Teach your children, well: Prescription-drug monitoring programs and parental time use

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Abstract

While prescription-drug monitoring programs (PDMPs) have been found effective in reducing prescriptions and misuse of medical opioids, the evidence on their impacts on other outcomes, particularly those related to child welfare, is mixed. Combining a difference-in-differences design with a heterogeneity-robust estimation approach, we estimate the effects of PDMPs on how, and how much, parents spend time with their children. We find that PDMPs increase time spent on both active and passive childcare, with much of the effect for active care driven by increases in relatively engaging forms of childcare *per se*, education care, and medical care. We find much larger negative effects for parents with disabilities or mobility issues, and argue that this type of heterogeneity can help reconcile some of the apparently conflicting results from the literature on PDMPs and child outcomes. We further show that the positive effects of PDMPs are amplified in states with legal marijuana laws. Our findings highlight the role of policy to address the needs of sensitive populations and mitigate the potential downsides of substance-related policy interventions.

Keywords: prescription drug monitoring programs, PDMPs, drug policy, opioids, time use, parenting, parental investment, household behavior, family economics, public health, child care

JEL codes: D13, D19, D64, L18, J13, J18

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1 Introduction

The opioid crisis has affected countless households in the United States, deeply impacting families through overdose deaths and their far-reaching consequences for children. Despite recent data from the CDC indicating a downward trend in opioid overdose deaths, the misuse and abuse of opioids continue to impact many homes (Centers for Disease Control and Prevention, 2024). In response to this crisis, many states have implemented policies aimed at reducing the over-prescription of opioids and mitigating the effects of prescription-opioid abuse. Among these, Prescription Drug Monitoring Programs (PDMPs)—databases of prescriptions for controlled substances—are one of the most widely adopted and widely studied policies.

In this paper, we estimate the effects of PDMPs on parenting behaviors, as measured by the amount of time that parents spend with their children, and the ways that they spend that time. Parental investments are crucial for child development (Fiorini and Keene, 2014; Del Boca, Flinn, and Wiswall, 2014), and time use is a key measure of those investments. Accordingly, our findings have important implications for the relationship between substance-abuse policies and child welfare in both the near and long term.

It is difficult to overstate the extent of parental substance use in the US. Recent estimates suggest that, for each year between 2015 and 2019, an average of over 21 million children in the US lived with a parent who misused substances, and over 2.1 million of these children lived with a parent diagnosed with a substance-use disorder (Ghertner, 2022). Opioid misuse is particularly prevalent among households in the US. Clemens-Cope, Lynch, Epstein, and Kenney (2019) show that, on average between 2015 and 2017, 623,000 parents with an opioid-use disorder lived with a child younger than 18 years, with less than a third receiving treatment for illicit drug or alcohol use. Griesler, Hu, Wall, and Kandel (2019) find that 13.5 percent of parents misused prescription opioids between 2004 and 2012.

Previous research has consistently shown that parental substance use has detrimental effects on child outcomes, ranging from maltreatment and increased foster-care caseloads to negative perinatal and neonatal outcomes (Cunningham and Finlay, 2013; Ghertner, 2022; Suchman, Decoste, McMahon, Dalton, Mayes, and Borelli, 2017). Earlier studies have established the negative effects of substance use on parenting skills and child development (Suchman, Decoste, McMahon, Dalton, Mayes, and Borelli, 2017). Focusing specifically on opioid use, Bullinger and Ward (2021) and Ghertner (2022) show that increases in drug overdose deaths and emergency department visits are associated with increases in child maltreatment and foster-care admissions, linking the opioid crisis with child wellbeing.

PDMPs are now present in all US states. While there is a consensus that PDMPs are associated with decreases in the misuse or abuse of prescription opioids and prescription-opioid-related mortality (see, e.g. Kaestner and Ziedan, 2019, 2023; Neumark and Savych, 2023), the evidence on their broader socioeconomic and health impacts is mixed, with several studies identifying a range of unintended downstream consequences of PDMPs and other opioid-related policies. For example, Kaestner and Ziedan (2023) find evidence of marginal disemployment and earnings effects consequent to the adoption of PDMPs, while Gupta and Mazumder (2023) find that PDMPs reduce labor-force attachment and credit scores. A significant concern is that the restrictions imposed by PDMPs may lead dependent users to switch to other, more harmful, drugs, which can have debilitating effects on their health and social circumstances (Alpert, Powell, and Pacula, 2018; Buchmueller and Carey, 2018; Powell and Pacula, 2021; Evans, Lieber, and Power, 2019; Evans, Harris, and Kessler, 2022; Maclean, Mallat, Ruhm, and Simon, 2022).

A large segment of the literature, and one to which this paper adds, focuses on the consequences of PDMPs for child outcomes. Here, too, the evidence on the effects of PDMPs is mixed. Gihleb, Giuntella, and Zhang (2020) find that mandated PDMPs (which require physicians to check opioid-seeking patients against a database before issuing prescriptions) reduce cases of neonatal abstinence syndrome, a finding supported by evidence presented in Kaestner and Ziedan (2021) that PDMPs lead to marginal improvements in infant health outcomes. Gihleb, Giuntella, and Zhang (2019) find that mandated PDMPs reduce instances of children being removed from their homes and placed in foster care, with larger reductions in removals due to child neglect or physical abuse.

On the other hand, Evans, Harris, and Kessler (2022) find that the adoption of must-access PDMPs (and the reformulation of OxyContin to make it more difficult to abuse) led to increases in substantiated child maltreatment, primarily neglect and physical abuse.[1] The authors attribute this increase in maltreatment to substitution towards more addictive unregulated substances, citing scientific evidence that the biological states of addiction or withdrawal may interrupt the neurological processes that normally make parenting rewarding, and lead to behavioral traits that render parents ill-suited for parenting.

Although our focus is on PDMPs, there is also evidence that other opioid-related interventions have had mixed consequences. For example, Mackenzie-Liu (2021) finds increases in foster-care admissions following the abuse-resistant reformulation of OxyContin, due to increases in inquiries from Child Protective Services, and Bradford, Fu, and You (2024) find that this reformulation led to an increase in evictions. Moore and Schnepel (2024) find that a reduction in overdoses due to a shock to Australia's heroin supply was initially offset by drug substitution and crime-related homicides.

Our paper also adds to a nascent literature on the mutual relationships between substance abuse, public policy, and parental time investments in children. There is strong evidence that parental time investments are crucial for child development, and that these parental investments respond to public policies. Fiorini and Keene (2014) and Del Boca, Flinn, and Wiswall (2014) present evidence that parental time investments promote the development of children's cognitive skills, while Bastian and Lochner (2022) show that expansions of the earned-income tax credit reduce some types of maternal time investments. Focusing on drug policy, Bansak and Kim (2024) show that medical marijuana laws promote time investment among parents who use the drug in moderation.

Despite these wide-ranging literatures on the opioid crisis, PDMPs, child outcomes, and

[1]Bruzelius, Levy, Okuda, Suglia, and Martins (2022), in contrast, present evidence that PDMPs are associated with fewer instances of child maltreatment, with the largest effects for neglect and physical abuse.

parental time investments, little is known about how policies like PDMPs affect the quantity and quality of time that parents spend with their children. We aim to fill this critical gap by estimating the effects of PDMPs on parental time use, a key measure of parental investment in a child's development.

We identify the effects of PDMPs on parental time investments by applying a difference-in-differences design to the staggered adoption of PDMPs across US states from 2003 to 2019. To address the issues associated with traditional differences-in-differences regressions in the presence of staggered adoption, we estimate average treatment effects using the robust two-stage difference-in-differences estimator (Gardner, 2021; Gardner et al., 2024). While the timing of adoption of PDMPs depends on how precisely they are defined, we focus primarily on the effects of "Modern PDMPs," defined as PDMPs that are accessible to any authorized user, which have been shown to reduce opioid misuse (Horowitz, Davis, McCleland, Fordan, and Mera, 2020; Kaestner and Ziedan, 2019; Ziedan and Kaestner, 2024; Wang, 2021) and reflect the effects of PDMPs as otherwise defined (Kaestner and Ziedan, 2019, 2021).

We find that Modern PDMPs increase both active childcare (where parents directly interact with children) and passive childcare (where children are present during other activities), with the increases in active childcare occurring due to increases in childcare *per se* (the direct provision of childcare), education care (time spent on educational activities), and parent-provided medical care. To give a sense of the magnitudes of these effects, our preferred estimates imply that parents spend about six additional minutes on active childcare and 12 additional minutes on passive childcare, on average per day. These average effects are taken across the population of all parents; a conservative back-of-the-envelope calculation implies that the effects among parents who abuse prescription opioids are on the order of 45 minutes for active care and 90 minutes for passive care. Given the evidence on the importance of parental time investments for child outcomes, these effects are substantial.

Further examining the determinants of these broad sub-categories of childcare, we find that PDMPs encourage parents to spend more time with their children on relatively engaging activities, such as talking to them, playing with them, or helping them with homework. The effects of PDMPs may be heterogeneous with respect to the nature of individuals' relationship to prescription opioids, which we proxy for using whether respondents report having a disability or difficulty walking or climbing stairs. In these subpopulations, we find significant negative effects of PDMPs on active care, driven by decreases in time spent helping children with their homework, with effect sizes twenty times larger in magnitude than the positive effects that we estimate for the population at large. We also show that, while the positive effects of PDMPs on time use are independent of the presence of Pill Mill laws, they are magnified in the presence of medical and recreational marijuana laws. Indeed, we find that the positive effects of PDMPs on parental investments in children occur entirely in states where patients have legal access to medical marijuana.

Our findings provide a fresh empirical perspective on the implications of PDMPs for children, helping to bring clarity to some of the evidently conflicting findings of the existing literature. The overall increases in parent-child engagement that we estimate support previous evidence that PDMPs can improve child welfare. At the same time, our findings for parents with disabilities and mobility difficulties demonstrate that the effects of PDMPs (and other substance-use policies) can vary widely with respect to individual differences in underlying factors. Such heterogeneity may help explain how PDMPs might, for example, increase child maltreatment and, at the same time, decrease foster-care admissions, particularly if the effects of PDMPs are similarly heterogeneous with respect to the severity of the addiction problem. Finally, our results for marijuana laws underscore the importance of legal medical access to relatively safe substitutes for prescription opioids in mediating the welfare effects of PDMPs.

In Section 2.1, we provide a detailed description of the time-use and PDMP data used in our analysis. In Section 3, we outline the identification and estimation approach that our difference-in-differences design uses. In Section 4.1, we present our main empirical results. Refining these results, we present estimates for other aspects of adult time use in Section

4.2, and for heterogeneity in the effects of PMDPs on time use in Section 4.3. Finally, we offer concluding remarks in Section 5.

2 Data

2.1 Parental time use

Our study combines data from several sources. The data on parental time use come from the American Time Use Survey (ATUS, Flood, Sayer, Backman, and Chen, 2023), an ongoing survey of time use administered by the Bureau of Labor Statistics (BLS). The survey provides information on how people allocate their time between activities, and who they spend this time with, based on daily time diaries. In addition, the ATUS is linked to the Current Population Survey (CPS) and therefore provides rich demographic and geographic information.

To ascertain the effects of PDMPs on parenting behavior, we define parents as respondents who had children less than 18 years of age in the household at the time of the survey. Based on the time diaries, we determine whether the time devoted to an activity was spent with children. Following Bastian and Lochner (2022) and Bansak and Kim (2024), our primary outcome measures decompose time spent with children by parents into two types: Active childcare and Passive childcare.

Active care consists of time-use activities that involve active interactions between parents and children. We divide active childcare activities into three broad sub-categories: childcare (*per se*), school care, and medical care. Childcare activities include time parents actively look after the child, play with the child, and plan for children's activities. Schooling care includes the time parents spend helping their child with homework and engaging with the child's teachers. Medical care includes time spent providing or obtaining medical care for children. These activities are likely to have direct effects on the learning or health outcomes of the child (Bastian and Lochner, 2022). We provide comprehensive lists of the components of these subcategories in Section 4.1.

Passive childcare, on the other hand, involves activities that include little direct interaction between parents and children. These may include parental activities in the presence of children, such as housework, waiting, relaxing, eating, and socializing at parties and events (Bastian and Lochner, 2022; Bansak and Kim, 2024). Fiorini and Keene (2014) and Del Boca, Flinn, and Wiswall (2014) suggest that the effects of active parental care and passive care on child outcomes may be different. Thus, we explore the effects of PDMPs on both parental time-use categories, as well as the sub-categories of active care.[2]

Since our primary focus is on the time parents devote to their children, we restrict our sample to parents with at least one child under the age of 18 living in the household. In addition, we only retain time-use data for the years 2003 to 2019.

2.2 PDMPs

PDMPs are one of the most widely adopted policies aimed at reducing prescription-opioid misuse and abuse, and are now present in all US states. We exploit the timing of the implementation of PDMPs across states to identify their effects on parental time use. PDMPs have a long history, with some of the original programs implemented as early as the 1930s (Horowitz et al., 2020). They also vary in terms of their characteristics, particularly whether they provide electronic access to prescription databases (Electronic PDMPs) and whether prescribers are required to cross-reference those databases (Mandated PDMPs). As a consequence, the estimated effects of PDMPs depend sensitively on precisely how PDMPs are defined and when they are considered to have been implemented.

We rely on Horowitz et al. (2020), Kaestner and Ziedan (2019), and Ziedan and Kaestner (2024) to define our measure of PDMPs as the adoption of "Modern PDMPs." A Modern PDMP is adopted when the PDMP becomes accessible to any authorized user. Previous studies (Kaestner and Ziedan, 2019; Ziedan and Kaestner, 2024; Wang, 2021) have shown

[2]Passive childcare is difficult to divide cleanly into subcategories, since it includes any activity that an adult might engage in in the presence of a child.

that PDMPs with electronic access and the promotion of health information technology records effectively reduce opioid misuse with or without mandating the use of PDMPs. Furthermore, Kaestner and Ziedan (2019) and Ziedan and Kaestner (2024) provide evidence that Mandated PDMPs do not have any additional effect on opioid prescriptions conditional on the implementation of Modern PDMPs. Primarily as a robustness check, we also examine the effect of Mandated PDMPs on parenting behavior using information on the interstate adoption of Mandated PDMPs from Horowitz et al. (2020), Kaestner and Ziedan (2019), Ziedan and Kaestner (2024), and PDMPs Policy Data by RAND-USC Schaeffer Opioid Policy Tools and Information Center (2024).

Some states adopted Modern PDMPs before 2003. Since the ATUS data became available in 2003, we restrict our sample for the analysis of Modern PDMPs to states that adopted the policy between 2003 and 2019. This restriction enables us to observe time use by parents before and after the adoption of Modern PDMPs, and ensures that we do not use states that adopted Modern PDMPs prior to 2003 as control states.

2.3 Additional policy data

In addition to our main specifications, we also estimate models that control for the presence of Medical Marijuana Laws (MMLs), Recreational Marijuana Laws (RMLs), and Pill Mill Laws (PMLs). We use data on the adoption of MMLs and RMLs from RAND (RAND-USC Schaeffer Opioid Policy Tools and Information Center, 2024). Our data on PMLs are taken from the Prescription Drug Abuse System (Prescription Drug Abuse Policy System (PDAPS), 2024).

2.4 Summary statistics

Table 1 provides basic descriptive statistics for our time-use data. Across all sample years, parents spend an average of about an hour per day engaged in active childcare activities, and about five hours engaged in passive care. Within these categories, parents spend an average of about an hour on childcare *per se*, as well as about five minutes on school care and about a minute and a half on medical care. Turning to demographics, about 87% of the respondents in our sample are white, with an average age of 37, and their youngest child is between seven and eight, on average. In our sample, 58% of respondents are women, and 63% are married. Regarding education, 81% of respondents have a high-school degree, an additional 59% have some college, and 33% more have a college degree. Finally, 3% of our sample have a self-reported disability.

3 Empirical strategy

3.1 Identification and estimation

We leverage variation across time and over states in the adoption of PDMPs to identify their effects on parental time use via a differences-in-differences design. This approach to identification is premised on the notion that, absent the adoption of PDMPs, counterfactual untreated outcomes would evolve similarly in treated and untreated states (that is, counterfactual outcomes in treated and untreated states exhibit parallel trends).[3]

Under this parallel trends assumption, observed time use satisfies

$$\text{Parental Time Use}_{ist} = \alpha_s + \delta_t + X_{it}'\gamma + W_{st}'\theta + \beta_{it}\text{PDMP}_{st} + \varepsilon_{ist},$$

where Parental Time Use_{ist} is the amount of time (in minutes) that a parent spends caring for their children per day, X_{it} and W_{st} are vectors of individual- and state-level covariates, our main policy variable PDMP_{st} is an indicator for whether state s has adopted PDMPs in year t, and α_s and δ_t are state and time fixed effects. Note that we allow for heterogeneity in the effect of PDMPs on outcomes. In our empirical analysis, parental time use may represent

[3]Identification also requires that the treatment is not anticipated (and therefore does not affect outcomes in treated states prior to adoption). The tests that we present below for parallel trends also represent tests for anticipation effects.

the amount of time parents spent on active or passive childcare, or the various subcategories of these types of care.

To allow for the possibility of differential trends in parental time use due to differences in socioeconomic and demographic characteristics, many of the specifications we estimate include individual and state-level covariates. In these specifications, X_{it} includes gender, race, age, age squared, education (high school, some college, college), and marital status, while W_{st} includes the unemployment rate and real minimum wage. As we discuss below, we also estimate specifications that control for other drug-related policies, including the presence of "Pill Mill" laws, and the legality of medical or recreational marijuana. For all of the estimates we present, standard errors are clustered at the state level.

To overcome the problems associated with difference-in-differences analyses based on traditional two-way fixed-effects regression in the presence of heterogeneous treatment effects and staggered adoption (see, e.g., Goodman-Bacon, 2021), we estimate the effects of PDMPs using two-stage differences in differences (2SDD for short; Gardner, 2021; Gardner et al., 2024). This methodology estimates the state and time fixed effects, as well as the coefficients on the covariates, in a first-stage regression that uses the sample of untreated observations. Treatment effects are then identified in a second stage by regressing adjusted outcomes $\tilde{Y}_{ist} = Y_{ist} - \hat{\alpha}_s - \hat{\delta}_t - X_{it}'\hat{\gamma} - W_{st}'\hat{\theta}$ on treatment status. This procedure identifies the average effect of the treatment across all periods and treatment cohorts (or, in the case of our event study regressions, the average duration-specific treatment effects).[4] Standard errors are corrected for the first-stage estimation of the fixed effects and coefficients on the covariates.[5]

[4]Our event study regressions take the form

$$\tilde{Y}_{ist} = \sum_{r \in \{-8,\ldots,0,\ldots,8\}} \beta^r D_{st}^r + \varepsilon_{st},$$

where for $r < 0$, the D_{st}^r represent $|r|$-period leads of treatment status (i.e., indicators for whether s first adopts the treatment r periods after t), while for $r \geq 0$, they represent r-period lags of treatment status (whether s first adopted the treatment r periods before t). Thus, for $r < 0$, the β^r represent tests of parallel trends (i.e., that the first-stage regression is correctly specified), while for $r \geq 0$, they represent the dynamic, or duration-specific, average effects of the treatment on the treated.

[5]We obtain our estimates using Kyle Butts' did2s package (Butts, 2021).

4 Empirical results

4.1 PDMPs and childcare

Figure 1 presents a visual summary of our main empirical findings. The figure plots two-stage difference-in-differences estimates of the average duration-specific effects of PDMPs on different uses of parental time. The top panel of the figure plots these effects for Modern PDMPs (labelled "Mo"), our preferred set of dates for the adoption of PDMPs.

In each subgraph, the points plotted to the left of the dashed line represent the estimated second-stage coefficients from regressions of adjusted outcomes on the leads of treatment status (i.e., indicators for whether a state first adopts PDMPs in one year, two years, etc.).[6] These estimated coefficients represent tests of the parallel trends assumption, since they should be zero if the first-stage regression is correctly specified (i.e., if parallel trends holds). For both active and passive childcare, the graphs do not exhibit any statistically significant deviations from parallel trends in the periods preceding adoption of PDMPs, suggesting that the identifying assumption that underlies our difference-in-differences design is satisfied.

The points plotted to the right of the dashed line represent estimates of the coefficients on the lags of treatment status, which can be interpreted as the dynamic, or duration-specific, average effects of the treatment. As the figure shows, parental time spent on both active and passive childcare increases consequent to the adoption of Modern PDMPs, with the effects becoming individually statistically significant in the fourth year of adoption for active childcare and the fifth for passive childcare (although time spent on either type of care appears to be trending up even before these periods).[7]

Although we prefer Modern PDMPs as our conceptual measure of treatment exposure, the bottom panel of the figure repeats this analysis, defining treatment status in terms of the

[6]Note that all of our event-study plots are based on specifications that control for covariates.

[7]The delay with which these estimated effects become significantly positive is reminiscent of Moore and Schnepel's (2024) finding that reductions in overdose deaths after a shock to Australia's heroin supply were initially overwhelmed by drug substitution and crime-related homicides. Kaestner and Ziedan (2019, 2021, 2023) also find that the effects of PDMPs occur at a lag.

adoption of Mandated PDMPs (labelled "Ma"). Here, while parallel trends still appears to hold, the effects of PDMPs on time use are considerably muted, consistent with the evidence from Horowitz et al. (2020) cited previously.[8]

In Table 2, we summarize these duration-specific effects, providing two-stage estimates of the effects of PDMPs across all treatment cohorts and periods. As the estimates in the top panel of the table show, on average, parents in states that adopt PDMPs spent about five or six more minutes per day on active childcare and eleven or twelve more minutes on passive childcare subsequent to the passage of Modern PDMPs, depending on whether the estimating equation includes covariates (all of these estimates are statistically significant at the 5% level or lower). In contrast, the estimates for Mandated PDMPs are mostly small and all statistically insignificant.

In interpreting the magnitudes of these estimates, it is important to remember that, while we estimate effects over the entire treated population, only a fraction of that population is actually affected by the introduction of PDMPs. The ATUS data do not report whether respondents use prescription opioids, and even if it did, it would be exceedingly difficult to identify whether a given respondent *abused* them to the extent that their use behaviors would be impacted by the introduction of a monitoring program. To give a back-of-the-envelope calculation, assuming that Griesler et al.'s (2019) finding that 13.5 percent of parents misused prescription opioids between 2004 and 2012 holds throughout our sample period, and that all of these parents were at risk of being affected by PDMPs, the effects reported in Table 2 imply increases of about 37-44 minutes of active care, and 81-89 minutes of passive care, per day, among parents affected by PDMPs.

As a robustness test, we also estimate the effects of PDMPs on active and passive care, as well as their broad constituents, using a traditional two-way fixed effects specification. The results, summarized in Appendix Table 16, are broadly similar to our more robust two-stage

[8]While there does appear to be a large positive effect for passive childcare in the last period of treatment, this estimate should be taken with a grain of salt since it is estimated with data from a single treatment cohort.

estimates, although the point estimates are uniformly smaller, and the estimated effect for medical care is not statistically significant for Modern PDMPs. As a further robustness test, we also estimate the effects of PDMPs after redefining the adoption dates to correspond to the availability of any electronic prescription database (as opposed to the more narrow definition of Modern PDMPs, which also requires that these databases are available to all prescribers). The results (estimated by our preferred two-stage approach and presented in Appendix Table 17) for active and passive childcare are comparable to the estimates that we obtain using the modern definition of adoption of PDMPs, although the average effects for schooling and medical care are no longer statistically significant. Taken together, these results show that our primary results are not sensitive to either how we define the adoption of (non-mandatory) PDMPs or the method used to estimate them.

Active care, as we have defined it, consists of a combination of childcare *per se*, schooling care, and medical care. In Figure 2, we consider the effects of PDMPs on these broad subcategories of active childcare. Regardless of the type of PDMPs, we find no evidence of pre-adoption differential trends in these components of active childcare between treated and untreated states. For Modern PDMPs, the overall increase in active childcare is driven by increases in childcare *per se* and in medical care, with more tentative evidence of increases in education care. For Mandated PDMPs, the apparent effects are mostly individually statistically insignificant.

We present the corresponding effect-summary estimates in Table 3, which shows that, for Modern PDMPs, the average effect on childcare is between four and five minutes, and the average effects on schooling and medical care are a bit shy of one minute. Perhaps surprisingly, for Mandated PDMPs, the average effect of medical care is statistically significant, and roughly comparable to the Modern effect.

We further decompose these broad subcategories into their constituent time-use activities. Figure 3 summarizes the results for the components of childcare itself: providing physical care for, looking after, talking to, playing with, reading to, planning for, playing sports with, and doing arts and crafts with the child (the corresponding overall-effect summaries are presented in the first panel of Table 4). In addition to showing that parallel trends holds within the components of the broader sub-categories of active care, the figure shows that the childcare effect is driven primarily by increases in time spent looking after (about one minute, on average), talking to (about one minute), and playing with (about two minutes) the child, with decreases in time spent planning for the child (about half a minute). The apparent tradeoff between more engaging activities (looking after, talking to, and playing with the child) and planning for the child suggests that abstinence from opioid abuse encourages, or otherwise enables, parents to spend more "quality time" with their children.

Figure 4 presents the results for schooling care. The panels of the figure corresponding to Modern PDMPs suggest that parents in PDMP states spend more time helping their children with their homework, although the corresponding average effect estimate in the second panel of Table 4 is statistically insignificant. The suggestive evidence that parents spend more time helping their children with homework subsequent to the adoption of PDMPs is in line with the evidence presented above that parents exposed to PDMPs tend to substitute towards more engaging forms of childcare. The estimates for Mandated PDMPs are small and mostly statistically insignificant.

Lastly, Figure 5 summarizes the results for medical care. The figure shows that the increases in medical care for Modern PDMPs are driven by increases in providing medical care for the child (although the effect summaries in the bottom panel of Table 4 suggest that the average effect is not statistically significant). For Mandated PDMPs, the estimated average effect is statistically significant, at about half a minute, on average. Our finding that PDMPs increase time spent providing, rather than obtaining or waiting for, medical care is also consistent with the notion that PDMPs tend to increase the time that parents spend on more engaging activities with their children.

4.2 PDMPs and other uses of adult time

To provide a more comprehensive picture of how PDMPs influence adult time use, we also examine the effects of PDMPs on non-childcare time use. Figure 6 presents a visual summary of the relationship between PDMPs and some key measures of non-childcare uses of adults' time. While the majority of the variables that we examine do not appear to be affected by PDMPs (especially Mandated PDMPs), there are some notable exceptions.

As the first graph of panel (a) shows, the adoption of PDMPs is accompanied by increases in time spent on tobacco and drug use. Unfortunately, the ATUS data do not further decompose this variable into its constituent substances, so we are unable to infer which drugs parents in PDMP states spend more time using. For example, it is possible that parents continue using prescription or other opioids, but spend more time obtaining them, or substitute from opioids to less potent drugs that they use with greater frequency, or some combination of the two. Regardless, this finding is at least consistent with prior evidence that opioid-control policies may lead to substitution towards other substances (Alpert, Powell, and Pacula, 2018; Buchmueller and Carey, 2018; Beheshti, 2019; Powell and Pacula, 2021; Evans, Lieber, and Power, 2019; Evans, Harris, and Kessler, 2022). We do note in passing that the graph also shows some evidence of significant deviations from trend in the pre-treatment period; while these deviations are small, they may suggest that our results for tobacco and drug use should be interpreted with care.

Along similar lines, the fourth graph of panel (a) shows that parents in PDMP states spend more time receiving paid medical care. While the ATUS data do not provide more granular information on the type of care involved, this finding may signify that parents with opioid-abuse problems seek out non-opioid medical solutions for underlying health problems such as chronic pain (this is consistent with prior evidence on PDMPs and substitution from opioids to other medical solutions, see Neumark and Savych, 2023), or seek treatment for addiction problems. However, it may also indicate that some parents spend more time "doctor shopping" in states where PDMPs are widely available but not mandatory.

Table 5 provides overall effect summaries for these time-use outcomes. The average effects of (modern) PDMPs on tobacco and drug use and paid medical care are modest compared to the estimated effects for childcare, although they remain statistically significant. The implementation of Modern PDMPs is associated with a significant decrease in the amount of time that parents spend on housework as well as concomitant increases in the amount of time spent utilizing services, including household services. These service categories include activities such as paid childcare, medical care, and home-maintenance services, suggesting that parents in PDMP states use paid services to substitute from certain housework responsibilities towards childcare. This is consistent with our findings for childcare and education care activities that PDMPs increase parents' engagement with their children. Coupled with the fact that we do not find effects for work, education, or sleep, it also suggests that much of the post-PDMP substitution between activities takes place within the domain of household responsibilities.

4.3 Heterogeneity in the time-use effects of PDMPs

In order to better understand the effects of PDMPs on parental time use, and shed some light on the underlying causal channels, we disaggregate our previous results along a number of demographic dimensions.

Gender, marital status and race

Table 6 presents estimates of the effects of PDMPs on active and passive childcare, as well as broad sub-categories of active care, by gender and marital status. The first two panels of the table show that our main estimates (Table 2) are driven primarily by increases in childcare for men, among whom the average effects of PDMPs are substantially larger, at about ten minutes for active childcare and twenty for passive care. This finding suggests that men have more leeway to increase the amount of time they spend on childcare. However, we also find that women increase their time spent on medical care subsequent to adoption of PDMPs, further suggesting household specialization along gender lines.[9] While these results mainly hold for Modern PDMPs, we also find significant effects of Mandated PDMPs on passive childcare for men and medical care for women.

The bottom panels of Table 6 break down our baseline models by marital status. Focusing on the results for Modern PDMPs, we find that increases in childcare in PDMP states occur almost entirely among married parents, with significant increases across the board. Some of these estimates suggest effects that are considerably larger than the baseline results in Table 2; the estimated effects of PDMPs on active and passive childcare among married parents are about twice the baseline estimate, and we find a much larger overall effect for schooling care. For single parents, the only statistically significant estimate is a decrease in schooling care of a bit under one minute. One straightforward interpretation of this pattern is that single parents are more time constrained, reducing the elasticity of their parenting behaviors with respect to external factors.

When, in Table 7, we decompose our baseline results by race, we find that PDMPs primarily impact white parents, among whom there are significant increases in active childcare, occurring through the childcare *per se* and medical care channels. This is consistent with the finding in Gihleb, Giuntella, and Zhang (2019) that reductions in foster-care admissions after introducing PDMPs were more pronounced for white children, although some of the difference in statistical significance might be due to the relatively small size of our sample of Black parents. While PDMPs do not appear to impact time use on average for Black parents, the estimates do show a significant increase in medical care for that group, an increase that occurs for both definitions of PDMPs.

[9] An alternative explanation would be that PDMPs decrease opioid abuse among men. However, previous findings suggest that women are more likely to abuse prescription opioids (see Serdaveric, Striely, and Cottler, 2017).

Number and age of children

We also estimate a number of specifications that allow for heterogeneity in the number of children present in the household. In the first panel of Table 8, we re-estimate our baseline results, including the number of children as a control variable. The resulting estimates are nearly identical to the baseline estimates presented previously.

The remaining panels of Table 8 disaggregate the baseline results by the number of children in the household. Specifically, we estimate separate effects for households with one child, more than one child, and more than two children. In single-child households, PDMPs primarily increase time spent on active childcare, with significant increases childcare *per se*. In contrast, for households with more than one child or more than two children, PDMPs also lead to much larger increases in passive childcare, while the smaller increase in active care is driven primarily by increases in schooling and medical care. One simple interpretation of this is that time constraints make it difficult for parents in multiple-child households to increase the amount of time they spend engaged in active childcare.

In Table 9, we turn our attention to children's ages. The top panel shows that, in households where the youngest child is fewer than six years of age, there are significant increases in both active and passive childcare, accompanied by significant increases in all of the broad subcategories of active care. Furthermore, the corresponding increases in both active and passive care (at about eight and thirty minutes, respectively) are larger than the baseline results reported above. In contrast, parents whose youngest child is older than six primarily increase the time they spend on active childcare, with this increase driven by more time spent on childcare *per se*.

Disability status

An unavoidable reality in the analysis of prescription-opioid abuse is that even patients who go on to develop addiction problems often have legitimate medical reasons for initiating the use of opioids. PDMPs may exert a disproportional impact on these patients, either because the additional scrutiny makes it more difficult for them to get medications that help them, or because they are likely to develop more severe opioid dependencies.

To investigate heterogeneity in the effects of PDMPs on time use along this dimension, we use two proxies for such underlying conditions. In the top panel of Table 10, we reproduce our primary estimates for active care, passive care, and the broad components of active care for parents with self-reported disabilities. The results stand in stark contrast to our baseline estimates. For these parents, Modern PDMPs lead to large and statistically significant decreases in active care, suggesting that, after the introduction of PDMPs, disabled parents spend two hours fewer engaged in active care per day. In contrast, the population average effect is an increase of about six minutes. At the same time, we also find that PDMPs increase time spent on passive care by nearly an hour (compared with a population-average increase of about twelve minutes).[10]

We also use self-reported difficulty walking or climbing stairs as a proxy for pain issues. The second panel of Table 10 shows that, among parents reporting this difficulty, there is an even larger decrease in active childcare (over 2.5 hours) subsequent to the introduction of Modern PDMPs, accompanied by a somewhat smaller (though still large compared to the population-average effect) increase in passive care.

These decreases in active care for disabled parents and those with mobility issues are driven by reductions in time spent on schooling care, with simultaneous increases in childcare *per se*. Among parents without such difficulties, there is a smaller increase in active care, driven by childcare and medical care.

To provide a more comprehensive picture of how PDMPs affect time use for disabled parents, in Table 11 we disaggregate the effects of PDMPs for these parents into the components of childcare, education care, and medical care. As the table shows, disabled parents in post-PDMP states actually spend more time providing physical care for, looking after,

[10]Results for parents without disabilities are similar to the baseline results reported above. Note that the increased magnitude of the effects for disabled parents might be due in part to the fact that disabled parents are more likely to use prescription opioids, and hence be affected by the policy.

and talking to their children (about ten minutes per day for each activity). At the same time, they spend about four fewer minutes per day reading to their children, and nearly three fewer hours per day helping their children with their homework. For medical care, we find no statistically significant effects. Hence, PDMPs cause disabled parents to spend less time engaged with their children in relatively cognitively demanding tasks such as reading and helping with homework. As further evidence of the robustness of these findings, we obtain similar results when, in Appendix Table 19, we reproduce this exercise for parents with difficulties walking or climbing stairs. One potential explanation for this pattern is that, subsequent to the adoption of PDMPs, parents with disabilities struggle with pain (or potentially withdrawal) issues that reduce their ability (or tolerance) for such tasks.[11]

The contrast between our baseline estimates (Table 2) and the disability-specific estimates (Table 10) highlight the importance of heterogeneity in the effects of PDMPs on parenting behavior. While our baseline estimates imply that PDMPs lead to measurable increases in all types of childcare, our disability-specific estimates show that, within particularly vulnerable subpopulations, they lead to much larger decreases in childcare. Furthermore, the effects of PDMPs are mixed even within these subpopulations, with increases in childcare *per se* trading off with large decreases in education care. This type of heterogeneity may help reconcile some of the apparently conflicting results from the literature on PDMPs, with studies finding decreases in foster-care admissions on one hand (Gihleb, Giuntella, and Zhang, 2019) and increases in child maltreatment on the other (Evans, Harris, and Kessler, 2022). Although our estimates attempt to proxy for underlying medical conditions, the magnitudes of the differences between the disability-specific estimates may suggest that treatment effects are similarly heterogeneous with respect to, for example, the severity of the addiction problem.

[11] An alternative explanation is that PDMPs affect time investments among the disabled by changing the composition of the disabled population. To test for this, we use our main specification to estimate the effect of PDMPs on disability status. The results, presented in the lower panel of Appendix Table 18, do not suggest that PDMPs affect disability status.

Time of week

We also examine how the effects of PDMPs vary between weekdays and weekends. The estimates in Table 12 show that increases in both active and passive care occur during weekdays and weekends alike. However, increases in childcare itself are marginally larger during weekends, and increases in schooling care (presumably driven by helping with homework) are only statistically signficant during the weekend, while increases in medical care occur almost entirely during the work week.

Children in the household

While our primary measure of parental investment in children is time spent on activities with children living in the household, PDMPs may also affect investments in children (under the age of 18) who do not live with the parent. To investigate this possibility, we use our main specification to estimate the effects of PDMPs on time spent on activities with non-household children. The results, presented in the top panel of Appendix Table 18, suggest that PDMPs primarily affect investments in children living in the household, with no evidence of significant effects for those not living with the parent.

A related possibility is that part of the causal mechanism through which PDMPs impact time spent on parenting activities is by increasing the number of children living in the household—for example, if reformed opioid abusers have additional children, or regain custody of existing children. The estimates in the bottom panel of Appendix Table 18, which we obtain by estimating our main specification after replacing parental time use with the number of children in the household, suggest that this is not the case, at least for modern PDMPs (while mandated PDMPs appear to increase the number of children in the household, the preceding estimates do not suggest that mandated PDMPs increase time spent with children).

Other substance-use policies

Although our analysis focuses on the introduction of PDMPs, states have implemented other policies directed at substance use, and these policies do not operate in a vacuum. One prominent class of policies aimed at reducing opioid abuse are "Pill Mill" laws targeting clinics that over-prescribe opioids. Our baseline estimates may confound the causal effects of PDMPs and Pill Mill laws if states attempting to curb opioid abuse simulateneously enact both types of policies. To address this possibility, we also estimate models that control for the presence of Pill Mill laws.

The top panel of Table 13 presents estimates of our main specification that includes an indicator for the presence of Pill Mill laws as a control. As the table shows, the results are substantially similar to those from our baseline specification, with the exception that the effect of PDMPs on passive childcare, while still positive, is smaller and no longer statistically significant. However, we still find evidence of increases in active childcare through all three of its broad categories. In the lower panel of the table, we estimate models in which the second-stage of the estimator includes both an indicator for PDMPs and an interaction between indicators for PDMPs and Pill Mill Laws (PML). For almost every measure of parental time use (including passive care), the main effect for PDMPs is statistically significant, while the interaction is insignificant. The exception is the provision of child medical care, which only appears to increase in states with both PDMPs and Pill Mill laws.

Another important class of policies concerns the legality of marijuana use. The presence of these policies is relevant to the analysis of PDMPs for two reasons: first, marijuana laws may have been enacted around the same time that PDMPs were implemented, and second, the legal status of marijuana may influence the pattern of substitution from opioids towards other substances in the aftermath of PDMPs.

We address the first issue in the top panel of Table 14, where we estimate a variant of our main specification that includes an indicator for whether marijuana is legal for medical use. As in the case of Pill Mill laws, the estimates are very similar to those from our baseline specification, with the exception that we now estimate a smaller (though still statistically significant) effect of PDMPs on passive childcare. In the lower panel, we estimate specifications that include both a main effect for PDMPs and an interaction between PDMPs and Medical Marijuana Laws (MML). In contrast to the results for PMLs, here we find that for every time-use category save for medical care, it is the interaction between PDMPs and MML that is statistically significant. These results suggest that the interaction between PDMPs and MML, which provides an important legal substitute for prescription opioids, plays an important role in mediating the effects of PDMPs on parental time use. This finding is also highly consistent with the finding in Evans, Harris, and Kessler (2022) that the negative effects of the reformulation of OxyContin to make it more resistant to abuse were concentrated in areas without medical marijuana laws.

In Table 15, we repeat this exercise for Recreational Marijuana Laws (RML). When, in the top panel, we control for the presence of RML, we find that PDMPs increase time use in every category except passive care. When we include PDMPs and their interaction with RML, we find that both the main effect and the interaction are positive and statistically significant for every category of childcare. While our findings for MML and RML are very similar, the fact that PDMPs have a main effect in RML states but not MML states suggests that the availability of marijuana for *medical* use (and the ability of doctors to write prescriptions for marijuana) plays an important role in offsetting some of the potential downsides of PDMPs, including limited access to some patients with legitimate medical uses for opioids, and the substitution from opioids towards potentially more harmful substances.

5 Conclusion

There is a consensus that the widespread adoption of prescription-drug monitoring programs have been effective in reducing the prescription and misuse of medical opioids. However, the literature has identified mixed evidence on the effects of these programs on other outcomes.

In the domain of child outcomes, some studies have found evidence that PDMPs improve child welfare, e.g., by reducing foster-care removals, while others suggest welfare reductions, e.g., through increases in child maltreatment.

This paper adds, and helps bring some clarity, to this growing literature. Combining a difference-in-differences design with a heterogeneity-robust identification strategy, we estimate the effects of PDMPs on the amount of time that parents spend with their children, and the kinds of activities that they participate in during that time. Understanding the relationship between PDMPs and adult time use is important for at least two reasons. First, time use is a fairly direct measure of the nature and intensity of parenting behaviors, themselves important childhood outcomes. Second, the literature on child development has shown that parental investments, for which time spent with children proxies, mediates the development of cognitive skills. This implies that PDMPs may also have long-run consequences for the children of parents whose behavior they impact.

We find that PDMPs cause a significant increase in both active and passive childcare, with the effects on active care driven by increases in all thee of its broad subcategories: childcare *per se*, education care, and medical care. Our preferred estimates imply that PDMPs lead the average parent to spend an additional six minutes per day on active childcare and twelve minutes per day on passive childcare. A conservative calculation suggests that these average effects translate to roughly 45 minutes of additional active care and 90 minutes of additional passive care per day among parents with opioid-abuse issues. Disaggregating active child care into its constituent activities, we find that PDMPs increase the time that parents spend on activities that involve a higher degree of engagement, such as talking to children, playing with children, or helping them with their homework.

Consistent with the findings of previous studies, we also find that PDMPs lead to increases in tobacco and drug use, although our data do not allow us to determine which substances parents spend more time using consequent to the adoption of drug-monitoring programs. We also find evidence that parents spend more time obtaining medical care after PDMPs are implemented, which may indicate that PDMPs incentivize parents to seek non-opioid solutions for underlying medical issues, or seek treatment for addiction issues.

Examining heterogeneity in the effects of PDMPs, we find that their time-use impacts accrue mostly for parents who are male, married, and white. Using self-reports of disability status and difficulty climbing stairs to proxy for underlying medical conditions, we find evidence of substantial heterogeneity in both the direction and magnitude of the effects of PDMPs. For parents with disabilities or mobility difficulties, PDMPs decrease time spent on active childcare, specifically helping children with their homework, and the sizes of these effects are much larger in absolute value than the corresponding increases that we estimate for the population at large.

By showing that the same policy can have moderate positive impacts on average, but large negative impacts on some outcomes for those belonging to sensitive populations, we believe that our findings vis-a-vis treatment-effect heterogeneity with respect to disability and mobility status help reconcile some of the apparently contradictory findings from the literature. If the effects of PDMPs and other opioid-control policies are similarly heterogeneous with respect to other underlying and difficult-to-observe factors, it might not be surprising to find welfare improvements along some dimensions accompanied by reductions along others.

Taken together, our findings suggest several roles for public policy with respect to opioid- and other substance-use interventions. First, we identify another dimension along which such programs improve outcomes, adding another mark in the "pros" column. Second, our heterogeneity results provide a concrete example of how PDMPs and related policies can have unintended consequences within sensitive populations, such as those with disabilities or mobility limitations. Third, our findings for marijuana laws, and medical marijuana laws in particular, provide a concrete demonstration that further policy interventions can mediate the effects of PDMPs and other substance-use-related policies, altering the balance of their welfare effects by helping to mitigate potential downsides. Ultimately, these conclusions underscore the need for such programs to be accompanied by support systems and policies that can flexibly address the challenges associated with substance-use interventions, and attend to the unique needs of populations with greater exposure to the potential adverse consequences of such interventions.

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Figure 1: PDMPs and parental time use: Active and passive childcare

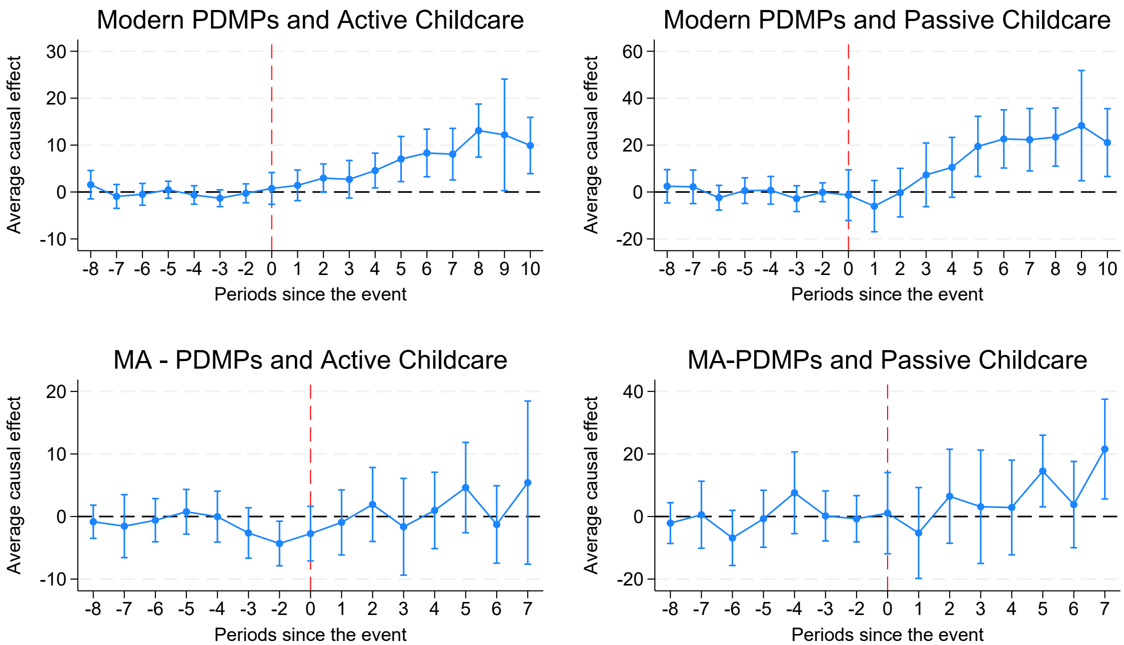


Figure 2: PDMPs and parental time use: Active childcare components

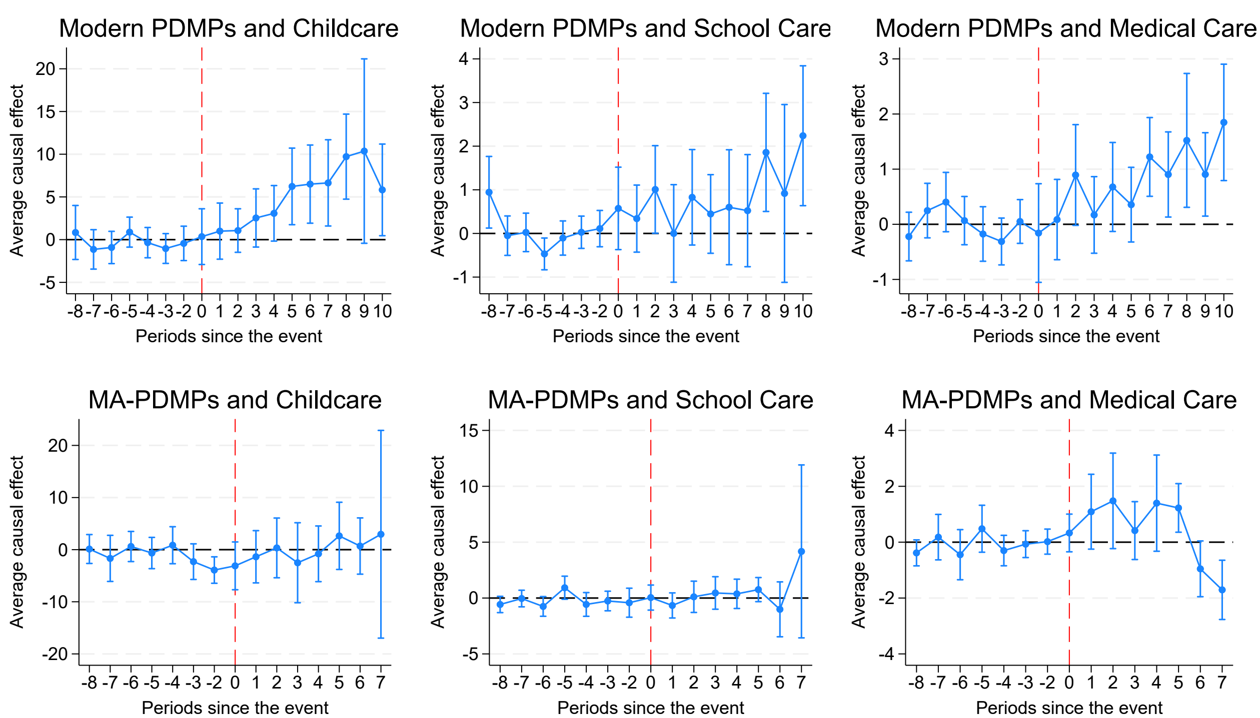
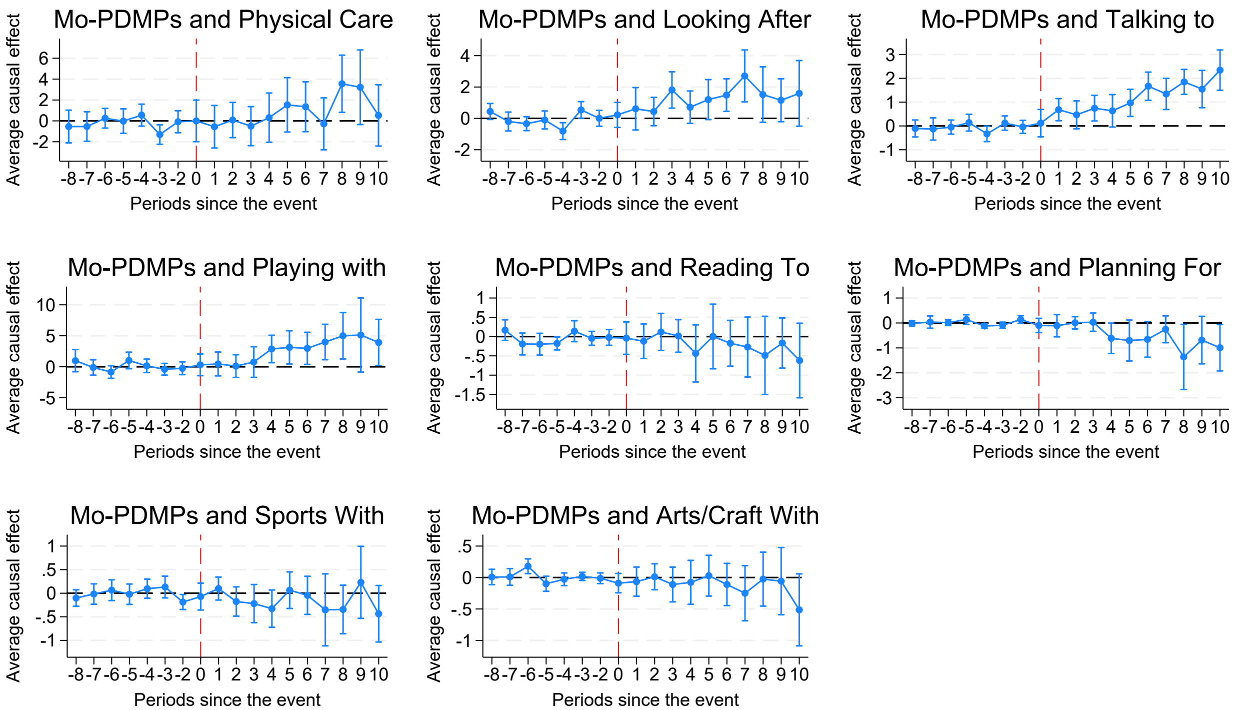


Figure 3: PDMPs and parental time use: Components of childcare activities

(a) Modern PDMPs



(b) Mandatory PDMPs

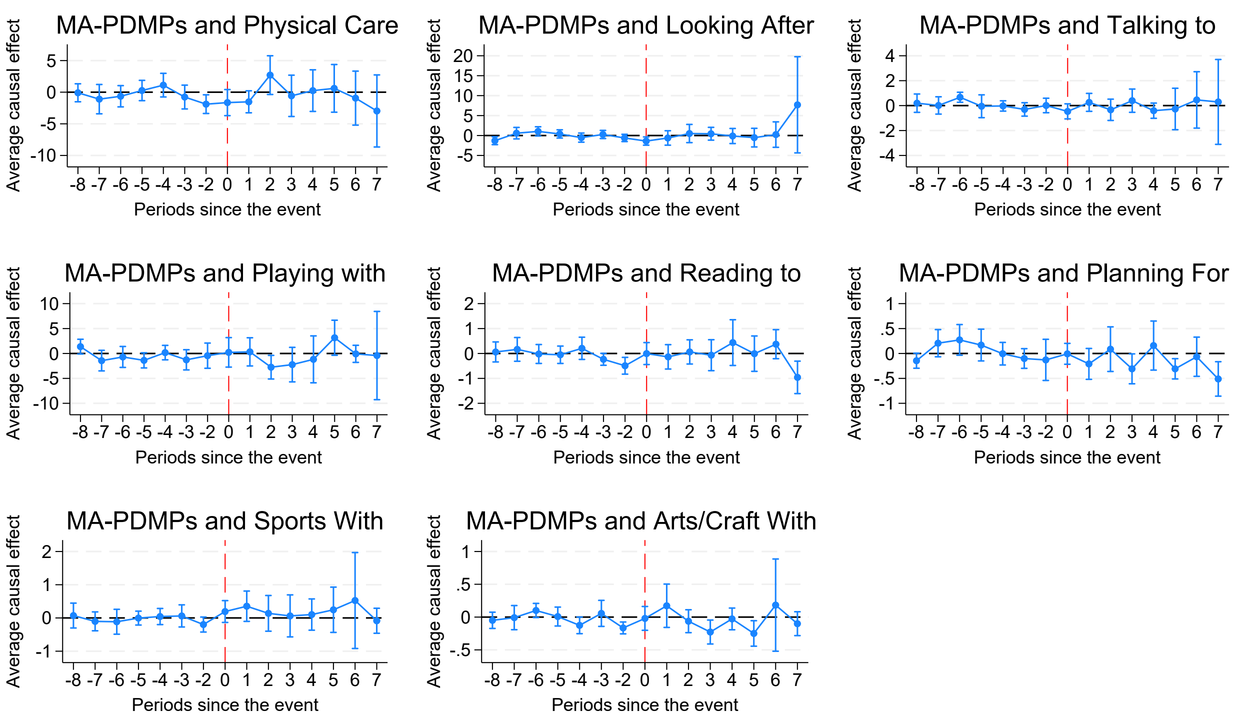


Figure 4: PDMPs and parental time use: Components of schooling care activities

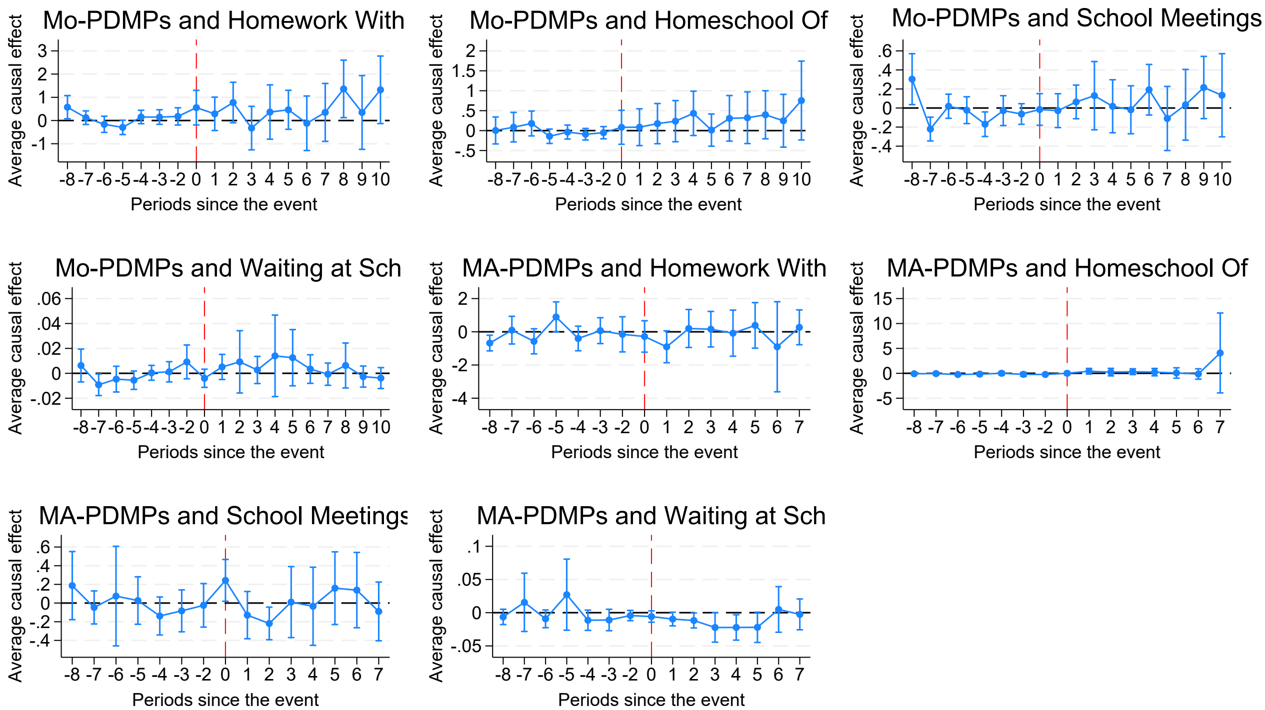


Figure 5: PDMPs and parental time use: Components of medical care activities

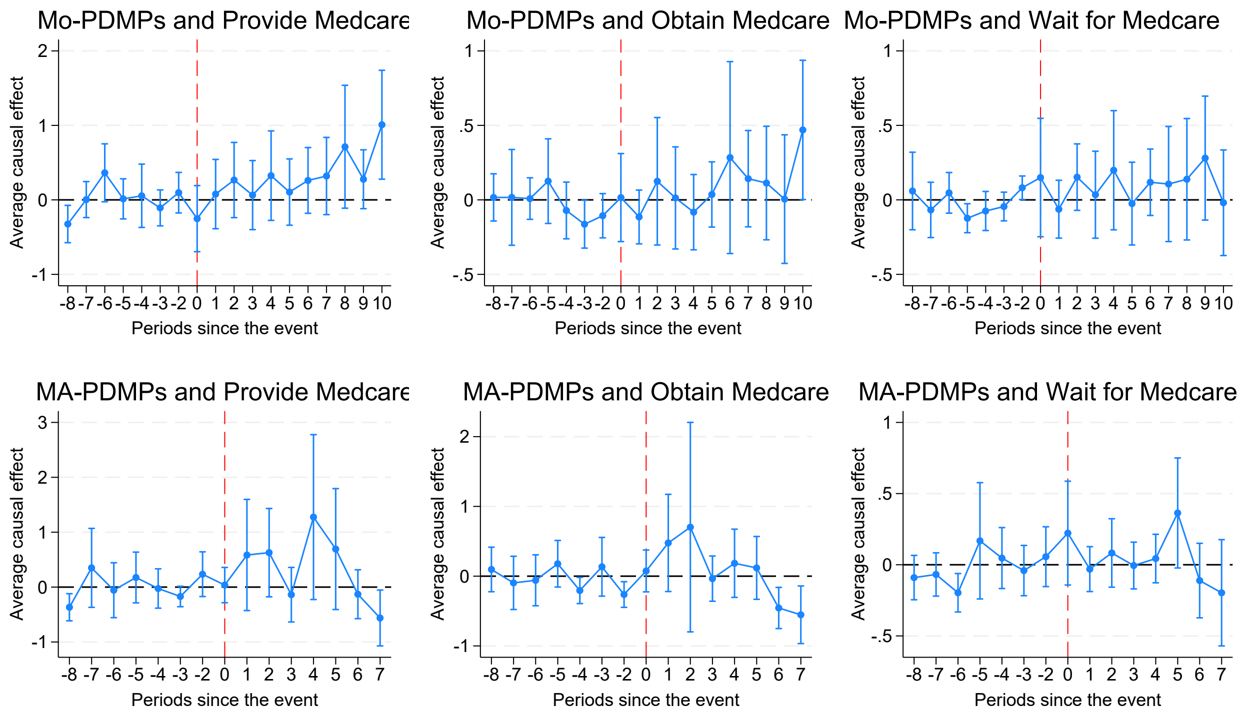
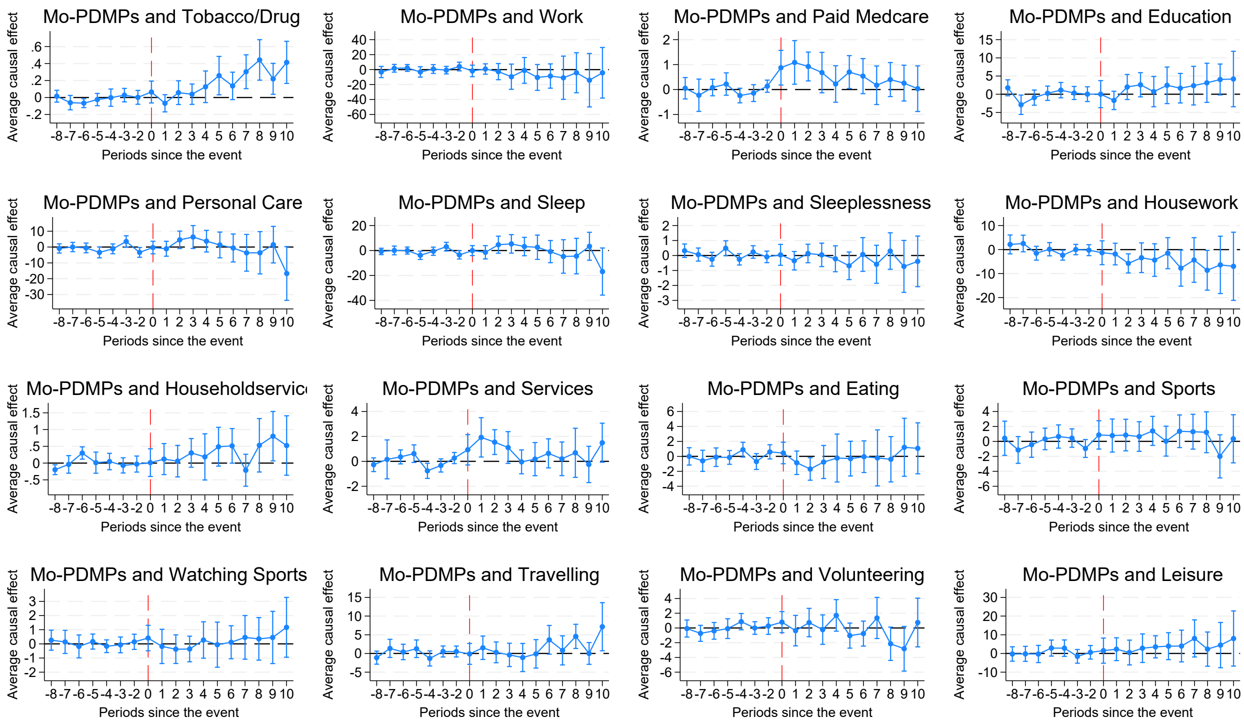


Figure 6: PDMPs and other parental time use

(a) Modern PDMPs



(b) Mandatory PDMPs

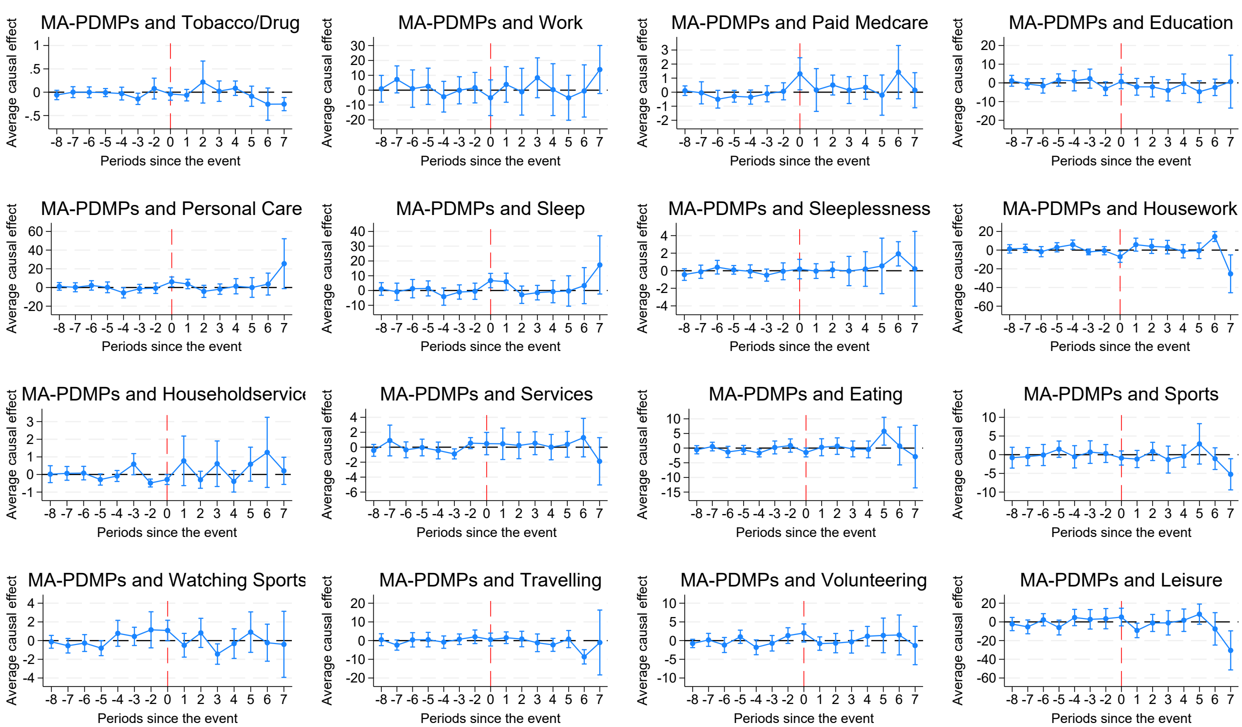


Table 1: Descriptive statistics

	N	Mean	Std. Dev.	Min	Max
Active Childcare	92837	60.88	100.2	0	1151
Passive Childcare	92837	289.56	275.44	0	1440
Childcare	92837	53.93	93.59	0	1140
Child's School care	92837	5.3	23.99	0	640
Child's Medical care	92837	1.65	19.48	0	1045
White	92837	0.82	0.39	0	1
Age	92837	37.09	12.23	15	85
Age of Youngest Child	92837	7.52	5.31	0	17
Female	92837	0.58	0.49	0	1
Married	92837	0.63	0.48	0	1
High School	92837	0.81	0.39	0	1
Some College	92837	0.59	0.49	0	1
College	92837	0.33	0.47	0	1
Disabled	92837	0.03	0.17	0	1

Table 2: Baseline estimates: PDMPs and parental time use

	Active Childcare		Passive Childcare	
Modern PDMPs	5.4919***	6.0441***	11.0353**	12.3093***
	(1.2966)	(1.2985)	(4.5508)	(3.9083)
N	92837	92837	92837	92837
Mandated PDMPs	-0.2808	0.5301	0.7067	3.4435
	(2.1232)	(1.9310)	(4.4048)	(3.3911)
N	94468	94468	94468	94468
Controls		X		X

Notes: Specifications with controls include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 3: PDMPs and active childcare activities

	Childcare		Schooling care		Medical care	
Modern PDMPs	3.8281***	4.6257***	0.9035**	0.7696**	0.7603***	0.6488**
	(1.1487)	(1.2503)	(0.3698)	(0.3646)	(0.2476)	(0.2756)
N	92837	92837	92837	92837	92837	92837
Mandated PDMPs	-1.2300	-0.5180	0.0766	0.1071	0.8727***	0.9265***
	(1.9601)	(1.8191)	(0.4464)	(0.4351)	(0.2917)	(0.2857)
N	94468	94468	94468	94468	94468	94468
Controls		X		X		X

Notes: Specifications with controls include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 4: PDMPs and components of childcare activities

	Childcare			
	Physical care	Looking after	Talking to	Playing with
Modern PDMPs	0.8960	1.2050***	1.0746***	2.2968***
	(0.5850)	(0.3372)	(0.1893)	(0.8090)
N	92837	92837	92837	92837
Mandated PDMPs	0.1018	0.1102	-0.0071	-0.8272
	(0.8087)	(0.5278)	(0.2023)	(0.9559)
N	94468	94468	94468	94468
	Reading to	Planning for	Sports with	Arts/Crafts
Modern PDMPs	-0.1559	-0.4238***	-0.1447	-0.1223
	(0.2021)	(0.1190)	(0.1207)	(0.1186)
N	92837	92837	92837	92837
Mandated PDMPs	0.0550	-0.1047	0.1964	-0.0423
	(0.1911)	(0.0956)	(0.1551)	(0.0678)
N	94468	94468	94468	94468
	Schooling care			
	Homework	Homeschooling	Meetings for school	Waiting at school
Modern PDMPs	0.4475	0.2286	0.0713	0.0046
	(0.3576)	(0.1973)	(0.0856)	(0.0040)
N	92837	92837	92837	92837
Mandated PDMPs	-0.1684	0.3186	-0.0535	-0.0154**
	(0.3913)	(0.2171)	(0.0802)	(0.0068)
N	94468	94468	94468	94468
	Medical care			
	Providing	Obtaining	Waiting for	
Modern PDMPs	0.2169	0.0669	0.0940	
	(0.1730)	(0.1179)	(0.1112)	
N	92837	92837	92837	
Mandated PDMPs	0.5211**	0.2523	0.0439	
	(0.2204)	(0.2099)	(0.0675)	
N	94468	94468	94468	

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 5: PDMPs and other adult time-use activities

	Tobacco/drug use	Work	Work (2)	Paid medical care	Education	Personal care
Modern PDMPs	0.1603***	-6.6015	-7.3085	0.6448***	1.4230	0.0248
	(0.0421)	(6.0530)	(6.2635)	(0.1985)	(1.3287)	(2.7248)
N	92837	92837	92837	92837	92837	92837
Mandated PDMPs	0.0206	2.1041	2.7622	0.2762	-2.4113	0.5206
	(0.0690)	(4.2895)	(4.5099)	(0.3133)	(1.6262)	(2.2659)
N	94468	94468	94468	94468	94468	94468
	Sleep	Sleeplessness	Housework	Services	Household services	Home production
Modern PDMPs	-0.0736	-0.1858	-4.4681**	0.9578**	0.2652	-4.6288
	(3.1609)	(0.2678)	(1.8496)	(0.4117)	(0.1829)	(5.4184)
N	92837	92837	92837	92837	92837	92837
Mandated PDMPs	0.7971	0.2204	2.9759	0.3180	0.3091	3.1291
	(2.1766)	(0.4515)	(2.0763)	(0.5706)	(0.2964)	(3.3854)
N	94468	94468	94468	94468	94468	94468
	Eating	Sports	Watching sports	Volunteering	Travel	Leisure
Modern PDMPs	-0.2674	0.6931	0.1417	0.0076	1.3522	4.1491**
	(0.7458)	(0.5698)	(0.3265)	(0.5713)	(0.9983)	(1.8481)
N	92837	92837	92837	92837	92837	92837
Mandated PDMPs	0.6799	-0.3014	-0.2188	0.0522	-0.5933	-2.2764
	(0.8182)	(0.7819)	(0.4272)	(0.7360)	(1.1369)	(2.8844)
N	94468	94468	94468	94468	94468	94468

Notes: All specifications include the covariates listed in the text. Work (2) refers to time spent working, including traveling to work. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 6: PDMPs and parental time use, by gender and marital status

	Women				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	3.2718**	4.8405	2.2873	0.0852	0.8993**
	(1.5002)	(4.4494)	(1.5050)	(0.5964)	(0.3970)
N	53452	53452	53452	53452	53452
Mandated PDMPs	2.3625	-1.6946	0.4798	0.2396	1.6431***
	(2.6330)	(5.1244)	(2.5119)	(0.6016)	(0.4997)
N	54395	54395	54395	54395	54395
	Men				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	10.5344***	21.5620***	8.5386***	1.5611***	0.4347
	(1.8028)	(4.8561)	(1.6057)	(0.3348)	(0.3230)
N	39379	39379	39379	39379	39379
Mandated PDMPs	-1.0410	12.9249***	-1.0434	-0.0293	0.0317
	(1.9852)	(3.9561)	(1.8234)	(0.4882)	(0.3053)
N	40068	40068	40068	40068	40068
	Married				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	7.1548***	18.7067***	5.0741***	1.1795**	0.9012**
	(1.8968)	(4.1350)	(1.8475)	(0.5767)	(0.3640)
N	58121	58121	58121	58121	58121
Mandated PDMPs	-2.0533	-2.4185	-3.5505	0.3213	1.1759***
	(2.4536)	(4.7109)	(2.2822)	(0.6572)	(0.3703)
N	59115	59115	59115	59115	59115
	Single				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	2.6176*	-2.1213	2.3418*	0.1093	0.1665
	(1.3607)	(6.6576)	(1.3314)	(0.3210)	(0.4274)
N	34716	34716	34716	34716	34716
Mandated PDMPs	2.3054	7.1786	1.9628	-0.1083	0.4509
	(2.1460)	(5.7430)	(1.9598)	(0.4351)	(0.4974)
N	35353	35353	35353	35353	35353

Notes: All specifications include covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 7: PDMPs and parental time use, by race

	White				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	5.6372***	10.1478**	4.5583***	0.4577	0.6212*
	(1.5562)	(5.1292)	(1.3895)	(0.3483)	(0.3293)
N	76005	76005	76005	76005	76005
Mandated PDMPs	1.6445	5.8846	0.2283	0.3206	1.0956***
	(2.1348)	(4.9340)	(2.0725)	(0.5572)	(0.2989)
N	77476	77476	77476	77476	77476
	Black				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	4.4402	-2.9843	2.4356	0.8159	1.1888*
	(5.0634)	(14.4728)	(5.0263)	(1.0266)	(0.6350)
N	9819	9819	9819	9819	9819
Mandated PDMPs	1.3745	7.0502	1.7043	-0.9354	0.6056
	(4.1733)	(11.1827)	(3.9801)	(0.6794)	(0.7318)
N	9949	9949	9949	9949	9949

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 8: PDMPs and parental time use, by number of children

	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
	Controlling for number of children				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	5.4964***	10.5815***	4.2101***	0.6651*	0.6212**
	(1.2309)	(3.5083)	(1.1933)	(0.3848)	(0.2701)
N	92837	92837	92837	92837	92837
Mandated PDMPs	0.1550	2.2952	-0.8142	0.0590	0.9102***
	(1.8689)	(3.4868)	(1.7878)	(0.4475)	(0.2846)
N	94468	94468	94468	94468	94468
	One child				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	7.6280***	6.8620	6.8101**	0.4533	0.3646
	(2.6847)	(4.8342)	(2.7109)	(0.3328)	(0.3383)
N	38124	38124	38124	38124	38124
Mandated PDMPs	-2.5074	0.1786	-1.6827	-0.8559*	0.0312
	(2.2470)	(5.1585)	(2.3698)	(0.4577)	(0.4411)
N	38883	38883	38883	38883	38883
	More than one child				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	4.6437*	16.0165***	2.8334	0.9699*	0.8404**
	(2.6348)	(3.4115)	(2.5786)	(0.5222)	(0.3892)
N	54713	54713	54713	54713	54713
Mandated PDMPs	2.3891	4.3889	0.0100	0.8163	1.5628***
	(2.7035)	(4.6336)	(2.4689)	(0.5530)	(0.4071)
N	55585	55585	55585	55585	55585
	More than two children				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	4.3687	16.8740***	1.6270	0.4548	2.2869***
	(4.2024)	(5.1217)	(4.0378)	(0.9239)	(0.5747)
N	19324	19324	19324	19324	19324
Mandated PDMPs	4.1547	6.5709	0.2303	1.6512	2.2731**
	(4.2095)	(9.6064)	(4.0195)	(1.2884)	(0.9884)
N	19615	19615	19615	19615	19615

Notes: All specifications include covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 9: PDMPs and parental time use, by age of child

	Youngest child < 6				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	8.4356***	30.3170***	5.3960**	1.3190***	1.7206***
	(2.8422)	(4.4853)	(2.6257)	(0.3950)	(0.5712)
N	38936	38936	38936	38936	38936
Mandated PDMPs	-1.4800	-1.5799	-3.7358	0.6522	1.6036***
	(3.6789)	(7.5925)	(3.2674)	(0.4076)	(0.5449)
N	39617	39617	39617	39617	39617
	Youngest child > 5				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	3.9400***	0.4534	3.6231***	0.4464	-0.1295
	(1.0001)	(4.1660)	(1.0267)	(0.5848)	(0.2780)
N	53901	53901	53901	53901	53901
Mandated PDMPs	1.9152	5.1164	1.6988*	-0.2127	0.4291
	(1.3453)	(4.0050)	(0.9749)	(0.7040)	(0.3692)
N	54851	54851	54851	54851	54851

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 10: PDMPs and parental time use, by disability status

	Parents with disabilities				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	-134.1909***	109.2377***	32.4439***	-168.9670***	2.3323
	(33.7290)	(39.8148)	(10.9570)	(38.8682)	(4.6763)
N	2620	2620	2620	2620	2620
Mandated PDMPs	0.3502	-23.1221	-3.4773	4.4796	-0.6521
	(9.6337)	(21.2320)	(7.5392)	(3.0783)	(1.8687)
N	2767	2767	2767	2767	2767
	Parents with difficulty climbing stairs				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	-161.0662***	45.9037**	35.6759***	-194.6546***	-2.0875
	(31.1485)	(22.0591)	(10.4367)	(39.6430)	(5.4720)
N	1322	1322	1322	1322	1322
Mandated PDMPs	-0.3597	-25.7352	-8.8535	7.2664**	1.2274
	(12.5487)	(34.5155)	(10.4390)	(2.9340)	(1.7591)
N	1361	1361	1361	1361	1361
	Parents without difficulty climbing stairs				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	7.5060***	-1.5981	4.9743**	0.8769	1.6548*
	(2.2678)	(4.9753)	(2.2565)	(0.6203)	(0.8554)
N	53026	53026	53026	53026	53026
Mandated PDMPs	0.8531	-1.4567	0.1705	-0.1776	0.8602**
	(1.9073)	(3.8172)	(1.7823)	(0.5513)	(0.3354)
N	53934	53934	53934	53934	53934

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 11: PDMPs and parental time use, childcare components for parents with disabilities

	Childcare			
	Physical care	Looking after	Talking to	Playing with
Modern PDMPs	11.8789***	11.2419***	9.0791***	3.3041
	(3.5712)	(2.6013)	(3.2002)	(6.8147)
N	2620	2620	2620	2620
Mandated PDMPs	0.4080	4.8959	-3.3210**	-2.5141
	(4.1800)	(4.4528)	(1.6805)	(4.6432)
N	2767	2767	2767	2767
	Reading to	Planning for	Sports with	Arts/Crafts
Modern PDMPs	-3.6906***	1.0319	-0.5589	0.1574
	(1.1353)	(1.0387)	(0.6597)	(0.2507)
N	2620	2620	2620	2620
Mandated PDMPs	-0.8500	-0.6927	-1.0933	-0.3100
	(0.8564)	(0.9052)	(0.7866)	(0.3433)
N	2767	2767	2767	2767
	Schooling care			
	Homework	Homeschooling	Meetings for school	Waiting at school
Modern PDMPs	-169.6475***	-0.4089	0.5202	0.0025
	(39.5636)	(1.2993)	(0.7554)	(0.0025)
N	2620	2620	2620	2620
Mandated PDMPs	3.7639	0.4948	0.1684	-0.0083
	(2.3206)	(1.4800)	(0.5314)	(0.0078)
N	2767	2767	2767	2767
	Medical care			
	Providing	Obtaining	Waiting for	
Modern PDMPs	2.2526	2.4856	-2.4955	
	(1.6263)	(2.2918)	(2.9618)	
N	2620	2620	2620	
Mandated PDMPs	1.4292*	-1.6493	-0.1038	
	(0.7668)	(1.3946)	(0.3281)	
N	2767	2767	2767	

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 12: PDMPs and parental time use, by time of week

	Weekdays				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	5.6349***	11.3859*	3.3161*	0.7474	1.5714***
	(1.8022)	(6.0744)	(1.7721)	(0.5051)	(0.3543)
N	45796	45796	45796	45796	45796
Mandated PDMPs	0.4993	2.2087	-1.0062	0.4714	1.0341*
	(3.1004)	(4.1874)	(2.7820)	(0.7651)	(0.5882)
N	46645	46645	46645	46645	46645
	Weekends				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	6.4047***	9.5951**	5.7113***	0.8782*	-0.1848
	(2.0174)	(4.6467)	(1.9881)	(0.4994)	(0.3610)
N	47041	47041	47041	47041	47041
Mandated PDMPs	0.3125	8.3870	-0.0302	-0.4020	0.7447*
	(1.9669)	(6.0958)	(1.9441)	(0.4565)	(0.4214)
N	47823	47823	47823	47823	47823

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 13: PDMPs, parental time use, and Pill Mill laws

	Controlling for Pill Mill laws				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	5.0672***	8.3165**	3.6126***	0.7990**	0.6556**
	(1.2817)	(3.8320)	(1.2082)	(0.3576)	(0.2704)
N	92837	92837	92837	92837	92837
Mandated PDMPs	1.1361	4.5132	-0.0408	0.1867	0.9903***
	(2.0611)	(3.5989)	(1.9226)	(0.4653)	(0.3258)
N	94468	94468	94468	94468	94468
	Interactions				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	4.5067***	7.8369*	3.3033**	0.6893*	0.5141*
	(1.4744)	(4.0653)	(1.3945)	(0.3692)	(0.3038)
Modern PDMPs×PML	2.8373	2.4274	1.5656	0.5553	0.7164
	(3.2697)	(7.0856)	(3.1599)	(0.5446)	(0.4604)
N	92837	92837	92837	92837	92837
Mandated PDMPs	-2.2696	3.7939	-2.7377	-0.0217	0.4898
	(2.2941)	(5.0198)	(2.2318)	(0.5845)	(0.3196)
Mandated PDMPs×PML	8.9480***	1.8897	7.0857**	0.5474	1.3150***
	(3.0034)	(5.6210)	(3.2937)	(0.8663)	(0.4942)
N	94468	94468	94468	94468	94468

Notes: PML denotes Pill Mill laws. All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 14: PDMPs, parental time use, and medical marijuana laws

	Controlling for medical marijuana laws				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	5.0779***	6.8076**	3.6916***	0.7068*	0.6795**
	(1.2501)	(3.3492)	(1.2144)	(0.3913)	(0.2913)
N	92837	92837	92837	92837	92837
Mandated PDMPs	0.6262	3.2550	-0.2761	0.0831	0.8192**
	(1.9538)	(3.3288)	(1.8320)	(0.4787)	(0.3372)
N	94468	94468	94468	94468	94468
	Interactions				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	2.3217	4.5246	1.2060	0.7467**	0.3691
	(1.6173)	(3.7730)	(1.3840)	(0.3513)	(0.2967)
Modern PDMPs×MML	6.7675***	11.1883**	6.1199***	0.0273	0.6204
	(1.884)	(5.6822)	(1.5531)	(0.2741)	(0.4859)
N	92837	92837	92837	92837	92837
Mandated PDMPs	0.9959	1.0238	-0.9792	0.5817	1.3933***
	(2.3687)	(4.3617)	(2.1559)	(0.6079)	(0.3958)
Mandated PDMPs×MML	-0.2964	6.8634	1.4172	-0.8508	-0.8628*
	(3.2388)	(5.6370)	(3.1650)	(0.7101)	(0.4542)
N	94468	94468	94468	94468	94468

Notes: MML denotes medical marijuana laws. All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 15: PDMPs, parental time use, and recreational marijuana laws

	Controlling for recreational marijuana Laws				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	5.4328***	3.6413	3.8238***	0.6986**	0.9105***
	(1.2634)	(4.8455)	(1.1718)	(0.3056)	(0.2769)
N	92837	92837	92837	92837	92837
Mandated PDMPs	1.4071	5.6476	0.2854	0.1626	0.9591***
	(1.9790)	(3.5975)	(1.8810)	(0.4560)	(0.3049)
N	94468	94468	94468	94468	94468
	Interactions				
	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Modern PDMPs	4.3193***	7.2018*	3.0865**	0.6732*	0.5596*
	(1.3272)	(4.3629)	(1.2201)	(0.3661)	(0.2904)
Modern PDMPs×RML	11.2230***	26.0059***	9.2657***	1.0161*	0.9412***
	(1.7460)	(4.1746)	(1.5523)	(0.5349)	(0.2827)
N	92837	92837	92837	92837	92837
Mandated PDMPs	0.9703	3.5559	-0.0376	-0.0310	1.0389***
	(1.9873)	(3.6734)	(1.8943)	(0.4566)	(0.2781)
Mandated PDMPs×RML	-2.2490	19.0729***	-3.1916	2.7238***	-1.7812***
	(4.1852)	(4.8678)	(3.8439)	(0.7757)	(0.2972)
N	94468	94468	94468	94468	94468

Notes: RML denotes recreational marijuana laws. All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Appendix

Table 16: Baseline estimates: PDMPs and parental time use, TWFE estimates

	Active Childcare		Passive Childcare		Childcare		Schooling care		Medical care	
Modern PDMPs	3.6988***	0.6571	-0.3668	-4.5191	3.2343***	0.0291	0.6059***	0.5160**	-0.1415	0.1119
	(1.045)	(1.1600)	(2.1638)	(3.2833)	(1.0226)	(1.1621)	(0.1517)	(0.2427)	(0.1519)	(0.2478)
N	92837	92837	92837	92837	92837	92837	92837	92837	92837	92837
Mandated PDMPs	3.9900**	0.503	2.0196	3.5536	3.3839*	-0.4805	0.0163	0.0354	0.5898**	0.9480***
	(1.9316)	(1.9687)	(3.5983)	(3.4209)	(1.7939)	(1.8710)	(0.3788)	(0.4237)	(0.2601)	(0.2990)
N	94468	94468	94468	94468	94468	94468	94468	94468	94468	94468
Controls		X		X		X		X		X

Notes: Active and passive childcare are defined in the text. Specifications with controls include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 18: Additional robustness tests

	PDMPs and time spent with non-household children			
	Active childcare	Childcare	Education care	Medical care
Modern PDMPs	0.1013	0.0457	-0.0091	0.0647
	(0.2626)	(0.2633)	(0.0172)	(0.0570)
N	92837	92837	92837	92837
Mandated PDMPs	-0.1254	-0.0421	-0.0446	-0.0387
	(0.2541)	(0.2507)	(0.0292)	(0.0427)
N	94468	94468	94468	94468
	PDMPs and other outcomes			
	Number of children	Disability status		
Modern PDMPs	0.0354	-0.0006		
	(0.0220)	(0.0028)		
N	92837	92837		
Mandated PDMPs	0.0344*	0.0005		
	(0.0209)	(0.0035)		
N	94468	94468		

Notes: Estimates in the top panel represent the effects of PDMPs on time spent with children not living in the household. Estimates in the bottom panel represent the effects of PDMPs on other outcomes (the number of children in the household and self-reported disability status). All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 17: Electronic PDMPs and parental time use

	Active childcare	Passive childcare	Childcare	Schooling care	Medical care
Electronic PDMPs	3.8392***	4.7130*	3.2026***	0.2386	0.3979
	(1.1310)	(2.7414)	(1.1416)	(0.3085)	(0.3480)
N	50148	50148	50148	50148	50148

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.

Table 19: PDMPs and parental time use, childcare components for parents with mobility limitations

	Childcare			
	Physical care	Looking after	Talking to	Playing with
Modern PDMPs	0.5937	13.1891***	14.1533***	7.6039
	(4.9630)	(4.3219)	(4.5507)	(4.8505)
N	1322	1322	1322	1322
Mandated PDMPs	0.5736	6.4528	-6.8180**	-8.4335
	(5.5854)	(5.1597)	(2.8761)	(5.3689)
N	1361	1361	1361	1361
	Reading to	Planning for	Sports with	Arts/Crafts
Modern PDMPs	0.2138	0.9453*	-0.7292	-0.2940
	(1.0376)	(0.5604)	(1.2423)	(0.3067)
N	1322	1322	1322	1322
Mandated PDMPs	-0.0330	0.6542	-1.2709*	0.0212
	(0.7389)	(0.8800)	(0.6912)	(0.0784)
N	1361	1361	1361	1361
	Schooling care			
	Homework	Homeschooling	Meetings for school	Waiting at school
Modern PDMPs	-194.6219***	-0.6701	0.4691**	0.0049
	(39.7219)	(1.6203)	(0.2014)	(0.0050)
N	1322	1322	1322	1322
Mandated PDMPs	6.4902**	0.2280	0.7229	-0.0153
	(2.9762)	(0.6356)	(0.8097)	(0.0152)
N	1361	1361	1361	1361
	Medical care			
	Providing	Obtaining	Waiting for	
Modern PDMPs	-0.9788	0.6475	-1.7562	
	(2.4470)	(1.8620)	(3.7916)	
N	1322	1322	1322	
Mandated PDMPs	1.2385	-0.2879	0.2769	
	(0.7980)	(0.8748)	(0.5180)	
N	1361	1361	1361	

Notes: All specifications include the covariates listed in the text. Standard errors clustered on state. ***, **, and * denote significance at the .01, .05, and .1 levels.