Social Costs of Work Disruptions: Evidence from Physicians and their Patients

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Abstract

Work disruptions among women are common, and costly for both workers and firms. Do consumers also shoulder some of the costs of these interruptions? We study the impact of physicians' births — a large shock to women's work — on their patients' access to care, using administrative insurance claims data from California and a triple difference design. We find that female physicians reduce their billed visits with Medicaid patients by 85% in the quarter following a birth, and then largely return to work, with modest and statistically insignificant reductions over the next two years. Nevertheless, this interruption generates negative spillovers for their child patients. Children whose primary care physician becomes a mother are 23% less likely to see their usual physician for up to 2 years afterward, and experience a persistent 50% reduction in vaccination claims and 42% reduction in lead testing. The vaccination decline coincides with fewer pediatrician encounters overall, which may explain the long-lasting impacts on children's medical interactions.

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1 Introduction

Work disruptions among women are common, and costly for both workers and firms.[1] But these interruptions may also impose costs for consumers; implying larger *social* costs that may not be fully considered in private employment decisions. For example, consumers may be harmed if replacement workers cannot readily substitute for a missing worker, which could lead to mistrust, communication gaps, or lapses in service. These problems may intensify when consumer-worker relationships boost productivity, replacement workers are scarce, or prices are set administratively.

In this paper, we examine the effects of a primary care physician's (PCP) childbirth — a large disruption to women's work — on her work volume and her patients' health outcomes over the short and medium run. The medical setting is ideal for this investigation because patients may be sensitive to hassles in accessing care (Brunner et al., 2020; Shepard and Wagner, 2025), and limited supply of high-skill physicians may make them difficult to replace. At the same time, growing use of electronic health records to improve care coordination could make provider substitutions more seamless. These opposing forces make it unclear whether a *modest*, *anticipated* interruption in physician access, such as from a childbirth, would harm patients.

We use a triple difference approach to study the impact of women's work interruptions around childbirth. In particular, we compare the outcomes of mother and father PCPs and their patients before and after childbirth, relative to gender gaps among non-parents. This allows us to separate the effect of new mothers' work interruptions from other time-varying changes around childbirth or among female physicians. We determine the timing of physician births through detailed birth records, and link these to administrative health records from the Medicaid program in California to track provider and patient outcomes.

We have four main sets of results. First, we find that childbirth leads to a substantial, but short-lived, disruption in female physicians' work. In the short run (first quarter after childbirth), mother's volume of office visits declines by 85%, and their likelihood of submitting *any* claims declines by 32 percentage points. These large effects on women's work output are temporary. In

[1] For evidence on the costs of lost work experience for women, see, for example, Mincer and Polachek (1974), Blau and Kahn (2017), Kuka and Shenhav (2024); and for replacement costs for firms, see Gallen (2019); Jäger and Heining (2022); Ginja, Karimi and Xiao (2023); Brenøe et al. (2024).

the medium run (1–7 quarters after childbirth), mothers' office visits recover substantially and remaining differences are not statistically significant.

Second, we show that children's office visits decline after their PCP becomes a mother. They have 0.4 fewer claims with their original PCP in the short run, reducing quarterly visits by 81%. Children continue to have 21% fewer claims with their original PCP in the medium run, indicating that the initial disruption permanently damages some primary care relationships. Children eventually substitute to other providers, but not fully or immediately. Children's total office visits (with any provider) decline by 14% in the short run and remain 6% lower over the subsequent two years.

Third, we find that the disruption in PCP access leads to persistent reductions in children's preventative care. This includes a 54% reduction in routine immunizations, a 53% reduction in seasonal flu vaccines, and a 42% reduction in lead screening tests. Hence, children become more vulnerable to a range of preventable harms: there may be a "scarring" effect of the initial physician interruption.

Fourth, and in contrast to the effects on children, we find that a female PCP's childbirth has much smaller effects on adult patients. While adults are less likely to see their usual PCP in the short run, they fully substitute to other providers, with no loss in office visits. They then return to their PCP afterwards, so there is no persistent effect on their provider relationship. We also find no effect on vaccinations, pharmacy claims, emergency department use, or Medicaid enrollment. This suggests that adults may be less susceptible to the effects of an interruption in provider availability.

We find support for two mechanisms that may contribute to children's decline in preventative care after a PCP interruption. First, worker shortages or search frictions may make it difficult for children to switch to alternative providers. In support of this, we show that the decline in children's PCP office visits is not offset by appointments with other providers in the PCP's practice, suggesting that replacements may not be easily accessible. Further, the decline is concentrated among appointments with pediatricians, who are more likely to monitor children's preventative care. Second, children may lose relational capital during PCP interruptions, which may be important for preventative care decisions. Consistent with this mechanism, we estimate greater harms to patients who have a longer history with their PCP; however, the differences are not statistically significant.

We also provide several pieces of evidence to demonstrate the robustness and validate the interpretation of our results. We find similar effects when we limit our analysis to women physicians, and use a difference-in-difference strategy that compares new mothers to women who are not parents. We also present event studies of patient outcomes around childbirth to verify that there was no change in care utilization leading up to a PCP's pregnancy. We show that patients of new parents and non-parents are balanced in demographic characteristics and health care utilization at baseline, which alleviates concerns about potential selection across these physicians. Finally, we replicate our results on physician work volume using a survey of physician's total hours (inclusive of non-Medicaid patients). This ensures that that our findings on physician work patterns generalize beyond the Medicaid population.

Overall, our findings point to meaningful effects of women's work interruptions on consumer well-being. Because women account for a growing share of the medical workforce — the majority of medical students and 37% of physicians (Boyle et al., 2024) — these costs may have significant cumulative effects on the profession's output. Thus, policies that reduce the duration of parental leaves or facilitate hand-offs between providers for vulnerable patients, such as children, could have significant consumer benefits.

Our results contribute to active areas of research in labor and health economics. We provide new evidence that becoming a parent has costs that extend beyond the worker and firm — to *consumer* outcomes. This complements a broad literature in labor economics demonstrating that motherhood depresses women's labor market outcomes (e.g. Lundborg, Plug and Rasmussen, 2017; Kleven et al., 2019; Cortés and Pan, 2023) and imposes costs on firms due to frictions replacing lost labor (Gallen, 2019; Jäger and Heining, 2022; Ginja, Karimi and Xiao, 2023; Brenøe et al., 2024). The most closely related paper to ours, Friedrich and Hackmann (2021), shows that a large-scale absence of nurses in Denmark (due to the introduction of a parental leave program) adversely affected outcomes of hospitalized patients. While Friedrich and Hackmann (2021) focus on a large, one-time shock affecting the entire labor market, we study how a common, short-term absence of a patient's PCP affects outpatient care among low-income children and adults. We find that female physicians' childbirth harms their patients, even after mothers have largely returned to work.

We also build on prior work in health care highlighting the importance of longitudinal patient-PCP relationships and trust (Rodriguez et al., 2007; Agha, Frandsen and Rebitzer, 2019; Mainous et al., 2001; Schwab, 2025), by investigating how interruptions in PCP access affects patient outcomes. Although permanent PCP exits have been found to harm adult patients (Sabety, Jena and Barnett, 2021; Staiger, 2022; Sabety, 2023; Zhang, 2022), we find that common, *temporary* PCP interruptions have no impact on adult care utilization or health outcomes. We provide new evidence that PCP disruptions generate long-lasting harms for children, a group overlooked in prior work.

Finally, we contribute to a growing literature on the determinants of preventive care. Prior research has emphasized behavioral hazard and limited trust as hurdles to increasing preventative care take-up among adults (Baicker, Mullainathan and Schwartzstein, 2015; Alsan, Garrick and Graziani, 2019). Recent work on children's vaccinations similarly shows that take-up depends on convenience and costs of non-compliance; vaccination rates increase when seasonal administration coincides with regular wellness visits, when subject to school mandates, or when disease prevalence is higher (Oster, 2018; Carpenter and Lawler, 2019; Schaller, Schulkind and Shapiro, 2019; Anderson et al., forthcoming). We identify children's PCP interruptions as another source of frictions for children that persistently reduces preventative care use. Our findings suggest that fostering longitudinal relationships between children and pediatricians may effectively increase vaccination rates.

2 Setting and Data

Our analysis brings together detailed data on physician births, patient health care utilization, physician work, and physician characteristics from multiple sources. To begin, we describe the Medicaid insurance program in California (Medi-Cal) and the administrative claim and encounter data from this program that provide the primary data for our analysis. We then elaborate on other data sources, and describe the matching process that we use to construct our analysis sample.

2.1 Setting: The Medi-Cal Program

Medi-Cal is a publicly-funded program that provides insurance to more than 14 million low-income individuals in California, including roughly 40% of all children, 50% of individuals with disabilities, and 20% of workers in California (Tatar and Chapman, 2019). Eligibility for the program depends on an individual's family income, as well as categorical factors, such as immigration status, disability, and age (which contributes to the high rates of youth participation).[2] These features of the program provide three main advantages for our empirical analysis. First, Medi-Cal accounts for roughly one sixth of all Medicaid participants nationally, which makes it a relevant context for analyzing potential strategies to improve outcomes in the national program (Centers for Medicare and Medicaid Services, 2024). Second, the large scope of the program ensures that we have a thick network of patient-provider relationships. Third, Medi-Cal enrollees often experience difficulty finding an accepting pediatrician or adult primary care provider (Pintor et al., 2019; Galbraith et al., 2005; Melnikow et al., 2020), perhaps due to low reimbursement rates (Polsky et al., 2015; Alexander and Schnell, 2024) and high administrative burden (Dunn et al., 2024). This context may amplify the disruptive effects of physician leaves.

2.2 Data Sources

Medi-Cal insurance claims. Our core data are Medi-Cal insurance claims and encounters from 2011-2019, which were provided by the California Department of Health Care Services. Our data include the full panel of claims for patients who ever saw (i) a PCP who became a new parent during our sample period or (ii) a PCP in a matched sample of physicians. We define PCPs as physicians who specialize in family practice, pediatrics, or internal medicine. We provide additional details on the construction of this sample and key outcomes in Appendix A1.

We use these health records to track quarterly outcomes for physicians and patients. We measure a physician's work volume as her total claims for outpatient evaluation and management (E&M) services, which we simply refer to as "office claims". We also create a binary indicator for having any office claims during the quarter, which we interpret as a measure of work leaves.

[2]For a detailed overview of the Medi-Cal program, see Tatar and Chapman (2019).

We also construct quarterly measures of patient care utilization across five domains. First, we measure encounters with a health care provider. Specifically, we count the patient's total number of office claims, as well as the number of office claims with their attributed PCP. For each office claim, we also measure the patient-provider familiarity based on the number of weeks elapsed since the patient's first observed claim with that provider. We aggregate this familiarity score to the quarterly level by taking the mean across all of a patient's office visits. (Quarters with no office claims have missing values of this familiarity measure.) Second, we measure a patient's use of preventative care using the total claims for vaccinations and children's lead screening tests.[3] Third, we use pharmacy claims to measure medication use. Fourth, we measure emergency department visits, which may be used as substitutes for primary care or could signal deteriorating patient health. Fifth, we create an indicator for whether a patient was ever enrolled in Medi-Cal during the quarter based on their enrollment dates. This allows us to investigate patients' attrition from Medicaid as a potential response to provider availability.

Vital Statistics. We obtain the timing of physicians' childbirths from the 2007–2017 California Vital Statistics Birth Records Data, which includes documentation for each child born in California. The birth records include the child's date of birth and their parents' names and occupations, among other demographics. We identify physicians who become parents based on the parent's occupation. We obtain the parents' National Provider Identifier (NPI) number by performing a fuzzy name match to link parent physicians' names to national physician registries. We then use the NPI to link to physicians in the Medi-Cal data. See Appendix A1 for further detail on the NPI match.

California Physician License Survey. We supplement the insurance claims with information on physicians' weekly hours of work from the Medical Board of California Physician and Surgeon License database (2010-2022). Physicians are required to renew their medical license every two years, and are surveyed at the time of renewal about their usual weekly hours dedicated to patient care. The license data also include medical school graduation year and gender, which we use as

[3]Children in Medi-Cal are required to have a lead screening test at ages 12 months and 24 months, and are recommended to have additional testing if they may have had lead exposure (California Department of Public Health, 2022).

covariates in our physician matching process. The license data do not contain NPIs, so we perform another fuzzy name match to link physician records in that database with the Medi-Cal claims.[4]

Physician Directory Data. We use two additional sources to identify physicians' NPI numbers (as discussed above) and to populate physician characteristics. We use the National Plan & Provider Enumeration System (NPPES, 2007-2022) to obtain physician specialty codes, gender and graduation years for physicians who do not appear in the license survey. We use the Center for Medicare & Medicaid Services (CMS) Doctors and Clinicians National Downloadable File (2015-2022) to fill in gender for remaining physicians.

2.3 Sample Construction and Characteristics

Sample construction and matching. We construct our analysis sample from the Medi-Cal and Vital Statistics records in two steps. First, we identify parent physicians who care for Medicaid patients prior to a first birth, and who have a first birth between 2011-2017.[5] Second, we use coarsened exact matching to identify non-parent physicians who are similar to parent physicians.[6] Similar matching processes have been used to compare workers in other highly skilled professions, such as elite scientists (Azoulay, Graff Zivin and Wang, 2010) and surgeons (Sarsons, 2024). We match physicians one-to-one: matching exactly on physician gender, specialty, and graduation year (except a few cases where an exact year match does not exist); and matching coarsely on their patient panel size (favoring closer matches on panel size). Appendix A3 describes the matching procedure in detail.

We then keep all patients cared for by physician parents and matched non-parents before the birth event. We attribute a patient to a PCP based on the physician who delivered the most office visit-days in a 12 month window before the PCP's birth (months -14 to -2). For non-parent PCPs, we use the birth timing of their matched parent to define this window. We focus on a PCP's patients

[4] About 90 percent of physicians in our sample match to a record in the license survey data. Our analysis additionally restricts to physicians who answered the survey at least once before childbirth.

[5] We exclude physicians who have a first birth between 2007–2010, since this precedes our Medicaid data.

[6] We define non-parent physicians as those without a birth in California over 2007–2017. Due to data limitations, our identification of non-parents is imperfect (i.e., some doctors whom we call "non-parents" may in fact be parents). We discuss the implications of this for our research design in Section 3.

two months before the birth, in case physicians adjust their practice volume in late pregnancy.[7] This follows attribution procedures used in past work, such as Agha et al. (2022) and Pham et al. (2009).

Our final sample includes 2,994 parent and matched non-parent physicians attributed to 364,650 individual patients. Because parent and matched non-parent PCPs may have slightly different numbers of patients, we weight the patient analysis to balance patient counts within matched physician pairs. Outcomes are defined at the quarterly level, with quarters anchored around the calendar month containing the physician's birth (or the birth of the placebo physician's matched parent). We index the quarter of the physician's birth as event quarter 0. Our analysis keeps observations 8 quarters before and after the birth.

Sample Characteristics. Table 1 provides baseline descriptive statistics on the patients in our sample, separately for children and adults. Younger and older patients differ in several important ways. First, they differ demographically: children are more likely to be Hispanic (64% vs 39%), less likely to be white (11% vs 21%), and less likely to be female (49% vs 64%). Second, they receive different kinds of care: children have more vaccination claims (0.37 vs 0.10), but have fewer office claims and prescriptions, and are less likely to use the emergency department. Children also tend to see physicians with whom they have a longer history (18 weeks vs 15 weeks). Given these varying backgrounds and health demands, we analyze adults and children separately throughout.

We assess balance in the patient characteristics of parent and non-parent PCPs in Appendix Tables A3 (child patients) and A4 (adult patients). Patients have similar patterns in race, gender, and year of birth across parent types, despite the fact that we didn't target any of these characteristics in our matching process. This provides reassuring evidence for our empirical strategy comparing these groups over time.

[7] To improve our PCP attribution, we require that children's PCPs specialize in family practice or pediatrics, and that adults' PCPs specialize in family practice or internal medicine.

3 Empirical Strategy

To quantify the impact of women's work interruptions after childbirth, we follow Kleven et al. (2019) and others in using an event study approach. Specifically, we estimate a triple difference event study, which compares the outcomes of women and men physicians and their patients, in the months before and after a birth. We then compare this difference to the gap in outcomes among a set of matched non-parents.

This triple difference approach allows us to isolate the differential effect of childbirth for women—separate from other time-varying changes around childbirth or among women physicians. For example, this specification will net out any effects of parenthood that operate through income effects or changing approaches to pediatric care (e.g. if having a child changes the doctor's efficacy or beliefs about optimal care delivery)—which would be experienced by both mothers and fathers. To provide transparency into these estimates, we also report results from two difference-in-differences analyses, limited to either female or male PCPs. We use these estimates to decompose the variation underlying our main results, as we discuss in Section 7.

Our event study specification takes the following form:

$$y_{igpt} = \alpha_i + \sum_{j=-7}^{7} \gamma_j \text{Mother}_{gp} \times \mathbb{1}(t = j) + X_{pgt}\eta + \varepsilon_{igpt}, \tag{1}$$

where y_{igpt} is the outcome of physician i (or their attributed patient), who is gender g and belongs to parent group p (parent or non-parent) and is observed t quarters since childbirth. $Mother_{gp}$ is an indicator for the physician becoming a mother during our sample.

The coefficients of interest are the γ_j's on the interaction between the indicator for becoming a mother and time relative to childbirth, $\text{Mother}_i \times \mathbb{1}(t = j)$. These coefficients trace out the change in the gender gap between parent physicians (compared to the gender gap among non-parents) in each quarter around a first childbirth, relative to the omitted quarter ($t = -5$). For physicians who become parents, t is the number of quarters that have elapsed since childbirth. For non-parents, t is the same as their matched parent.

To isolate the impacts on mothers (or mothers' patients), we include a flexible set of fixed effects.

First, we include individual fixed effects, α_i to absorb any time-invariant differences in outcomes, including in one's physical health, preferences for care, or location of care. Second, we include the vector X_{pgt}, which includes the standard two-way fixed effects for gender-by-event-time and parent-by-event-time, modified to allow heterogeneity in these effects across individuals. Specifically, we allow each of these coefficients to vary with (i) the calendar quarter and year of childbirth and, for the patient analysis, (ii) the length of a patient's relationship with a physician (at baseline). This addresses potential concerns that childbirth may be more prevalent in particular seasons or years, or may be correlated with the number of previous visits with a patient, which could affect subsequent patient outcomes. In practice, these modifications to the standard model have little effect on our results (see Section 7). For conducting inference, we cluster the standard errors by physician.

To summarize the event study results, we use a triple difference model:

$$\begin{aligned} y_{igpt} =& \alpha_i + \beta_1 \text{Mother}_i \times \text{Quarter 0} + \beta_2 \text{Mother}_i \times \text{Quarters 1-7} \\ &+ X_{pgt}\lambda + \epsilon_{igpt}. \end{aligned} \tag{2}$$

The treatment effects of childbirth on the gender gap are summarized by β_1 and β_2, which give the effects in the short run (quarter 0) and medium run (quarters 1-7), respectively. This allows us to distinguish between the immediate effects of having a child, such as recovery from delivery and take-up of paid leave benefits, and more persistent effects.

This research design relies on a parallel trends assumption: in the absence of childbirth, the gender gap in outcomes among parents relative to non-parents would have been on parallel trends. Our main evidence for this assumption comes from our event study analysis. Specifically, we test for the significance of the pre-pregnancy coefficients ($t < -4$) to check whether mothers exhibit different trends than fathers *prior* to having children. Similarly, we check whether the *patients* of mothers exhibit different trends than *patients* of fathers *prior* to the arrival of children.

We also provide two other pieces of support for this assumption. As described in Section 2.3 above, we find that characteristics of patients are balanced across parent and non-parent PCPs. We also show that the estimates are not sensitive to whether we: include flexible time-varying controls,

which could absorb potential confounds; exclude the pregnancy period from our baseline period, since it may be partially treated; or use an imputation estimator that is robust to heterogeneity in treatment effects (Borusyak, Jaravel and Spiess, 2024). The stability of our estimates across specifications gives us greater confidence in the interpretation of our results.

Because we are not able to perfectly identify non-parents (see Section 2), this could introduce measurement error in our treatment assignment. This error stems from the fact that there are some childbirths that we do not observe, such as: (i) older children born before 2007 (so at least 4 years old during our sample); (ii) births outside of California; and (iii) births in the last two years of our claims sample, 2018 or 2019. This contamination could potentially attenuate our estimates by blurring the distinction between our treatment and comparison groups.

However, in practice, we do not expect this to meaningfully affect our results. First, the impact of parenthood on careers largely stabilizes after a child's early years, so parents of older children are unlikely to have strong changes in their practice volume during our sample (e.g. Lundborg, Plug and Rasmussen, 2017; Kleven et al., 2019). Second, physicians in our sample are all actively practicing in California over the study period, which makes it unlikely that they have a birth in another state. Finally, we rule out contamination from more recent births by showing specifications that limit to first births between 2013–2015, which ensures that we have full coverage of births through the two-year post period (see Section 7).

4 Impacts on Physicians

We begin by examining the impact of childbirth on physicians' work volume. This allows us to measure the extent to which children differentially affect women physicians' work, and disrupt patients' access to a physician. Figure 1 presents the coefficients from our triple difference event study, and Table 2 summarizes these effects.

Figure 1 Panel A shows that mothers, relative to fathers, sharply reduce their office claims in the quarter of childbirth. While mothers return to baseline levels of work by the fourth quarter after delivery, they then appear to reduce claims modestly in the following quarters — possibly due

to second births (Adams, Jensen and Petrongolo, 2024).[8] Panel B similarly shows that mothers' likelihood of billing any claims dips markedly after childbirth, but recovers quickly in the subsequent two quarters. Importantly, both panels show small and statistically insignificant coefficients *prior* to childbirth, indicating that mothers do not pull back from work in anticipation of having a child.

Table 2 Column 1 reports that mothers' office claims fall by 119 in the quarter of birth ($P < 0.01$), which is an 85% decline relative to the mean. Consistent with the event study, mothers' claims largely rebound in quarters 1-7, and we cannot reject a full recovery (although the point estimate is negative). Column 2 shows that mothers are 28.5 percentage points (p.p.) less likely to have any claims in the quarter of childbirth (a 38% decline). This fades to a statistically insignificant 2.1 p.p. effect in the following quarters, implying that physician mothers' participation in the work force is unaffected by childbirth in the medium run.

Before turning to our patient analysis, we examine whether impacts on mothers' work vary across patient populations—children (columns 3-4) versus adults (columns 5-6). Effects could potentially vary across patient age groups due to differences in specialty-specific work norms, patient expectations, or physician preferences. To account for differences in the patient composition of PCPs, we weight estimates by each physicians' share of attributed patients in the respective group.

We find similar effects across children's and adults' PCPs, although the magnitudes and precision vary slightly. Mothers' office claims and participation fall substantially in the quarter of childbirth, and largely rebound in the following quarters. This suggests that any differences in patient responses across these groups are unlikely to reflect variation in physicians' return-to-work patterns after childbirth.

Finally, we address two potential questions about the the identification and the generalizability of these claims results. First, our triple difference results could either reflect disruptions among mothers or greater productivity among fathers—we test this by analyzing men and women separately. Appendix Figures A1–A2 and Appendix Table A2 report difference-in-differences analyses by gender. The patterns reveal that childbirth only reduces total claims of mothers, with no effect

[8] In Appendix Figures A5 and A6, we present results for a longer post-period extending 12 quarters beyond birth, which shows broadly similar results. While subsequent births among parents may contribute to longer-run effects, we also find similar results when restricting to parents with only a single childbirth during the sample period.

for fathers. Both mothers and fathers increase their likelihood of billing any Medicaid claims after a birth, suggesting parenthood may strengthen attachment to the Medicaid labor force – possibly through income effects. This increase among both parents illustrates an advantage of the triple difference analysis: we can separate the disruptive effects of motherhood from any general changes experienced by both parents.

Second, reductions in mothers' claims may reflect substitution away from Medicaid patients rather than declines in total effort. To distinguish these possibilities, we examine effects on physician's *total* weekly hours spent on patients. Because we only observe the year in which the hours survey was completed, we adapt Equation 2 to be at the annual level. The effects on patient hours are largely consistent with the claims patterns, although less precisely estimated: new mother's hours decline in the year of childbirth, but rebound in the subsequent year (Appendix Tables A5 and A6). This suggests that the effects on mothers' claims reflect changes in total work — and not just a shift away from Medi-Cal patients.

5 Impacts on Patients

Having established that childbirth strongly disrupts work for physician mothers, we now examine impacts on patient outcomes—starting with children and then adults. Throughout, we focus on five categories of health care utilization: (i) encounters with a health care provider; (ii) preventative care (vaccinations and lead testing); (iii) pharmacy claims; (iv) emergency care use; and (v) enrollment in Medi-Cal. This allows us to detect potential effects of a physician's absence on different margins of patient care.

5.1 Impacts on Children

Figure 2 presents our main event study results for children, with corresponding triple difference estimates in Table 3. Panel A examines effects on children's office claims with their attributed PCPs. Before a female PCP's pregnancy, children's visits with their PCP are relatively steady,

indicating that these patients initially received similar care to those with other providers.[9] After their PCP becomes a mother, however, children's PCP visits fall substantially. Children have 0.38 fewer PCP claims in the quarter of childbirth (Table 3 column 1), an 81% decline from baseline. Over the medium run, children have 0.1 fewer PCP claims per quarter, a 21% reduction.

Figure 2 Panel B shows that children also have fewer *total* office claims after their PCP becomes a mother. Children's office visits decline the most in the quarter of their PCP's birth (by 0.2 claims), with smaller reductions also occurring in the surrounding quarters. The short-run decline in office visits is roughly half as large as the decline in PCP visits (Table 3 column 2), suggesting that children substitute about half of their foregone PCP visits to other providers. We do not find an offsetting increase in claims in subsequent quarters, implying that this represents a reduction in care, not simply a delay. This incomplete substitution to alternative care could reflect difficulty obtaining appointments with other PCPs or reluctance to see new providers.

In addition to changes in the quantity of medical encounters, we also investigate whether PCP childbirth affects children's familiarity with their providers. In the short run, we find that children see physicians whom they have known for 8.1 fewer weeks, which is a 32% decline from the pre-childbirth mean (Table 3 column 3). The effect on physician familiarity remains negative over the medium run, although it is smaller in magnitude and not statistically significant.

Turning to preventative care, Figure 2 Panel C shows that children's vaccination claims also fall after their PCP becomes a mother. Immunizations drop immediately after their PCP's birth, and remain at this lower level over the next seven quarters. The short-run decline is 0.27 claims, which is a 67% reduction from the mean (Table 3 column 4). The medium-run decline is only slightly smaller (0.21 claims), indicating a substantial persistence of this initial disruption.

Table 4 shows that the decline in children's immunizations is largely driven by a reduction in routine, non-seasonal vaccinations, which protect against more severe illnesses. Routine vaccines fall by 57% in the medium run, with even larger effects in the short run. Flu vaccines also fall by 38% in the medium run, but represent a smaller share of the overall decline because of lower base

[9]PCP visits rise slightly in the quarter prior to pregnancy, which suggests that women PCPs may anticipate having reduced future contact with their patients. In case the attributed patients from this quarter are more weakly attached to their PCP, we control for baseline relationship length in our main specification.

rates. This reduction in vaccines leaves children more vulnerable to a range of diseases, including those that can cause significant health complications.

Figure 2 Panel D shows similarly large reductions in lead screening tests, another common preventative care measure for young children. These effects emerge more gradually than for vaccinations and grow over time, likely due to the lower frequency of these screenings. Table 3 column 5 reports that lead tests decline by 42% in quarters 1–7 after the PCP mother's childbirth. This suggests that children's reduction in care extends beyond an aversion to shots or vaccine skepticism, and includes other routine health monitoring.

In contrast, we find no effect on non-preventative care, which may be less discretionary. In particular, we find null effects on prescription drug fills (which include treatments for chronic health conditions) and use of the emergency department (Table 3 columns 6–7). We also do not find any effects of childbirth on enrollment in Medi-Cal (column 8), which confirms that the measured reductions in care do not reflect differential attrition from the Medicaid program.

Taken together, our findings suggest that continuing relationships with pediatric PCPs are particularly important for preventative care rather than acute care. This is consistent with past research that behavioral hazard reduces demand for preventative care (Baicker, Mullainathan and Schwartzstein, 2015) and patient's trust in their physician may be an important predictor of vaccine take-up (Alsan, Garrick and Graziani, 2019).

5.2 Impacts on Adults

Distinct from the effects on children, Table 3 Panel B shows more muted and transitory effects of a female PCP's childbirth on adult patients' care utilization. Adult patients have 0.33 fewer PCP office claims in the quarter that their physician becomes a mother, but this effect fades in subsequent quarters (column 1). Further, there is no impact on *total* office claims even in the short run, although physician familiarity declines, suggesting that the decline in PCP office claims is fully offset by visits to alternative providers (columns 2-3).

We also do not find any impact on other categories of care. Adults' vaccinations, prescriptions, and emergency claims are unaffected by the PCP interruption (columns 4-6). These patterns are

further corroborated by event studies with flat pre-trends and no treatment effect (Appendix Figure A3). Overall, this suggests that adults can more easily substitute to other providers after a PCP interruption, with no apparent effect on their health care utilization. This could reflect the fact that adults in Medi-Cal have better-established care plans or may be willing to exert greater effort to find a replacement physician.

We provide further support for this finding by examining whether effects vary for adults with different health care needs or demographic backgrounds (Staiger, 2022). Appendix Figure A4 finds no evidence of harm for adults with a higher diagnosis-based health risk score (Hierarchical Condition Category score), or any other tested subgroup. This confirms that temporary PCP absences broadly do not disrupt adults' care.

6 Mechanisms

Given the strong disruptive effects of PCP absences on children, we now examine potential mechanisms for these responses. Understanding these patterns may inform the development of policies to mitigate the harms of provider absences or could help predict the effects of other care disruptions. We study three main channels for our effects: (i) difficulty finding a new PCP; (ii) loss of relational capital between the patient and their provider; and (iii) disproportionate harms to vulnerable groups.

First, primary care shortages could make it difficult for children to find alternative providers accepting new Medicaid patients (Rittenhouse et al., 2019). Given that 76% of children have a pediatrician as their PCP at baseline, we predict that search costs may be concentrated in this specialty (Table 1). Thus, as an initial test of this channel, we examine whether children experience large reductions in pediatrician visits.

Consistent with this prediction, Table 5 shows that children's office claims with a pediatrician decline by nearly the same amount as total visits in the medium run. Thus, most of children's foregone care consists of pediatrician visits. We find no similar decline in claims with a female doctor (Column 2), ruling out effects that stem from losing access to female physicians.[10]

[10]For example, if women physicians were more effective at ensuring that children receive their recommended

To link these effects on pediatric care to reductions in preventative measures, we study the relationship between provider specialty and children's care. Appendix Table A7 shows that children who visit a pediatrician are 34% more likely to receive a vaccination and 30% more likely to have a lead screening on that day, compared to those who see family practice or internal medicine physicians (controlling for patient's age and month of visit). This suggests that a PCP birth may disrupt children's preventative care by reducing access to pediatricians, who are more likely to monitor vaccination and screening schedules.

As another test for the shortages mechanism, we examine substitution to other providers at a PCP's practice site. In group practice settings, a PCP's colleagues may provide cross-coverage and help ensure continuity of care during an absence. However, we find no such substitution: children reduce visits to the PCP's clinic as much as with the PCP herself (Appendix Table 5 Column 3). Moreover, we find similarly large reductions even when children have previously seen multiple different providers at their PCP's practice (Figure 3), as is common in team-based care (Pany et al., 2021). This further points to limited capacity as a barrier to maintaining access to care, rather than e.g., a lack of familiarity with other providers.

A second potential mechanism is the loss of relational capital between PCPs and their patients. Without this capital, patients may be less trusting of providers and forego preventative care. To test for this channel, we examine whether interruptions are more detrimental for children with a stronger baseline PCP relationship, as measured by a longer history together or greater use of care.

The patterns in Figure 3 provide mixed support for this channel. Children with greater relational capital experience larger reductions in vaccination claims and office visits. The differences between groups are also not statistically significant, though, which limits our ability to draw strong claims about relational capital effects.

Finally, we assess whether PCP interruptions disproportionately affect patients with high health care needs or from vulnerable groups. Figure 3 presents estimates for subgroups of children based on their health risk score; whether they are Black, Hispanic, or White; and whether they are under age 6. The estimates suggest that Black children and those under age 6 experience the largest care

vaccinations, then changing the gender composition of a patient's doctors could affect preventative care access. However, we do not find evidence for this channel.

reductions after a PCP's birth; however, we cannot statistically reject that the effects are the same across groups.

7 Alternative Specifications and Robustness

To probe the interpretation of our results, we test the sensitivity of our conclusions for children to several alternative specifications. First, we provide transparency into our main effects by showing difference in differences estimates by physician gender, which compare the patient outcomes of new parents to childless physicians of the same gender. This allows us to separate the effects of changes in fathers' and mothers' work, and to quantify how each of these contribute to our main estimates. While we expect work interruptions among new mothers to deteriorate patient care, our baseline (triple difference) results could also reflect improvements in care among new fathers.

Appendix Table A8 shows that the detrimental effects of PCP childbirth are concentrated among patients of female PCPs, and that there is little impact among patients of male PCPs. Patients of new mothers experience substantial, persistent declines in care utilization, including reduced PCP visits, total office visits, vaccinations, and lead tests. In contrast, patients of new fathers have small, statistically insignificant increases in utilization, which account for a small share of our triple difference effects. These patterns suggest that the relative decline in patient care among new mothers is primarily a response to mothers' work interruptions.

Second, we assess the potential for bias from using a conventional triple difference estimator by re-running our results with an imputation estimator (Borusyak, Jaravel and Spiess, 2024). Reassuringly, this produces results consistent in both magnitude and precision to our main estimates (Appendix Table A9). This suggests that common concerns with triple difference specifications, including negative weighting of long-run treatment effects and forbidden comparisons of early-treated and late-treated units, do not play a significant role in our main results.

Third, we experiment with estimating treatment effects relative to the *pre-pregnancy* period, rather than the *pre-childbirth* period.[11] This allows for potential anticipatory effects of childbirth

[11] We do this by adding interactions between fixed effects for each trimester of pregnancy and an indicator for being a mother to Equation 2.

that occur during the child's gestation. We find similar patient effects with this specification (Appendix Table A10), consistent with the small and insignificant effects of a PCP's pregnancy on patient care.

Fourth, we study the effects of removing our controls for doctor relationship and calendar time from X_{pgt}. The remaining controls in X_{pgt} are two-way fixed effects for event-time interacted with physician gender and parent status. Appendix Table A12 shows that this has little impact on the results, consistent with the fact that our sample is well-balanced on these characteristics at baseline.

Finally, we test the sensitivity of our results to limiting to births between 2013–2015, where we have full coverage of claims data and birth records in the 2-years before and after the birth. This reduces the scope for possible measurement error in our assignment of non-parents. Appendix Table A12 shows that we find similar effects with this sample restriction, although we lose some precision due to having fewer observations. In line with this, the estimates for physician productivity are also largely unchanged in this sample (see Appendix Table A11).

8 Discussion

Our results show that PCP disruptions compromise children's preventative care across several measures. While data and statistical power constraints prevent us from measuring the downstream consequences of this lapsed care, past work suggests that these gaps in care may create substantial harm to patients.

First, foregoing childhood influenza vaccinations has been linked to increased health interventions and risks to children (Anderson et al., forthcoming). Over the long run, infant respiratory disease— which influenza vaccines could help prevent —has lasting negative effects on earnings, educational attainment and mental health (Daysal et al., 2021). These individual harms take on broader significance in the context of declining routine childhood vaccination rates (Williams and Kates, 2024) and rising risk of preventable diseases like measles (Kiang et al., 2025); children with missed vaccines both contribute to disease spread and face greater risk of illness.

Second, higher childhood lead levels predict lower academic achievement and increased juvenile delinquency (Aizer et al., 2018; Hollingsworth et al., 2025; Aizer and Currie, 2019). Lead testing

is the crucial first step to identifying at-risk children and mitigating these harms. In California, an elevated lead test triggers local programs to monitor lead abatement in children's homes. Nevertheless, nearly half of eligible children did not receive screenings (Howle, 2020). Our findings reveal that disruptions to pediatric primary care access may contribute to this problem.

Finally, prior research has linked pediatric care disruptions to gaps in chronic disease management (Piwnica-Worms et al., 2021). Cross-sectional studies have found that children with chronic conditions who lack continuous pediatric primary care may suffer preventable harms (Raphael et al., 2015). Thus, our measured reductions in pediatric care access may contribute to broader adverse health effects.

9 Conclusion

This paper studies the spillover effects of workers' parenthood to consumers in the healthcare setting. Using administrative insurance data from California and a triple difference research design, we find that a female PCP's childbirth has significant negative effects on child patients. Over the two years after a PCP's childbirth, children have fewer visits with their attributed PCP; fewer overall office visits; and reduced vaccinations and lead testing. These results suggest that parenthood not only generates asymmetric career costs across female and male workers, but also for their *clients*.

In contrast, we find muted effects on adult patients' care utilization, suggesting that children may be more vulnerable to changes in PCP access. As a mechanism for these effects, we show that children have persistently fewer visits with a pediatrician (who are more attentive to preventative care), and do not substitute to other providers at their PCP's practice. Hence, it appears that ongoing pediatric care shortages may exacerbate the costs of provider interruptions (Gold, 2024).

One potential explanation for the divergent patterns across children and adults is that a greater share of children's health care consumption is preventative care, where behavioral hazard may reduce demand for care (Baicker, Mullainathan and Schwartzstein, 2015). Consistent with this explanation, the children in our sample are healthier, use fewer prescription medications, and use more preventative care than adults. Furthermore, while we find steep declines in preventative care (e.g. vaccines and lead tests) and check-ups, we see no change in emergency department care or

prescription drug use. This suggests that policies that facilitate access to children's preventative care during a provider's absence may have significant health benefits.

Our findings open several promising avenues for future work. First, while we document substantial disruptive effects of a PCP's childbirth, it remains unclear whether firm or public policies can mitigate these effects. Subsequent research could evaluate policies that facilitate parents' return to work or target vulnerable children during care transitions, such as direct outreach to patients (Zhang, 2022). Second, to complement our estimates of immediate costs to patients, it would be useful to identify downstream health or developmental effects of foregone preventative care.

Finally, we speculate that the consumer costs we document may extend to occupations beyond primary care — particularly those where qualified substitutes are scarce or relational capital is an important input into production. This characterizes many care occupations, including health care, social work, and teaching, where women comprise a large share of the labor force. We leave these extensions for future study.

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10 Figures and Tables

Table 1: Descriptive Statistics of Patient Sample

	Kids	Adults
Share White	0.113	0.211
	(0.317)	(0.408)
Share Black	0.064	0.100
	(0.244)	(0.299)
Share Hispanic	0.644	0.405
	(0.479)	(0.491)
Share female	0.493	0.640
	(0.500)	(0.480)
Year of birth	2007.115	1969.475
	(5.440)	(17.34)
Age	7.372	45.212
	(5.230)	(17.31)
Share with Pediatrician as PCP	0.761	0.002
	(0.426)	(0.0479)
PCP E&M claims (quarterly)	0.430	0.554
	(0.493)	(0.712)
E&M claims (quarterly)	1.428	2.006
	(1.531)	(2.165)
Prescription claims (quarterly)	1.060	4.453
	(2.204)	(7.437)
Emergency claims (quarterly)	0.241	0.452
	(0.496)	(1.299)
Vaccination claims (quarterly)	0.375	0.098
	(1.018)	(0.276)
Physician familiarity (weeks)	18.035	15.672
	(28.89)	(26.26)
Share of quarters enrolled in Medi-Cal	0.817	0.809
	(0.268)	(0.266)
Patients	199,515	165,135

Notes: This table presents means and standard deviations (in parentheses) based on insurance claims to the Medicaid program in California (2012–2019). Column 1 provides statistics for our sample of child patients (under age 18) and Column 2 for adult patients (over age 18). These baseline statistics are calculated over the 12 months prior to the childbirth "event" in the analysis.

Table 2: Impact of Childbirth on Gender Gap in Physician Claims

	All Patients		Child Patients		Adult Patients	
	(1)	(2)	(3)	(4)	(5)	(6)
	Total E&M Claims	Any E&M Claims (Quarterly)	Total E&M Claims	Any E&M Claims (Quarterly)	Total E&M Claims	Any E&M Claims (Quarterly)
Quarter of Child Birth x Mom	-119.447***	-0.285***	-150.811***	-0.345***	-82.996***	-0.274***
	(19.993)	(0.032)	(39.098)	(0.054)	(17.742)	(0.038)
1-7 Quarters Post-Birth x Mom	-36.224	-0.021	-49.295	-0.073*	-21.096	-0.013
	(24.795)	(0.025)	(44.783)	(0.043)	(22.993)	(0.030)
Outcome Mean Pre-Birth	140.755	0.755	231.771	0.800	97.030	0.738
Observations	45,087	42,545	20,013	19,066	36,318	34,274
Doctors	2,994	2,994	1,358	1,358	2,391	2,391

Notes: This table shows estimates of the impact of becoming a mother from a triple difference model (Equation 2). We show results for total office claims (in the odd columns), and on having any office claims (in the even columns). The unit of observation is physician × quarter. We perform estimation separately for three samples: (i) the full sample of matched doctors, with no weights (columns 1-2); (ii) doctors that have child patients (columns 3-4), weighted by the share of each doctor's patients who are children; and doctors with adult patients, weighted by the share of each doctor's patients who are adults (columns 5-6). Standard errors, shown in parentheses, are clustered at the matched parent/non-parent pair level.

Table 3: Children's Care Utilization Declines After a Physician's Childbirth

	Office visits			Preventative care		Other medical care		Enrollment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attributed PCP claims	Total claims	Familiarity with doctor (weeks)	Vaccination claims	Lead test claims	Pharmacy claims	Emergency care claims	Enrolled this quarter
A. Children								
Quarter of Child Birth x Mom	-0.380***	-0.209***	-8.116***	-0.267***	-0.005	-0.061	-0.002	-0.010
	(0.063)	(0.080)	(2.356)	(0.096)	(0.005)	(0.058)	(0.016)	(0.015)
1-7 Quarters Post-Birth x Mom	-0.100**	-0.106*	-3.922	-0.213**	-0.013**	0.008	-0.018	-0.005
	(0.047)	(0.062)	(3.761)	(0.096)	(0.005)	(0.047)	(0.014)	(0.015)
Outcome Mean Pre-Birth	0.470	1.525	25.038	0.398	0.031	1.126	0.254	0.818
Observations	2,908,349	2,908,349	1,383,799	2,908,349	2,908,349	2,908,349	2,908,349	2,908,349
Doctors	1,359	1,359	1,359	1,359	1,359	1,359	1,359	1,359
B. Adults								
Quarter of Child Birth x Mom	-0.325***	0.026	-3.443*	-0.009	-	-0.160	0.022	0.005
	(0.092)	(0.122)	(1.817)	(0.020)	-	(0.211)	(0.039)	(0.014)
1-7 Quarters Post-Birth x Mom	0.073	0.093	2.108	0.004	-	-0.032	0.040	0.008
	(0.067)	(0.083)	(2.497)	(0.014)	-	(0.201)	(0.026)	(0.014)
Outcome Mean Pre-Birth	0.599	2.112	23.850	0.107	-	4.713	0.484	0.821
Observations	2,560,781	2,560,781	1,347,061	2,560,781	-	2,560,781	2,560,781	2,560,781
Doctors	2,394	2,394	2,394	2,394	-	2,394	2,394	2,394

Notes: This table presents estimates of the impact of having a physician who becomes a mother from a triple difference model (Equation 2). Panels A and B present coefficients when we analyze outcomes of child and adult patients, respectively. Each column presents effects on a different patient outcome, including: office claims to one's attributed PCP (column 1); total office claims (column 2); familiarity with one's provider at an appointment (column 3); the number of vaccination claims (column 4); the number of lead screening test claims (column 5); the number of pharmacy claims (column 6); the number of emergency claims (column 7); and the likelihood of being enrolled in Medi-Cal (column 8). We omit results on lead screening tests for adults because these are very rare, and thus a less meaningful outcome for this population (mean = 0.001). Standard errors, shown in parentheses, are clustered at the attributed physician level.

Table 4: Impacts of a PCP's Childbirth on Child Patients' Detailed Preventative Care

	(1) Vaccination claims	(2) Non-seasonal vaccines	(3) Flu vaccine	(4) Any vaccine
Quarter of Child Birth x Mom	-0.267***	-0.224***	-0.043**	-0.024*
	(0.096)	(0.082)	(0.021)	(0.013)
1-7 Quarters Post-Birth x Mom	-0.213**	-0.183**	-0.029*	-0.022**
	(0.096)	(0.081)	(0.016)	(0.011)
Outcome Mean Pre-Birth	0.398	0.321	0.077	0.114
Observations	2,908,349	2,908,349	2,908,349	2,908,349
Doctors	1,359	1,359	1,359	1,359

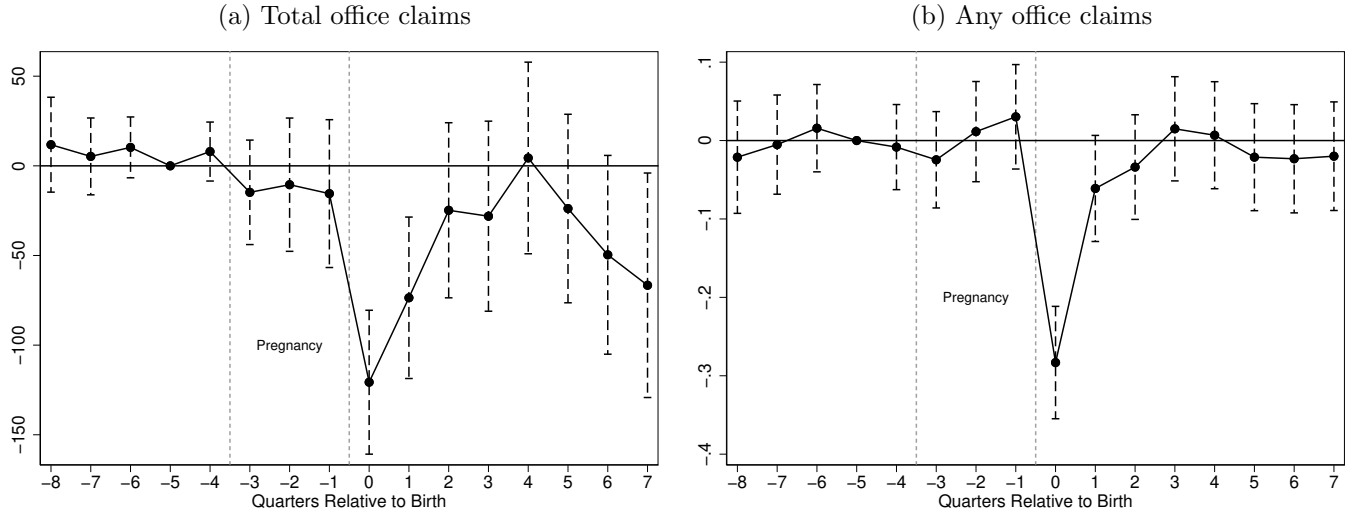
Notes: This table presents estimates of the impact of having a physician who becomes a mother from a triple difference model (Equation 2) for an analysis of child patients. Each column presents effects on a different patient outcome, including: total vaccination claims (column 1); non-seasonal vaccination claims (column 2); flu vaccination claims (column 3); and any vaccination claims (column 4). Standard errors are clustered at the attributed physician level.

Table 5: Children's Access to Pediatricians, Women Physicians, and Care at their PCP's Clinic after PCP Childbirth

	Office visits with...		Office visits at...
	(1)	(2)	(3)
	Pediatrician	Woman Doctor	PCP's Clinic
Quarter of Child Birth x Mom	-0.211***	-0.273***	-0.087
	(0.073)	(0.052)	(0.057)
1-7 Quarters Post-Birth x Mom	-0.098*	0.008	-0.098*
	(0.052)	(0.040)	(0.051)
Outcome Mean Pre-Birth	0.665	0.508	0.716
Observations	2,908,349	2,908,349	2,908,349
Doctors	1,359	1,359	1,359

Notes: This table presents estimates of the impact of having a physician who becomes a mother from a triple difference model (Equation 2) for an analysis of child patients. Column 1 presents effects on the number of E&M claims with a pediatrician, column 2 presents effects on the number of E&M claims with a female physician, and column 3 presents effects on the number of E&M claims at the PCP's primary clinic. Standard errors (in parentheses) are clustered at the attributed physician level.

Figure 1: Impact of Childbirth on Gender Gap in Physician Claims

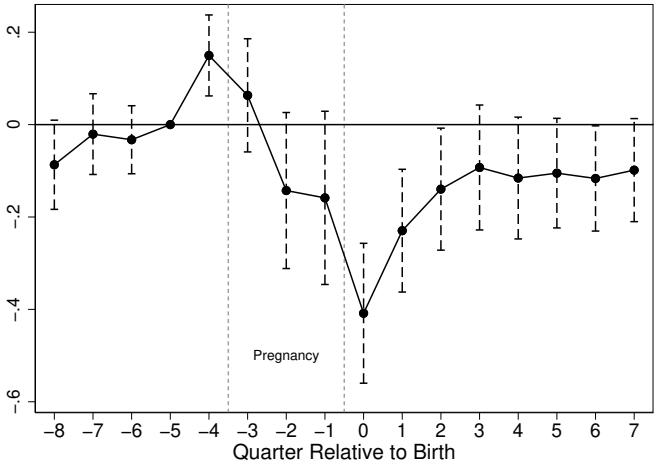


Notes: This figure reports the triple difference event study coefficients $\hat{\gamma}_j$ from Equation 1 in an analysis of physicians' work volume. The event studies in Panels A and B show impacts of becoming a mother on total office claims and on having any office claims, respectively, in each quarter relative to birth. The birth event occurs in the first month of event quarter 0. The coefficient 5 quarters prior to the physician becoming a mother is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the matched parent/non-parent pair level.

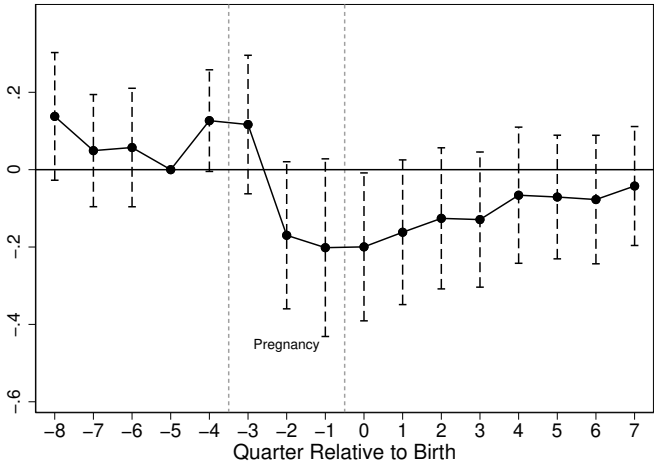
Figure 2: Children's Health Care Utilization Around a Physician's Childbirth

(a) Office claims

(i) PCP visits

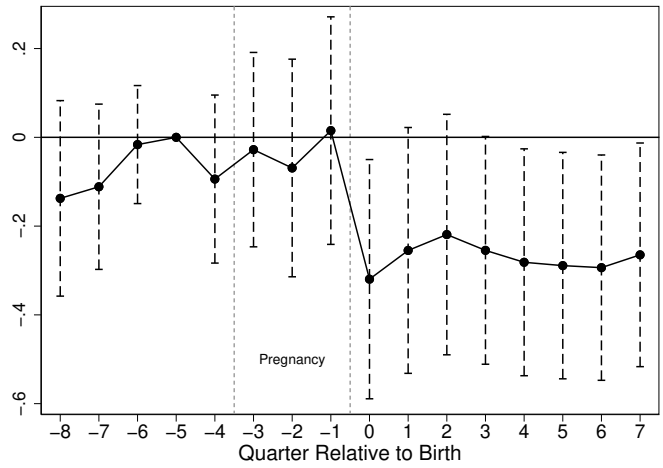


(ii) All visits

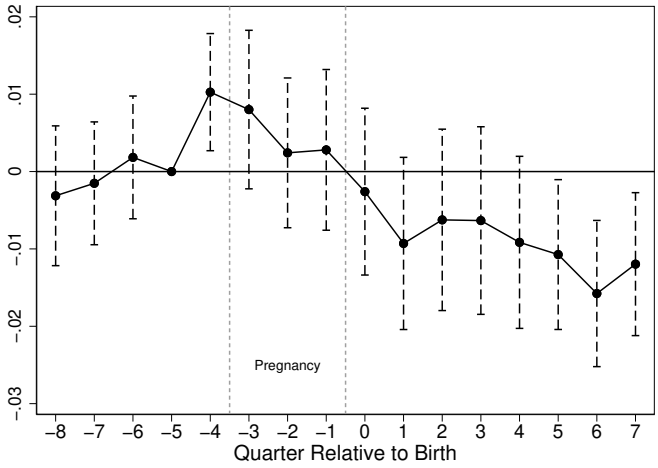


(b) Preventative care claims

(i) Vaccinations



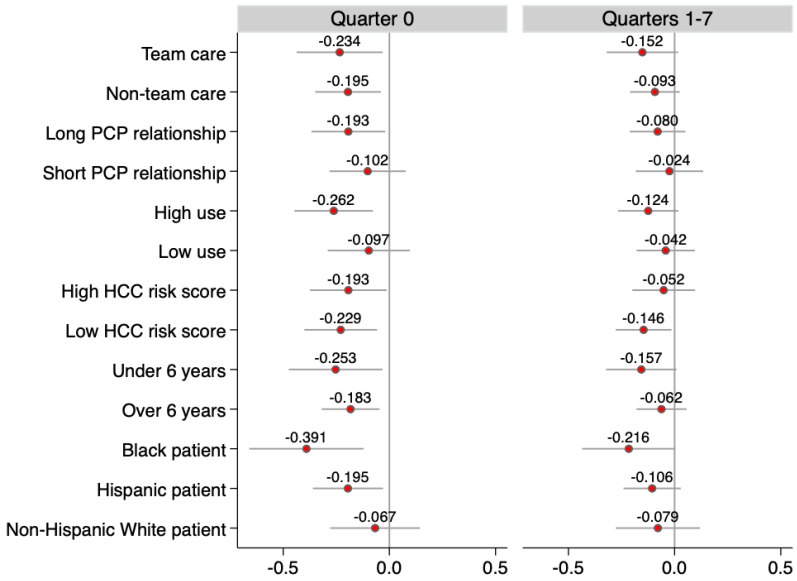
(ii) Lead screening tests



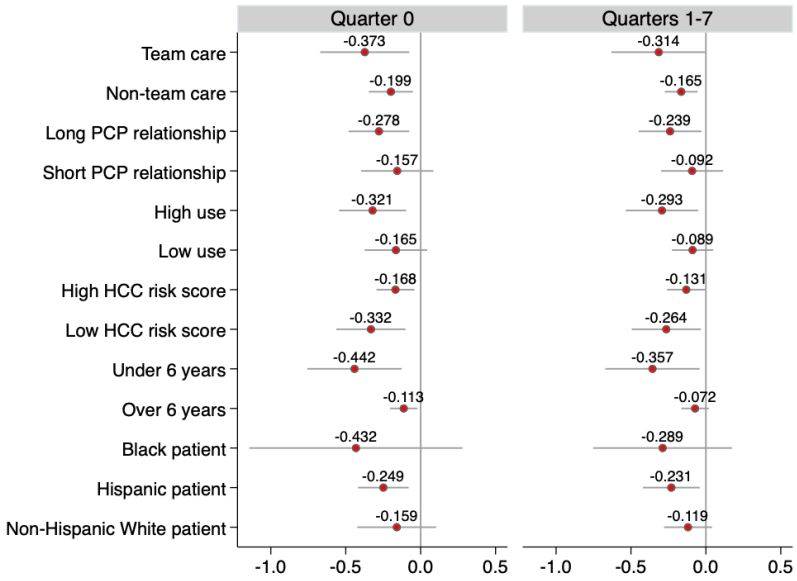
Notes: This figure reports the triple difference event study coefficients $\hat{\gamma}_j$ from Equation 1 in an analysis of child patients. Each panel of the figure shows the effects for a different dependent variable: the number of office claims with one's usual PCP (panel a, subfigure i); total office claims (panel a, subfigure ii); the total number of vaccination claims (panel b, subfigure i); and the total number of lead screening test claims (panel b, subfigure ii). The coefficient 5 quarters prior to the patient's physician becoming a mother is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the attributed physician level.

Figure 3: Heterogeneity in Children's Health Care Utilization Around Physician Childbirth

(a) Total office claims



(b) Vaccination claims



Notes: This figure presents estimates of the impact of having a physician who becomes a mother from a triple difference model (Equation 2) for an analysis of child patients. The dependent variable is the patient's quarterly total office visit claims in Panel (a), and the patient's quarterly total vaccination claims in Panel (b). Rows 1-2 divide the sample according whether the PCP practice uses a team-based care model, defined as whether the patient receives care from other providers at their PCP's primary clinic. Rows 3-4 divide patients by whether they had a longer or shorter than median relationship history with the PCP, at the time of the PCP's birth. Rows 5-6 divide patients based on whether they had above or below median number of office visits 9-24 months before the birth. Rows 7-8 split the sample by whether the patient has an above or below median Hierarchical Condition Category (HCC) score prior to the PCP birth; the HCC score is a risk adjustment metric using past diagnosis codes to predict future health care spending. Rows 9-13 split the sample by patient race, ethnicity, and age. Standard errors are clustered at the attributed physician level.

ONLINE APPENDIX:

Social Costs of Work Disruptions: Evidence from Physicians and their Patients

Leila Agha, Myles Wagner, Na'ama Shenhav

July 16, 2025

A1 Medi-Cal Data Construction

This section describes how we identify NPIs for parents in the Vital Statistics records, select candidates for the matched comparison group, and link these physicians to Medi-Cal records.

Identifying Parent NPIs in the Birth Records We identify NPIs for physician parents in the birth records through a name-based link to the NPPES and CMS physician directories described in Section 2. We use fuzzy name matching, and prioritize matches of physicians who practice in California. For mothers, we attempt matches using both married and maiden names when they differ. We drop duplicate matches that arise when multiple doctors in California share the same first and last names.

Selecting Candidates for Matched Comparison: Non-Parent Physicians We generate candidates for our matched comparison group based on two criteria: (i) being a physician in the NPPES who reports practicing in California during our sample period and (ii) not matching to our parent list. This excludes any physician whose name matches that of a physician parent, even if that match is ultimately discarded as non-unique.

Linking to Medi-Cal Claims Having arrived at this list of parent and non-parent NPIs, we limited this list to physicians who specialize in primary care: family practice, pediatrics, internal medicine, and obstetrics/gynecology.[12] We sent this list to DHCS, who linked these physicians to the Medi-Cal claims database. We then received a data set containing all claims for patients treated by any listed physician at any point during our 8-year sample period.

A2 Defining Claim-Level Variables

This section describes our methods for constructing claim-level variables from the Medi-Cal data.

Identifying Claim Type from Procedure Codes We use the 5-digit procedure code on each claim to determine the type of care provided. In particular, we identify outpatient evaluation and management (E&M), vaccine administration, and lead testing claims using standard CPT/HCPCS code definitions. Many claims in the Medi-Cal data use non-standard procedure codes, including codes specific to specialized providers in California, like Federally Qualified Health Centers (FQHCs). For these claims, we follow a codebook provided by DHCS to identify E&M, vaccine and lead testing claims. The accompanying replication packet provides a full list of relevant procedure codes and details the data construction process.

Defining Site of Care We approximate the location (e.g., practice site or clinic) where care was delivered by the combination of the Billing NPI and 5-digit ZIP code listed on each claim. Since a given physician can practice in multiple locations, we define a patient's primary practice site *with their PCP* as the most commonly visited location when seeing their PCP over the previous 12 months.

[12] We focus on these specialties because they are common among physicians of both genders, and because Medicaid patients make up a substantial proportion of the market for their services in California.

A3 Matching Procedure

This section describes the matching procedure used to construct control groups for the physician and patient analyses.

Matching Physicians For each parent physician, we select a matched, non-parent physician using the following criteria: (i) same gender, specialty, and medical school graduation cohort; (ii) practicing in the same month; (iii) coarse match on the number of patients attributed ten months before the focal parent's childbirth. In particular, doctors are matched based on their decile of attributed patient counts and a dummy for being in the top 5% of attributed patients to capture especially high-volume doctors. When there are multiple possible matches, we choose the one with the closest number of attributed patients.

We match without replacement, so each parent and non-parent can only be matched once (at most). A small number of parents remain unmatched due to the graduation year requirement. For these cases, we perform a second round of matching in which we instead match coarsely on graduation year, minimizing the difference between graduation years.

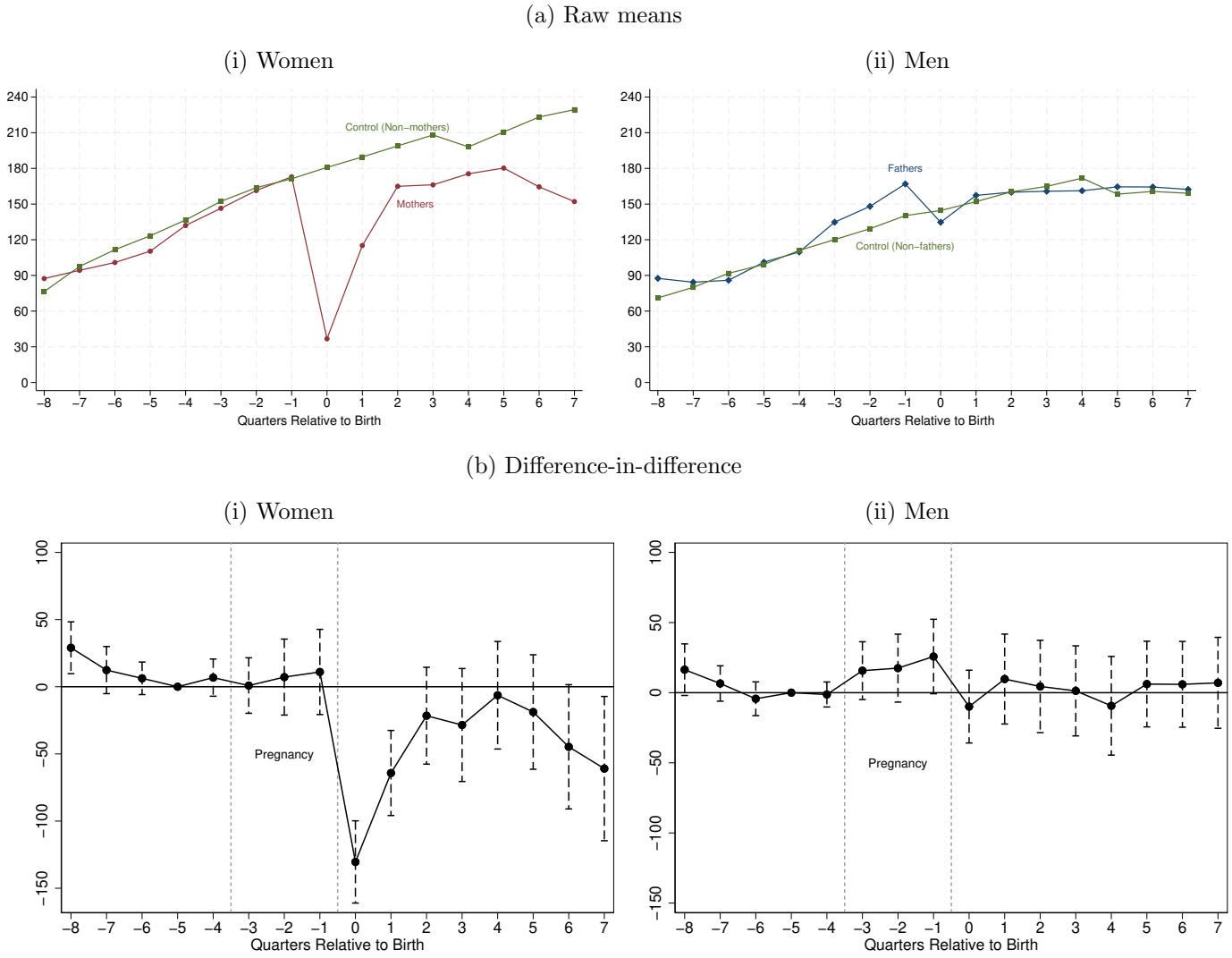
To address potential concerns about patient mis-attribution to organizations billing under a single NPI, we exclude matched pairs where either physician has over 3,000 attributed patients in their panel.[13]

Constructing Patient Panel We keep all claims for patients who are attributed either to a parent or matched non-parent from our matched sample. Because of differences in timing across different parent/non-parent matched pairs, a small number of patients appear in multiple physician panels over time. When this occurs, we keep only their earliest chronological patient appearance.

[13] This condition seldom binds; it removes six pairs (12 physicians) from the sample.

A4 Appendix Tables and Figures

Figure A1: Total Office Claims Around Childbirth: Raw Means and Difference-in-Differences

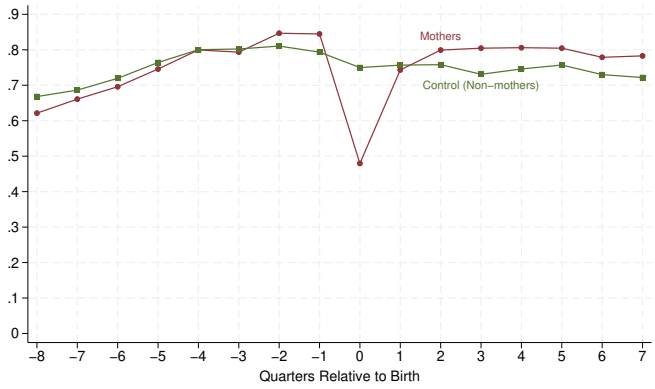


Notes: The figure shows raw means and difference-in-differences event study coefficients for physicians' total office claims per quarter. Panel (a) shows quarterly means for (i) women and (ii) men, where mothers' means are indicated with red circles, fathers' means are indicated with blue diamonds, and matched non-parent means are shown with green squares for both men and women. Panel (b) shows difference-in-differences event study coefficients measuring the effect of parenthood for (i) mothers and (ii) fathers. The coefficient 5 quarters prior to the physician becoming a parent is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the matched parent/non-parent pair level.

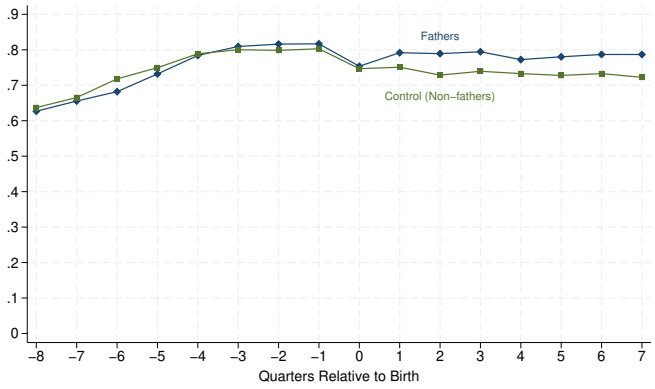
Figure A2: Any Office Claims Around Childbirth: Raw Means and Difference-in-Difference

(a) Raw means

(i) Women

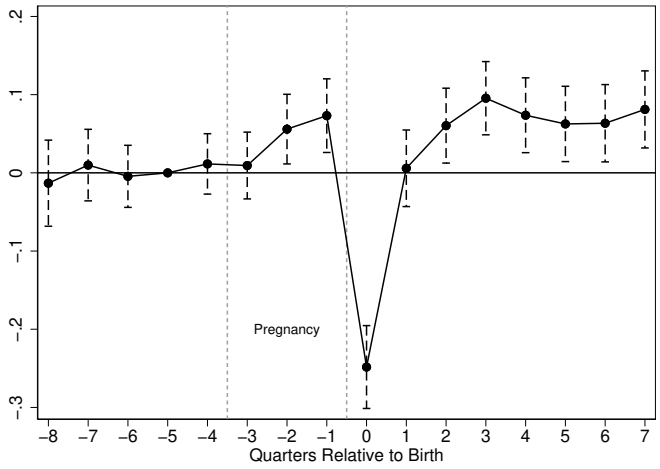


(ii) Men

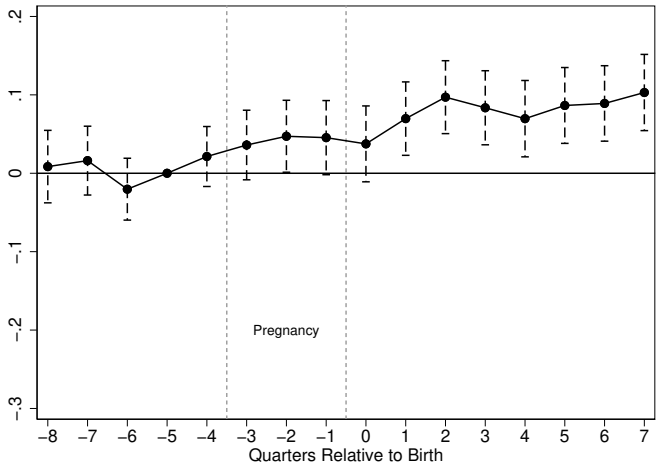


(b) Difference-in-difference

(i) Women



(ii) Men



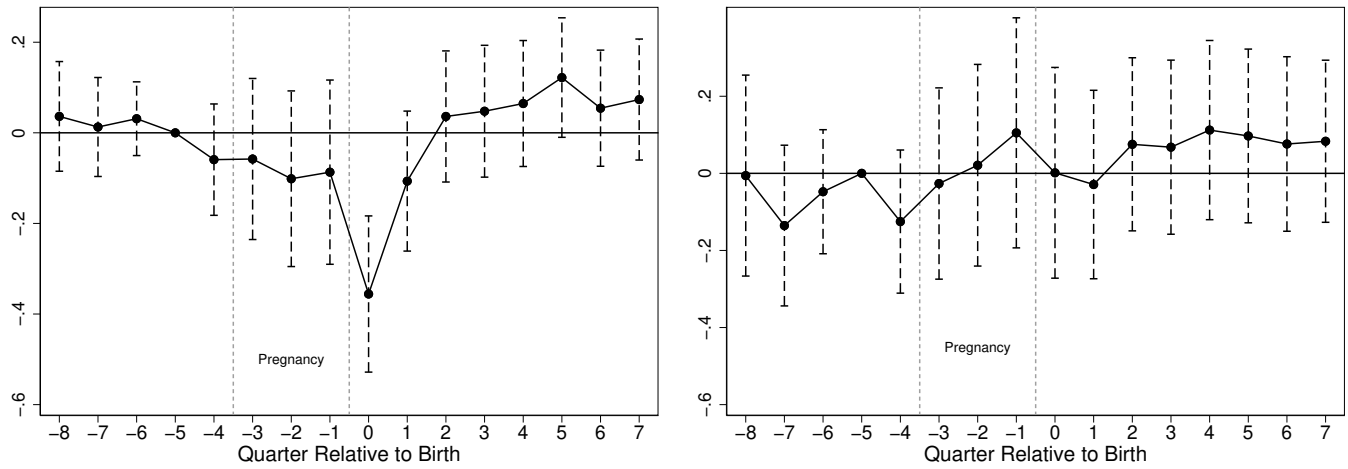
Notes: The figure shows raw means and difference-in-differences event study coefficients for whether the physician had any office claims per quarter. Panel (a) shows quarterly means for (i) women and (ii) men, where mothers' means are indicated with red circles, fathers' means are indicated with blue diamonds, and matched non-parent means are shown with green squares for both men and women. Panel (b) shows difference-in-differences event study coefficients measuring the effect of parenthood for (i) mothers and (ii) fathers. The coefficient 5 quarters prior to the physician becoming a parent is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the matched parent/non-parent pair level.

Figure A3: Adults' Health Care Utilization Around a Physician's Childbirth

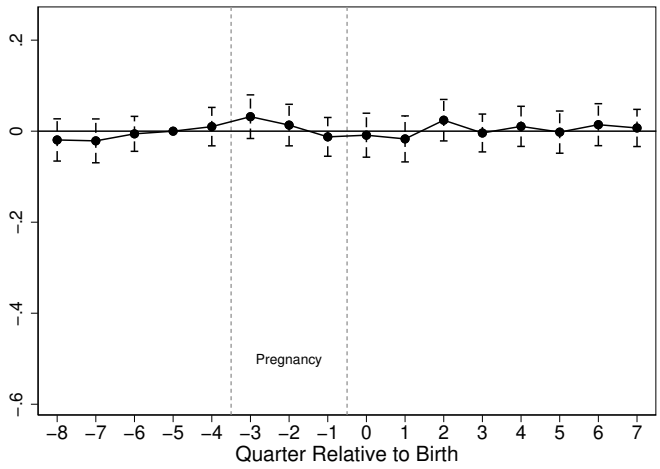
(a) Office visits

(i) PCP claims

(ii) All claims

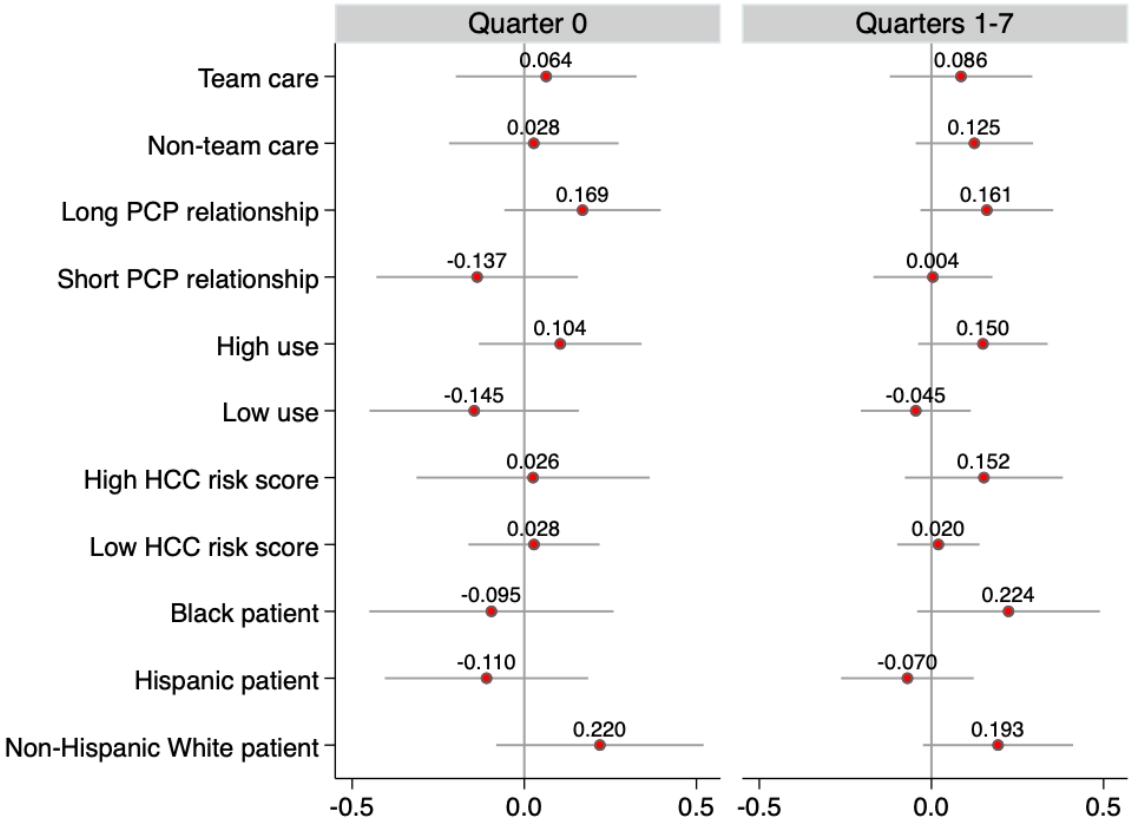


(b) Vaccination claims



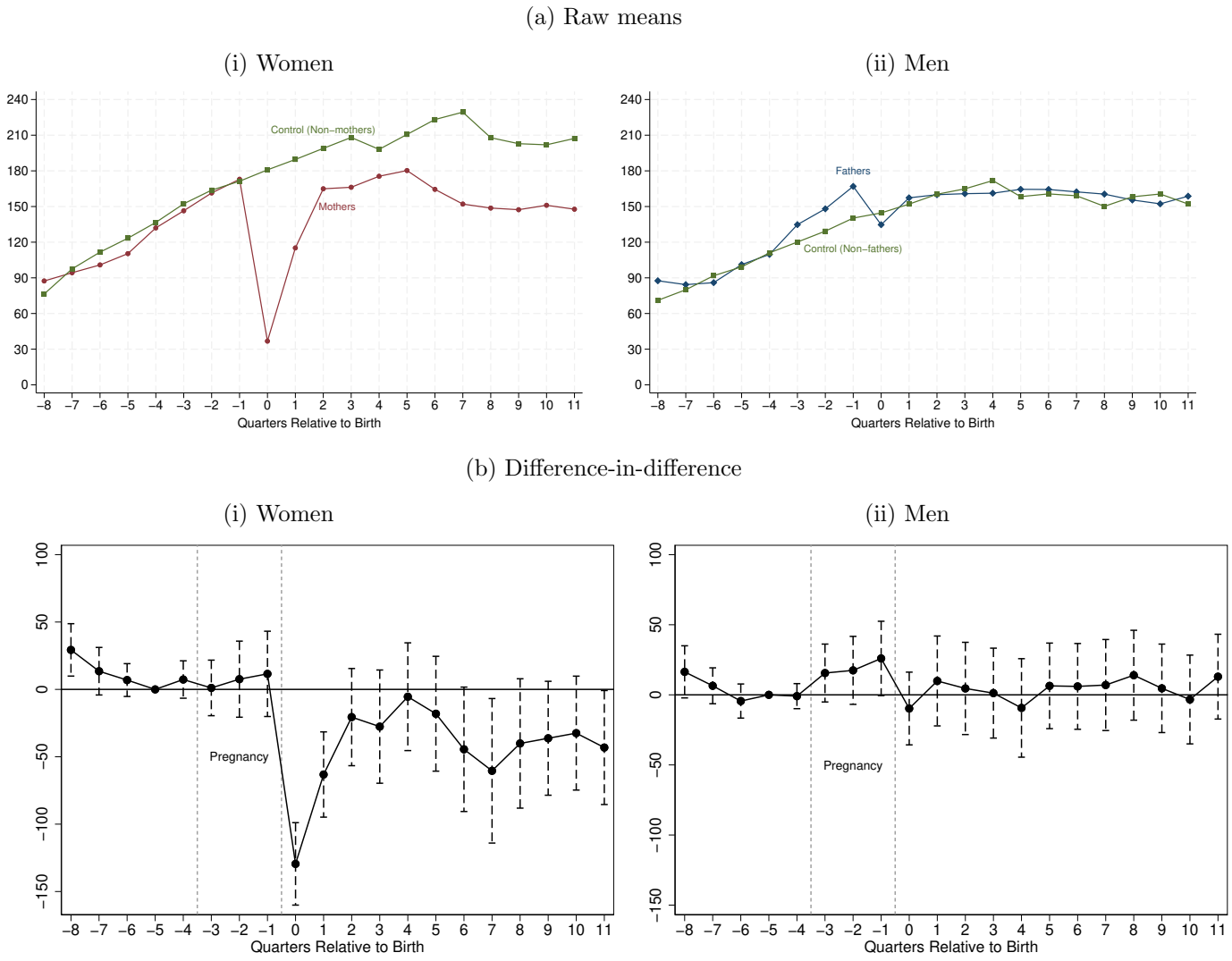
Notes: This figure reports the triple-difference event study coefficients $\hat{\gamma}_j$ from Equation 1 in an analysis of adult patients. Each panel of the figure shows the effects for a different dependent variable: the number of office claims with one's usual PCP (panel a, subfigure i); total office claims (panel a, subfigure ii); and the total number of vaccination claims (panel b). The coefficient 5 quarters prior to the patient's physician becoming a mother is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the attributed physician level.

Figure A4: Heterogeneity in Impacts on Adult's Office Claims Around Physician Childbirth



Notes: This figure presents estimates of the impact of having a physician who becomes a mother from a triple difference model (Equation 2) for an analysis of adult patients. The dependent variable is the patient's quarterly total office visit claims. Rows 1-2 divide the sample according whether the PCP practice uses a team-based care model, defined as whether the patient receives care from other providers at their PCP's primary clinic. Rows 3-4 divide patients by whether they had a longer or shorter than median relationship history with the PCP, prior to the birth. Rows 5-6 divide patients based on whether they had above or below median number of office visits 9-24 months before the birth. Rows 7-8 split the sample by whether the patient has an above or below median Hierarchical Condition Category (HCC) score prior to the PCP birth; the HCC score is a risk adjustment metric using past diagnosis codes to predict future health care spending. Rows 9-11 split the sample by patient race and ethnicity. Standard errors are clustered at the attributed physician level.

Figure A5: Total Office Claims Around Childbirth: Extended Post-Period

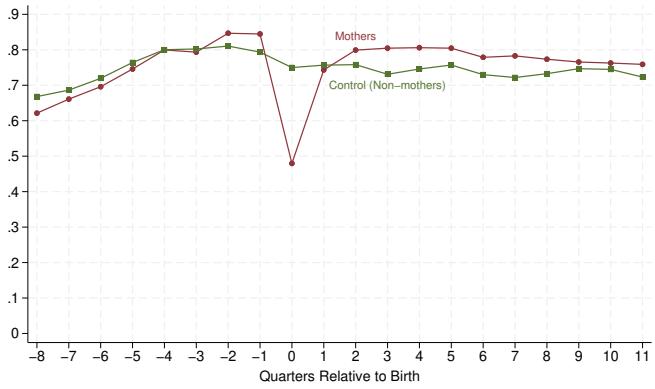


Notes: The figure shows raw means and difference-in-differences event study coefficients for physicians' total office claims per quarter. Panel (a) shows quarterly means for (i) women and (ii) men, where mothers' means are indicated with red circles, fathers' means are indicated with blue diamonds, and matched non-parent means are shown with green squares for both men and women. Panel (b) shows difference-in-differences event study coefficients measuring the effect of parenthood for (i) mothers and (ii) fathers. The coefficient 5 quarters prior to the physician becoming a parent is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the matched parent/non-parent pair level.

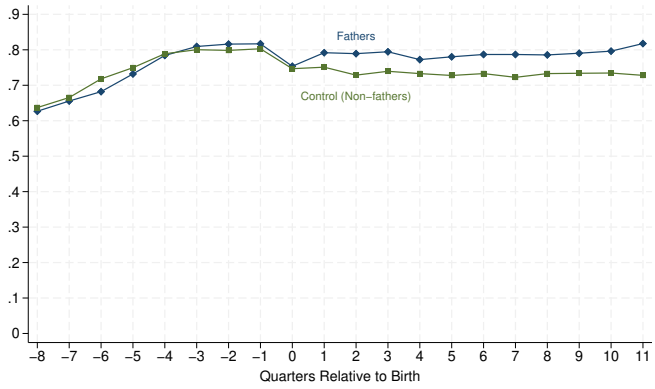
Figure A6: Any Office Claims Around Childbirth: Extended Post-Period

(a) Raw means

(i) Women

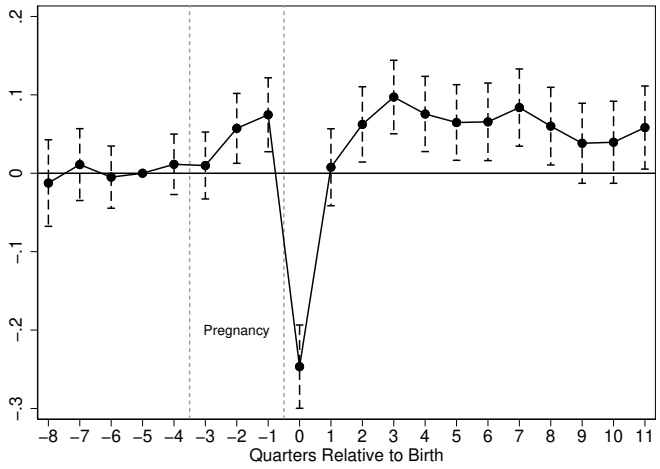


(ii) Men

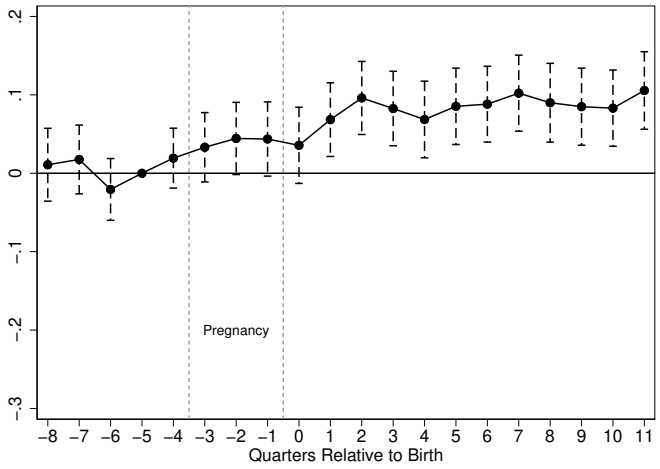


(b) Difference-in-difference

(i) Women



(ii) Men



Notes: The figure shows raw means and difference-in-differences event study coefficients for whether the physician had any office claims per quarter. Panel (a) shows quarterly means for (i) women and (ii) men, where mothers' means are indicated with red circles, fathers' means are indicated with blue diamonds, and matched non-parent means are shown with green squares for both men and women. Panel (b) shows difference-in-differences event study coefficients measuring the effect of parenthood for (i) mothers and (ii) fathers. The coefficient 5 quarters prior to the physician becoming a parent is normalized to zero. The dashed vertical lines around each dot are estimates of the 90 percent confidence interval. Standard errors are clustered at the matched parent/non-parent pair level.

Table A1: Descriptive Statistics: Matched Physician Sample

	Women			Men		
	(1)	(2)	(3)	(4)	(5)	(6)
	Moms	Matched Women	All Sampled Docs w/o Childbirth	Dads	Matched Men	All Sampled Docs w/o Childbirth
Specialty: Primary Care	0.680	0.680	0.591	0.857	0.857	0.783
	(0.467)	(0.467)	(0.492)	(0.351)	(0.351)	(0.412)
Specialty: Pediatrician	0.320	0.320	0.253	0.143	0.143	0.150
	(0.467)	(0.467)	(0.434)	(0.351)	(0.351)	(0.357)
Med. School Grad. Year	2007	2006	2003	2005	2004	1998
	(4.2)	(4.4)	(6.4)	(5.9)	(6.2)	(9.2)
Avg. E&M Claims (Qtrly)	111.418	103.539	68.129	86.070	84.622	66.164
	(294.8)	(244.5)	(278.3)	(252.1)	(221.8)	(285.7)
Share of Months w/ Medicaid Claims	0.673	0.675	0.606	0.713	0.708	0.647
	(0.305)	(0.309)	(0.345)	(0.311)	(0.315)	(0.350)
Start of Medicaid Claims History	2012	2013	2013	2012	2012	2013
	(1.5)	(1.6)	(2.2)	(1.5)	(1.6)	(2.2)
Physicians	737	737	9,081	760	760	11,823

Notes: This table presents means and standard deviations (in parentheses) for our analysis sample of matched parent and non-parent physicians, in addition to the full sample of physicians without a childbirth. Columns 1–3 show summary statistics for female physicians, while columns 4–6 show summary statistics for male physicians. Specialty and graduation year are fixed physician characteristics. The measures of claims volume shown are calculated over the first 24 months of each physician's Medicaid claims panel, starting from their first observed claim.

Table A2: Impacts of Childbirth on Parent's Work Volume (Difference-in-Differences)

	All Patients		Child Patients		Adult Patients	
	Total E&M Claims	Any E&M Claims (Quarterly)	Total E&M Claims	Any E&M Claims (Quarterly)	Total E&M Claims	Any E&M Claims (Quarterly)
A. Female Physicians						
Quarter of Child Birth	-139.237***	-0.271***	-216.154***	-0.306***	-90.135***	-0.259***
	(15.203)	(0.024)	(23.450)	(0.039)	(14.369)	(0.030)
1-7 Quarters Post-Birth	-43.827**	0.041**	-72.723***	0.014	-22.351	0.048**
	(19.537)	(0.018)	(26.565)	(0.028)	(19.203)	(0.023)
Outcome Mean Pre-Birth	150.542	0.754	206.558	0.788	108.191	0.737
Observations	22,088	20,779	12,009	11,413	16,073	15,107
Doctors	1,474	1,474	818	818	1,055	1,055
B. Male Physicians						
Quarter of Child Birth	-19.655	0.015	-58.538*	0.038	-8.383	0.015
	(13.007)	(0.020)	(31.274)	(0.037)	(10.434)	(0.023)
1-7 Quarters Post-Birth	-6.122	0.063***	-14.087	0.088***	-1.721	0.060***
	(15.242)	(0.017)	(36.049)	(0.032)	(12.607)	(0.019)
Outcome Mean Pre-Birth	131.356	0.756	275.625	0.821	88.723	0.739
Observations	22,999	21,766	8,004	7,653	20,245	19,167
Doctors	1,520	1,520	540	540	1,336	1,336

Notes: This table shows estimates of the impact of becoming a parent from a difference-in-differences model restricted to either female (Panel A) or male (Panel B) physicians. We show results for total office claims (in the odd columns), and on having any office claims (in the even columns). We perform estimation separately for three samples: (i) the full sample of matched doctors, with no weights (columns 1-2); (ii) doctors that have child patients (columns 3-4), weighted by the share of each doctor's patients who are children; and doctors with adult patients, weighted by the share of each doctor's patients who are adults (columns 5-6). Standard errors, shown in parentheses, are clustered at the matched parent/non-parent pair level.

Table A3: Descriptive Statistics on Child Patient Sample, by PCP Parent Status

	Women:		Men:	
	Parent	Placebo	Parent	Placebo
Share white	0.107	0.115	0.121	0.114
	(0.309)	(0.319)	(0.326)	(0.318)
Share Black	0.072	0.066	0.063	0.049
	(0.259)	(0.248)	(0.242)	(0.216)
Share Hispanic	0.642	0.638	0.630	0.668
	(0.479)	(0.481)	(0.483)	(0.471)
Share female	0.515	0.508	0.464	0.468
	(0.500)	(0.500)	(0.499)	(0.499)
Year of birth	2,007.103	2,006.997	2,007.252	2,007.165
	(5.398)	(5.390)	(5.488)	(5.522)
Age	7.242	7.310	7.708	7.332
	(5.244)	(5.204)	(5.223)	(5.239)
Patients	60,787	57,765	39,053	41,910

Notes: This table presents summary statistics of our analysis sample of child patients. Each column shows statistics for a different subsample: we show statistics for patients of physicians who become mothers in column 1; for patients of women physicians in the matched non-parent sample in column 2; for patients of physicians become who fathers in column 3; for patients of men physicians in the matched non-parent sample in column 4.

Table A4: Descriptive Statistics on Adult Patient Sample, by PCP Parent Status

	Women:		Men:	
	Parent	Placebo	Parent	Placebo
Share white	0.192	0.190	0.214	0.249
	(0.394)	(0.392)	(0.410)	(0.432)
Share Black	0.100	0.103	0.104	0.090
	(0.300)	(0.304)	(0.306)	(0.286)
Share Hispanic	0.391	0.432	0.415	0.383
	(0.488)	(0.495)	(0.493)	(0.486)
Share female	0.678	0.689	0.605	0.589
	(0.467)	(0.463)	(0.489)	(0.492)
Year of birth	1,970.654	1,971.276	1,968.549	1,967.473
	(16.72)	(16.75)	(17.87)	(17.69)
Age	44.181	43.562	46.097	46.950
	(16.76)	(16.71)	(17.80)	(17.71)
Patients	43,792	38,027	43,297	40,019

Notes: This table presents summary statistics of our analysis sample of adult patients. Each column shows statistics for a different subsample: we show statistics for patients of physicians who become mothers in column 1; for patients of women physicians in the matched non-parent sample in column 2; for patients of physicians who become fathers in column 3; for patients of men physicians in the matched non-parent sample in column 4.

Table A5: Evidence from License Surveys: Short- and Medium-Run Effects on Physician Work

	All Patients		Child Patients		Adult Patients	
	(1) Patient Hours (Imputed)	(2) Any Survey	(3) Patient Hours (Imputed)	(4) Any Survey	(5) Patient Hours (Imputed)	(6) Any Survey
Year of Child Birth x Mom	-1.241	0.027	-5.013***	0.083	0.136	0.030
	(0.943)	(0.049)	(1.889)	(0.090)	(1.111)	(0.058)
1 Year Post-Birth x Mom	0.655	0.020	1.300	-0.034	0.614	0.018
	(0.904)	(0.044)	(1.772)	(0.083)	(1.131)	(0.052)
Outcome Mean Pre-Birth	35.048	0.544	34.362	0.544	35.330	0.544
Observations	4,310	8,213	1,855	3,585	3,447	6,554
Doctors	2,074	2,074	907	907	1,655	1,655

Notes: This table shows estimates of the impact of becoming a mother from a triple difference model (Equation 2). We show results for weekly hours of patient care among survey respondents (in the odd columns), and a binary indicator for participation in the hours survey (in the even columns). Because the survey collects usual weekly hours only within 10-hour bins, we impute hours at the mid-point of the selected bin. Doctors reporting 40 or more hours of work (the highest bin) are imputed to 40 hours exactly. We perform estimation separately for three samples: (i) the full sample of matched doctors, with no weights (columns 1-2); (ii) doctors that have child patients (columns 3-4), weighted by the share of each doctor's patients who are children; and doctors with adult patients, weighted by the share of each doctor's patients who are adults (columns 5-6). Standard errors, shown in parentheses, are clustered at the matched parent/non-parent pair level.

Table A6: Evidence from License Surveys: Short- and Medium-Run Effects on Physician Work

	All Patients					Child Patients					Adult Patients				
	(1) Patient Hours (≥ 40)	(2) Patient Hours (≥ 30)	(3) Patient Hours (≥ 20)	(4) Patient Hours (≥ 10)	(5) Patient Hours (>0)	(6) Patient Hours (≥ 40)	(7) Patient Hours (≥ 30)	(8) Patient Hours (≥ 20)	(9) Patient Hours (≥ 10)	(10) Patient Hours (>0)	(11) Patient Hours (≥ 40)	(12) Patient Hours (≥ 30)	(13) Patient Hours (≥ 20)	(14) Patient Hours (≥ 10)	(15) Patient Hours (>0)
Year of Child Birth x Mom	-0.019	-0.052	-0.038	-0.013	-0.021*	-0.265**	-0.176*	-0.070	-0.106**	-0.033	0.030	-0.003	-0.021	0.030	-0.013
	(0.060)	(0.046)	(0.030)	(0.021)	(0.012)	(0.113)	(0.091)	(0.058)	(0.042)	(0.022)	(0.072)	(0.055)	(0.035)	(0.026)	(0.012)
1 Year Post-Birth x Mom	-0.020	0.057	0.021	0.001	-0.006	-0.064	0.114	0.060	-0.002	-0.021	-0.016	0.052	0.017	0.001	0.001
	(0.052)	(0.047)	(0.031)	(0.020)	(0.011)	(0.095)	(0.094)	(0.060)	(0.032)	(0.021)	(0.062)	(0.057)	(0.040)	(0.025)	(0.013)
Outcome Mean Pre-Birth	0.575	0.819	0.929	0.972	0.995	0.496	0.783	0.934	0.975	0.993	0.608	0.835	0.925	0.971	0.996
Observations	4,310	4,310	4,310	4,310	4,310	1,855	1,855	1,855	1,855	1,855	3,447	3,447	3,447	3,447	3,447
Doctors	2,074	2,074	2,074	2,074	2,074	907	907	907	907	907	1,655	1,655	1,655	1,655	1,655

Notes: This table shows estimates of the impact of becoming a mother from a triple difference model (Equation 2). Dependent variables are indicators for potential responses to the license survey, in which doctors indicate their weekly working hours from among five bins. We perform estimation separately for three samples: (i) the full sample of matched doctors, with no weights (columns 1-5); (ii) doctors that have child patients (columns 6-10), weighted by the share of each doctor's patients who are children; and doctors with adult patients, weighted by the share of each doctor's patients who are adults (columns 11-15). Standard errors, shown in parentheses, are clustered at the matched parent/non-parent pair level.

Table A7: Children Are More Likely to Get a Vaccination or Lead Screening After a Pediatrician Visit

	Billed by same doctor as office visit		Billed by any provider on day of visit			
	(1) Any vaccine	(2) Any lead test	(3) Any vaccine	(4) Num. vaccines	(5) Any lead test	(6) Num. lead tests
Pediatrician	0.105***	0.007***	0.099***	0.194***	0.011***	0.013***
	(0.006)	(0.001)	(0.006)	(0.014)	(0.002)	(0.002)
Outcome Mean	0.261	0.017	0.290	0.724	0.037	0.045
Observations	3,856,306	3,856,306	3,856,306	3,856,306	3,856,306	3,856,306

Notes: This table shows the relationship between a child's vaccination or lead screening test claims (shown in the column header) and the specialty of her provider. The sample consists of claims from 2019 for child patients who have an E&M claim with a physician in a primary care specialty. The data are collapsed to the patient-by-provider-by-day level. We include fixed effects for child age in years and month of visit. Standard errors are clustered at the physician level.

Table A8: Impacts on Children, Separately by Female and Male Physicians (Difference-in-differences)

	Female Physicians				Male Physicians			
	(1) Attributed PCP office claims	(2) Total office claims	(3) Vaccination claims	(4) Lead test claims	(5) Attributed PCP office claims	(6) Total office claims	(7) Vaccination claims	(8) Lead test claims
Quarter of Child Birth	-0.506***	-0.327***	-0.127**	-0.002	-0.128***	-0.116**	0.125*	0.003
	(0.056)	(0.070)	(0.057)	(0.003)	(0.044)	(0.056)	(0.065)	(0.004)
1-7 Quarters Post-Birth	-0.083***	-0.110***	-0.097**	-0.007**	0.011	-0.011	0.092	0.005
	(0.025)	(0.041)	(0.046)	(0.003)	(0.038)	(0.044)	(0.063)	(0.004)
Outcome Mean Pre-Birth	0.470	1.596	0.418	0.031	0.469	1.419	0.369	0.032
Observations	1,755,210	1,755,210	1,755,210	1,755,210	1,153,139	1,153,139	1,153,139	1,153,139
Doctors	853	853	853	853	506	506	506	506

Notes: This table presents difference-in-difference impacts of having a physician who becomes a parent. Specifically, we estimate:

$$y_{igpt} = \alpha_i + \beta_1 \text{Parent}_i \times \text{Quarter } 0 + \beta_2 \text{Parent}_i \times \text{Quarters 1-7} + Z_{pgt}\lambda + \epsilon_{igpt}.$$

where Z_{pgt} includes interactions between indicators for event time and the year and quarter of childbirth. We present effects for patients of female physicians in columns 1–4, and for patients of male physicians in columns 5–8. Standard errors are clustered at the attributed physician level.

Table A9: Impacts on Children, Using Borusyak, Jaravel, and Spiess Imputation Estimator

	Office visits			Vaccinations		Other medical care		Enrollment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attributed PCP claims	Total claims	Familiarity with doctor (weeks)	All vaccination claims	Lead test claims	Pharmacy claims	Emergency care claims	Enrolled this quarter
A. Children								
Quarter of Child Birth x Mom	-0.397***	-0.240**	-7.337***	-0.273***	-0.005	-0.039	0.006	0.004
	(0.079)	(0.101)	(2.560)	(0.092)	(0.005)	(0.060)	(0.016)	(0.018)
1-7 Quarters Post-Birth x Mom	-0.100**	-0.116*	-5.384	-0.206**	-0.012**	0.023	-0.017	0.003
	(0.048)	(0.066)	(3.791)	(0.086)	(0.005)	(0.054)	(0.014)	(0.017)
Outcome Mean Pre-Birth	0.470	1.525	25.068	0.398	0.031	1.126	0.254	0.818
Observations	2,908,349	2,908,349	1,390,616	2,908,349	2,908,349	2,908,349	2,908,349	2,908,349
Doctors	1,359	1,359	1,359	1,359	1,359	1,359	1,359	1,359

Notes: This table presents estimates of the impact of having a physician who becomes a mother from a modified version of our triple difference model (Equation 2). Specifically, we apply the imputation-based approach developed by Borusyak, Jaravel and Spiess (2024), which is robust to treatment effect heterogeneity. Similar to our baseline model, we include two-way fixed effects for gender-by-event-time and parent-by-event-time, and allow each of these coefficients to vary with the calendar quarter and year of childbirth. We also control for gender-by-event time and parent-by-event-time interacted with the length of a patient's relationship with a physician (at baseline). Standard errors are clustered at the physician level.

Table A10: Impacts on Children and Adults, Using Quarters Before Pregnancy as Pre-Period

	Office visits			Preventative care		Other medical care		Enrollment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Attributed PCP claims	Total claims	Familiarity with doctor (weeks)	Vaccination claims	Lead test claims	Pharmacy claims	Emergency care claims	Enrolled this quarter
A. Children								
Quarter of Child Birth x Mom	-0.414***	-0.273***	-6.871**	-0.249**	-0.004	-0.130*	-0.004	-0.017
	(0.082)	(0.105)	(3.360)	(0.116)	(0.007)	(0.073)	(0.020)	(0.021)
1-7 Quarters Post-Birth x Mom	-0.134**	-0.170**	-2.686	-0.195**	-0.012**	-0.061	-0.019	-0.012
	(0.060)	(0.076)	(4.556)	(0.092)	(0.006)	(0.059)	(0.016)	(0.021)
Outcome Mean Pre-Birth	0.470	1.525	25.038	0.398	0.031	1.126	0.254	0.818
Observations	2,908,349	2,908,349	1,383,799	2,908,349	2,908,349	2,908,349	2,908,349	2,908,349
Doctors	1,359	1,359	1,359	1,359	1,359	1,359	1,359	1,359
B. Adults								
Quarter of Child Birth x Mom	-0.359***	0.065	-3.187	-0.002	-	-0.176	0.027	0.007
	(0.102)	(0.152)	(2.262)	(0.023)	-	(0.272)	(0.047)	(0.022)
1-7 Quarters Post-Birth x Mom	0.038	0.132	2.361	0.012	-	-0.047	0.045	0.010
	(0.073)	(0.102)	(2.912)	(0.018)	-	(0.243)	(0.031)	(0.021)
Outcome Mean Pre-Birth	0.599	2.112	23.850	0.107	-	4.713	0.484	0.821
Observations	2,560,781	2,560,781	1,347,061	2,560,781	-	2,560,781	2,560,781	2,560,781
Doctors	2,394	2,394	2,394	2,394	-	2,394	2,394	2,394

Notes: This table presents estimates of the impact of having a physician who becomes a mother from a modified version of our triple difference model (Equation 2) for an analysis of child patients. Relative to the baseline model, we also include interactions between fixed effects for each trimester of pregnancy and an indicator for being a mother. Including these additional controls changes the reference period for our triple difference model to be the period prior to *pregnancy*, rather than the period prior to having a child (inclusive of pregnancy). Each column presents effects on a different patient outcome, including: office claims to one's attributed PCP (column 1); total office claims (column 2); familiarity with one's provider at an appointment (column 3); the number of vaccination claims (column 4); the number of lead screening test claims (column 5); the number of pharmacy claims (column 6); the number of emergency claims (column 7); and the likelihood of being enrolled in Medi-Cal (column 8). We omit results on lead screening tests for adults because these are very rare, and thus a less meaningful outcome for this population (mean = 0.001). Standard errors are clustered at the attributed physician level.

Table A11: Impact on Gender Gap in Physician Claims, Restricting to 2013-2015 Births

	All Patients		Child Patients		Adult Patients	
	(1)	(2)	(3)	(4)	(5)	(6)
	Total E&M Claims	Any E&M Claims (Quarterly)	Total E&M Claims	Any E&M Claims (Quarterly)	Total E&M Claims	Any E&M Claims (Quarterly)
Quarter of Child Birth x Mom	-114.837***	-0.224***	-127.750**	-0.308***	-89.393***	-0.187***
	(27.457)	(0.043)	(50.624)	(0.068)	(24.972)	(0.053)
1-7 Quarters Post-Birth x Mom	-0.695	-0.002	13.130	-0.042	4.762	0.016
	(29.089)	(0.026)	(51.848)	(0.042)	(23.985)	(0.032)
Outcome Mean Pre-Birth	153.745	0.747	226.322	0.800	109.940	0.724
Observations	28,719	27,259	12,820	12,284	22,899	21,720
Doctors	1,486	1,486	674	674	1,176	1,176

Notes: This table shows estimates of the impact of becoming a mother on physicians' claims volume from a triple difference model (Equation 2). The sample is restricted to births between 2013-2015, for which we observe all California births in the 2-year pre- and post-periods. We show results for total office claims (in the odd columns), and on having any office claims (in the even columns). We perform estimation separately for three samples: (i) the full sample of matched doctors, with no weights (columns 1-2); (ii) doctors that have child patients (columns 3-4), weighted by the share of each doctor's patients who are children; and doctors with adult patients, weighted by the share of each doctor's patients who are adults (columns 5-6). Standard errors, shown in parentheses, are clustered at the matched parent/non-parent pair level.

Table A12: Impacts on Children and Adults, Removing Controls for Doctor Relationship and Calendar Time

	PCP Office Claims			Total Office Claims			Vaccinations		
	(1) Base	(2) No controls	(3) 2013-2015 births	(4) Base	(5) No controls	(6) 2013-2015 births	(7) Base	(8) No controls	(9) 2013-2015 births
A. Children									
Quarter of Child Birth x Mom	-0.380***	-0.381***	-0.369***	-0.209***	-0.196*	-0.270**	-0.267***	-0.227**	-0.296*
	(0.063)	(0.082)	(0.097)	(0.080)	(0.103)	(0.133)	(0.096)	(0.094)	(0.169)
1-7 Quarters Post-Birth x Mom	-0.100**	-0.082	-0.077	-0.106*	-0.098	-0.094	-0.213**	-0.211**	-0.231
	(0.047)	(0.053)	(0.081)	(0.062)	(0.074)	(0.103)	(0.096)	(0.097)	(0.163)
Outcome Mean Pre-Birth	0.470	0.470	0.470	1.525	1.525	1.525	0.398	0.398	0.398
Observations	2,908,349	2,908,349	1,389,536	2,908,349	2,908,349	1,389,536	2,908,349	2,908,349	1,389,536
Doctors	1,359	1,359	688	1,359	1,359	688	1,359	1,359	688
B. Adults									
Quarter of Child Birth x Mom	-0.325***	-0.364***	-0.541***	0.026	-0.038	-0.053	-0.009	-0.020	-0.021
	(0.092)	(0.126)	(0.136)	(0.122)	(0.170)	(0.192)	(0.020)	(0.025)	(0.029)
1-7 Quarters Post-Birth x Mom	0.073	0.031	-0.004	0.093	0.051	0.061	0.004	0.005	-0.009
	(0.067)	(0.082)	(0.087)	(0.083)	(0.102)	(0.121)	(0.014)	(0.016)	(0.021)
Outcome Mean Pre-Birth	0.599	0.599	0.599	2.112	2.112	2.112	0.107	0.107	0.107
Observations	2,560,781	2,560,781	1,339,616	2,560,781	2,560,781	1,339,616	2,560,781	2,560,781	1,339,616
Doctors	2,394	2,394	1,188	2,394	2,394	1,188	2,394	2,394	1,188

Notes: This table presents estimates of the impact of having a physician who becomes a mother from two modified versions of our triple difference model (Equation 2). Relative to our baseline model, we first remove our controls for doctor relationship and calendar time from X_{pgt}. The remaining controls in X_{pgt} are two-way fixed effects for event-time interacted with physician gender and parent status. We also show a second version that uses our baseline model, but restricts to parents with a childbirth between 2013–2015. Panel A presents coefficients from an analysis of child patients, while Panel B presents coefficients from an analysis of adult patients. The odd-numbered columns show the estimates from the baseline model, while the even-numbered columns show the estimates when we remove these controls. Standard errors are clustered at the attributed physician level.