visits" files where the event is marked as related to a diagnosis in the Medical Conditions file. This is as granular a classification as available in MEPS due to privacy issues. Ideally, we would be able to confirm that the visit was for asthma and not other conditions.

4. Finally, we calculate the average number of events within each age bin and year, weighting by the population weights provided by MEPS.

Figure A4 shows the trend in the raw averages by group. Consistent with Binney et al. (2024), we find that there is generally a decreasing trend for pediatric asthma patients leading up to 2020, and also find a flat trend within adults. The number of events decreased sharply between 2019 and 2020 for three of the four groups, but only the youngest group exhibited a significant increase in 2021 and 2022.

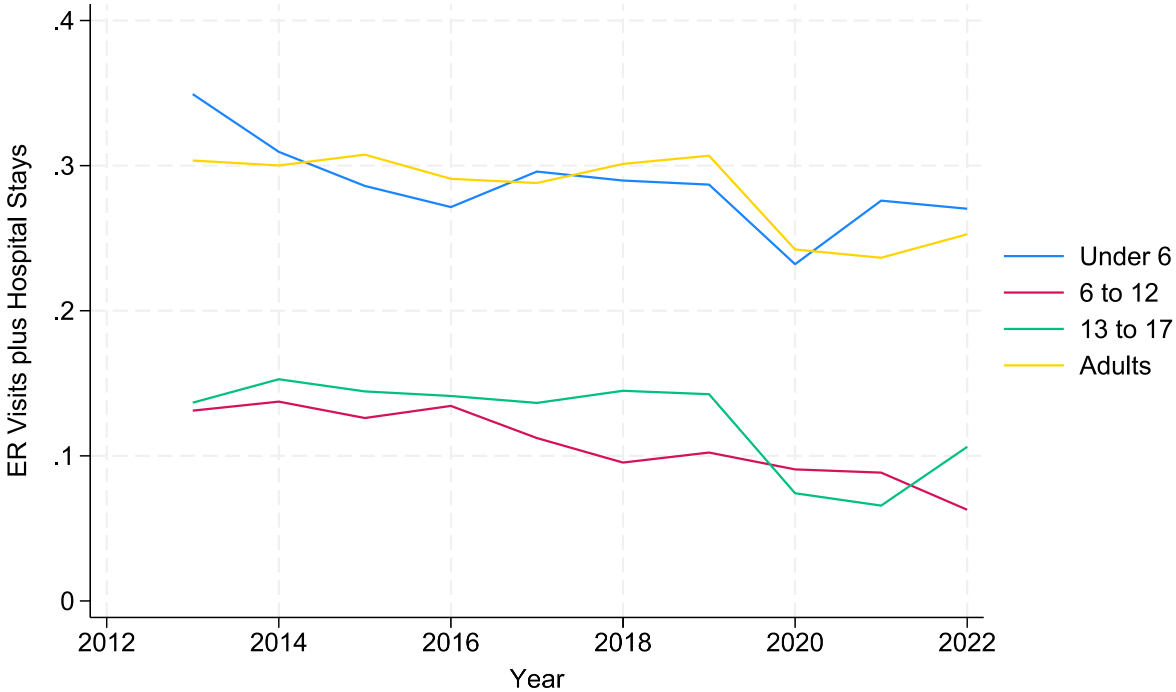
We also formally compare outcomes at the individual level using the repeated cross-sections in MEPS. Formally, we run the following regression:

$$y_{igt} = \alpha_g + \gamma_t + \beta \cdot I_{age_i<6} + \gamma \cdot I_{t\geq 2021} \cdot I_{age_i<6} + \epsilon_{it} \tag{D.1}$$

where g indexes the age group (under 6, 6–12, 13–17, and adults), t indexes the year, and the outcome of interest is total ER visits and inpatient stays for patient i in year t. We allow for year fixed effects (common trend across groups) and try to estimate the differential response of the youngest group in the two years after COVID.

Table A11 reports the estimates. Column 1 uses the full population, and Column 2 uses just the pediatric population. We find statistically significant and quantitatively large and positive estimates for the differential impact on children under 6 (at the ten percent level in Column 1 and at the one percent level in Column 2). We caution that this is only circumstantial evidence using a small sample of nationally representative individuals.

Figure A4: Trends in Emergency Room Visits and Inpatient Stays by Age Group



Notes: Trends in average number of emergency room visits plus inpatient stays for individuals diagnosed with asthma within different age groups. We only include events that are marked as related to an existing medical condition.

Table A11: Differences in ER Visits and Hospitalizations between Youngest Group

	ER Visits Plus Hospitalizations	
	(1)	(2)
Under 6	-0.00310*	0.00347**
	(0.00166)	(0.00173)
Under 6 x Post 2021	0.0274*	0.123***
	(0.0153)	(0.0157)
Population	All	Under 18
Observations	217470	43600
Adjusted R^2	0.040	0.045

Notes: This table reports estimates of differences in hospitalization rates based on Equation (D.1), using MEPS data from 2013 to 2022. Regressions are weighted by population weights from MEPS. We report robust standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.