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ABSTRACT

We estimate the relationship between local labor market opportunities and child health using state unemployment rates and demand-induced changes in mothers' and fathers' employment opportunities. In contrast with studies of adult health, we find little evidence that aggregate economic conditions are correlated contemporaneously with children's health. However, we find important patterns by gender. In particular, improvements in women's employment opportunities are consistently associated with worse child health, while better labor market conditions for men have positive effects. These patterns suggest that both family income and maternal time are important inputs to child health.

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I. Introduction

We investigate the extent to which changes in labor market opportunities affect children's health. An extensive literature documents that negative shocks to labor market demand are, perhaps counterintuitively, associated with reductions in mortality and improvements in adult health.[1] We know very little, however, about how children's health responds to changes in labor market conditions.[2] Understanding this relationship is important, as health in early life is increasingly appreciated as a significant input to human capital development and a determinant of long-term health and socioeconomic status (Almond and Currie 2011). A contemporaneous relationship between labor market opportunities and children's health may have important implications for the wellbeing of the next generation of workers.

Economic theory (Grossman 1972) does not provide clear predictions about how changes in aggregate labor market conditions should affect child health. On one hand, the decreases in family income that typically accompany a labor market contraction might lead to reductions in parental investments in children's health.[3] On the other hand, declining labor market opportunities are associated with reductions in the opportunity cost of parental time, which could lead to improvements in children's health by causing parents to substitute parental care for market-based childcare (reducing their children's exposure to infectious diseases, for example) or through increases in time-intensive health investments. Meanwhile, both recessions and individual job loss have been linked to declines in adult mental health (Dooley, Catalano, and Rook 1988; Fenwick and Tausig 1994; Bradford and Lastrapes 2014; Schaller and Stevens 2015), which may affect children's health either directly or indirectly (Conger and Conger 2007). When combined with cyclical changes in environmental contributors to children's health, such as pollution, the multitude of potentially changing within-family inputs leaves the overall relationship as an empirical question.

Moreover, there is reason to believe that the estimated effect of an aggregate economic downturn on children's outcomes might mask contradictory effects of changes in labor market outcomes (employment, hours, and wages) for mothers versus fathers. For example, as fathers are often primary earners, average income effects from changes in

1. A nonexhaustive list of studies includes Ruhm (2000, 2003, 2005a, 2005b); Ruhm and Black (2002); Evans and Graham (1988); Gruber and Frakes (2006); Stevens, Miller, Page, and Filipski (2015); Xu (2013). Ruhm (2015) shows that the relationship between recessions and adult mortality has weakened during the Great Recession but remains procyclical, particularly for deaths due to cardiovascular disease and transport accidents. Note that these studies are distinct from those that examine the relationship between individual job loss and adult health. Indeed, a puzzle in the broader literature linking economic circumstances with health outcomes is that studies focusing on aggregate economic conditions generally find that poor economic conditions are associated with improved health, whereas studies focusing on individual job loss find that individual job loss is harmful to individuals' health (Sullivan and von Wachter 2009; Eliason and Storrie 2009a, 2009b; Browning and Heinesen 2012). The sources of this discrepancy in findings between the two branches of the literature are explored in Lindo (2015).

2. Two exceptions are Dehejia and Lleras Muney (2004) and Lindo (2015). Both of these studies focus on infant health (mortality and birth weight).

3. Reductions in employer-sponsored health insurance coverage in an economic downturn may also lead to reductions in children's health. However, Cawley, Moriya, and Simon (2015) document that children's overall health insurance coverage is not significantly correlated with the state unemployment rate, suggesting that increases in public health insurance coverage may counteract reductions in employer-sponsored coverage.

fathers' labor market opportunities may be larger. Research in psychology and sociology has suggested that fathers may also experience greater increases in stress than mothers following job displacement (Kalil and Ziol-Guest 2008). Meanwhile, women are more likely than men to substitute time in the labor market directly for time spent with children, which suggests that changes in mothers' labor market opportunities may have larger effects on the source and quality of childcare (see Aguiar, Hurst, and Karabarbounis 2013; Lindo, Schaller, and Hansen 2018; Pailhé and Solaz 2012). Perhaps not surprisingly, recent empirical studies exploiting plausibly exogenous changes in individual employment status do find differing effects of fathers' and mothers' employment on child health, typically finding that mothers' employment is associated with worse health for children, while fathers' employment has the opposite effect.[4]

A key challenge in estimating the effects of shocks to parental labor market outcomes on child health is endogeneity. In particular, family income and labor supply decisions are likely to be correlated with unobservable preferences and attributes of children and families that are related to child health. It is also likely that child health directly affects parental labor supply. These concerns are particularly salient when considering maternal employment outcomes, making it difficult to compare the effects of labor market shocks facing fathers and mothers using standard (individual or aggregate) employment variables. For example, though it seems natural to use gender-specific unemployment or employment rates to proxy for aggregate shocks to male and female labor market opportunities, the correlation between child health and parental labor supply will likely cause these estimates to be biased.

This paper makes three contributions. First, we are among the first to provide estimates of the relationship between cyclical changes in aggregate labor market opportunities and children's health in the United States and (to our knowledge) the first to consider cyclical variation in child health outcomes other than infant health or mortality. Combining restricted data from the National Health Interview Survey with state monthly unemployment rates, we examine the effect of contemporaneous aggregate economic conditions on a variety of outcomes for children, including general ratings of health, the incidence of specific health conditions, and a standardized index summarizing a set of costly health conditions. This analysis complements existing work that uses a similar empirical approach to explore changes in adult health outcomes over the business cycle.

Second, in order to address the potential endogeneity of aggregate unemployment rates, we generate predicted employment growth rates that exploit variation in base-period industry employment shares across states, together with national rates of industry employment growth. These "shift-share" indices, which are similar to those used by Bartik (1991), Katz and Murphy (1992), and Blanchard and Katz (1992), allow us to isolate variation in child health due to demand-induced changes in aggregate labor market opportunities.

Finally, in a variation on the shift-share strategy, we create separate predicted employment growth rates that capture plausibly exogenous changes in labor demand facing men and women. This approach, which is in the spirit of the work of Schaller (2016), Shenhav (2016), Aizer (2010), and Bertrand, Kamenica, and Pan (2015), allows us to

4. See Anderson, Butcher, and Levine (2003); Gennetian et al. (2010); Morrill (2011); Lindo (2011); Liu and Zhao (2014); and Schaller and Zerpa (2017).

separately estimate the effects of shocks to aggregate labor market opportunities facing fathers and mothers on child health, without the endogeneity bias that results from using observed male and female unemployment or employment rates. We show that results based on these demand-driven proxies for male and female labor market conditions reveal patterns that are not present in results using gender-specific unemployment rates, particularly with respect to the effects of shocks to female labor demand on child health.

Our findings are summarized as follows. In contrast with recent studies that focus on adult health, we find little evidence that general labor demand conditions are associated with contemporaneous measures of children's health. A limited number of health outcomes appear to vary with the unemployment rate, but the magnitudes of these estimated effects are small, and the associations become weaker when we use predicted employment growth as our measure of economic conditions.

Turning to the effects of gender-specific labor market conditions, we find that focusing on broad measures of employment opportunities obscures the true extent to which the labor market affects children. Specifically, when we use plausibly exogenous measures of labor demand conditions facing males and females, the pattern of estimates consistently shows that improvements in labor market conditions facing women are associated with worse child health, while improvements in men's labor market conditions are associated with better child health. These patterns are consistent across all outcomes, and many of the estimates are nonnegligible in magnitude and statistically different from zero. Thus, it appears that the correlation between children's health and a gender-inclusive measure of employment opportunities averages together positive associations between male labor market opportunities and child health and negative associations between female labor market opportunities and child health, masking important underlying patterns.

We explore a number of possible mechanisms, including changes in parental employment and time use, changes in health insurance coverage and healthcare utilization, and changes in parental mental health, smoking, and drinking. Ultimately, our results are consistent with the notion that mothers and fathers provide different inputs into the production of children's health, with mothers making relatively larger time investments, on average, and fathers providing higher levels of monetary support. While a negative employment shock for either parent is associated with both a reduction in family income and a change in parental time use, the balance between these two effects is likely to be different for mothers and fathers. Our findings underscore the importance of both monetary and time inputs in the production of children's health. We also investigate potential confounding factors that might be differentially associated with shocks to male and female labor market conditions, such as changes in reporting, sample composition, overall economic conditions, and fertility.

The remainder of our paper is organized as follows. In Section II we provide a review of the related literature, showing that there are reasons to expect that labor market opportunities might affect children's health and that the impact of male and female employment conditions might be expected to differ. In Section III we describe our data. We then explain our empirical framework in Section IV, where we also describe the construction of the predicted employment growth rates that we use to address potential endogeneity. Our results are presented in Section V, followed by a discussion of potential confounding factors and possible mechanisms in Section VI. Section VII concludes.

II. Literature and Theoretical Framework

Many studies have documented that higher unemployment rates are associated with reductions in overall mortality (Ruhm 2000, 2003, 2005a, 2005b), reductions in mortality due to cardiovascular disease and transportation accidents (Ruhm 2015), and improvements in other measures of health (Ruhm 2003, 2005b). These relationships are often thought to result from improvements in health-related behaviors that occur as a result of changes in the opportunity cost of time that accompany declining labor market opportunities (Evans and Graham 1988; Ruhm and Black 2002; Ruhm 2005b; Gruber and Frakes 2006; Freeman 1999; Xu 2013).[5] Nearly all of these studies focus on adult health, but mortality is known to vary cyclically across all age groups. Stevens et al. (2015), for example, find that a one percentage point increase in the unemployment rate is associated with a 0.3 percent reduction in mortality overall, but a 1.4 percent reduction in mortality among children aged 0–4 and a statistically insignificant reduction of 0.04 percent among adults aged 45–61. This suggests that, relative to adults, children's health may be particularly sensitive to cyclical variation in labor market conditions.

To our knowledge, the only studies to date that have focused on the impact of aggregate economic conditions on children's health have focused on infant health. Using U.S. vital statistics data, Dehejia and Lleras-Muney (2004) document that higher unemployment rates are associated with reductions in infant mortality, and Dehejia and Lleras-Muney (2004) and Lindo (2015) find that higher unemployment rates are associated with reductions in the incidence of low birth weight. Dehejia and Lleras-Muney (2004) attribute these effects to both positive selection and changes in maternal health behaviors, such as smoking and drinking. They conclude that changes in the opportunity cost of women's time may be an important determinant of cyclical changes in health during pregnancy and more generally suggest that reducing the opportunity cost of maternal time inputs may be a possible mechanism for improving children's health outcomes.

Dehejia and Lleras-Muney's conclusion is echoed in a larger literature that focuses on identifying the effect of maternal employment on children's health outcomes. That literature, largely framed in the context of understanding the implications of long-term trends in women's labor force participation, generally finds that mothers' employment negatively affects children's health. An empirical challenge faced by all of these studies, however, is that mothers' labor supply decisions may be partly determined by unobserved factors that also affect their children's outcomes. While two recent studies make some headway on this endogeneity problem—Gennetian et al. (2010) use experimental variation in maternal work incentives that was generated by the 1990s welfare-to-work experiments, and Morrill (2011) uses variation in maternal employment induced by the youngest child's eligibility for kindergarten—there is a dearth of causal evidence on the effect of maternal employment on children's health.

5. An exception is Stevens et al. (2015), who note that most of the cyclically induced deaths are among older individuals, for whom the opportunity cost of time is not likely to be strongly affected by changes in labor demand. In addition, studies that link individual job loss to individual health outcomes find that job loss is associated with increases in mortality and hospitalizations (see Sullivan and von Wachter 2009; Eliason and Storrie 2009a, 2009b; Browning and Heinesen 2012), which is inconsistent with the "opportunity cost of time" hypothesis.

Fewer studies directly investigate the impact of father's employment, but among those that do, there is no evidence that paternal employment has negative effects on children's health, and there is some suggestive evidence that it has positive causal effects (Anderson, Butcher, and Levine 2003; Phipps, Lethbridge, and Burton 2006; Morrissey, Dunifon, and Kalil 2011). Lindo (2011), for example, compares the birth weight of infants born before and after a paternal job displacement and finds that father's job loss reduces birth weight by more than 4 percent. When considered together with the literature on maternal employment, this finding suggests that mothers and fathers may influence the production of children's health very differently. Recent studies that consider the impacts of both mothers' and fathers' job losses or unemployment provide further evidence in this regard: Schaller and Zerpa (2017) find that maternal job loss is associated with reductions in the incidence of acute infectious conditions, while paternal job loss is associated with worse mental health among children. Liu and Zhao (2014) examine the impacts of job displacement in China and find that while mother's job loss has no effect on children's height and weight, father's job loss has a negative impact. By contrast, using Swedish data and focusing on the effects of having a parent who is currently unemployed and searching for work, Mork, Sjogren, and Svaleryd (2014) find that maternal (active) unemployment spells lead to a greater increase in hospitalizations among children than paternal unemployment spells.

There are a number of reasons that mothers' and fathers' job losses may have different effects on the production of child health. Even conditional on work status, mothers spend approximately twice as much time engaged in child-care-related activities as do fathers (Guryan, Hurst, and Kearney 2008; Kalil and Ziol-Guest 2013), and more of that time is devoted to routine care (Bryant and Zick 1993; Pleck 1997). Changes in mothers' employment status may, therefore, have larger impacts on time inputs into children's health. Recent research suggests that, indeed, recession-induced declines in work generate relatively larger increases in the amount of time mothers spend with their children (Aguiar, Hurst, and Karabarbounis 2013; Lindo, Schaller, and Hansen 2018). These findings suggest that if parental time inputs are important to the production of children's health, then a mother's job loss may have a more positive effect than a father's job loss.

Furthermore, in the majority of American families, husbands' earnings contribute more to household income than wives' earnings (Bertrand, Kamenica, and Pan 2015). For most families, therefore, a father's job displacement will generate a larger shock to family income. Given the well-documented positive correlation between income and child health (Case, Lubotsky, and Paxson 2002), the income losses associated with a paternal job loss might have a negative impact on child health that exceeds that of a maternal displacement. Paternal job loss might also have a larger effect on the level of stress that a family experiences. Existing studies have shown that negative employment shocks are associated with reductions in adult mental and physical health (Brand, Levy, and Gallo 2008; Browning and Heinesen 2012; Eliason and Storrie 2009a, 2009b; Schaller and Stevens 2015; Sullivan and von Wachter 2009) and impaired family functioning (Conger et al. 1994). The Family Stress Model (Conger et al. 1994) predicts that this will have a direct, negative effect on children's outcomes.

By suggesting that male and female employment opportunities may have different effects on children's health, the opposing mechanisms outlined above make it difficult to

predict the sign of the relationship between overall labor market opportunities and children's health. It is also important to keep in mind that parental job loss is only one route by which labor market conditions might affect children's health. Recessions lead to changes in time use, reduced earnings and wealth, and higher stress levels even among parents who hold onto their jobs (Dooley, Catalano, and Rook 1988; Fenwick and Tausig 1994; Kalil and Ziol-Guest 2013; Morrill and Pabilonia 2015). If such channels are important to children's health outcomes, then studies that focus on the impacts of individual employment shocks, such as parental job displacement, will understate the overall effects that result from labor market contractions. Labor market contractions may also affect children's health through environmental, rather than family-level changes. For example, a growing body of research documents that pollution from manufacturing activity and traffic congestion affects children's health.[6]

III. Data

Our analyses are based on data from the 1997–2012 National Health Interview Survey (NHIS), which is one of the primary surveys used to monitor health trends in the United States population. The NHIS is a repeated cross-sectional survey that collects health information on 34,000–40,000 families each year. We use the restricted-use version of the NHIS because the public-use version does not include state identifiers, which are necessary to our identification strategy: a child's state of residence is required to assign the relevant state–year labor market variables. We include in our main sample all children ages 0–17 (or 5–17 for school-related outcomes).[7]

The NHIS has two components that we use in our analyses. The Person-Core questionnaire includes demographic and health data for each member in each surveyed household. The Sample Child questionnaire includes detailed questions about health and well-being for one randomly sampled child from each household. The answers to the questions in the Sample Child survey are provided by a knowledgeable adult, who is the child's parent more than 90 percent of the time. Because we use data from these two separate NHIS files, the number of observations in our sample varies across outcome variables. In particular, the estimates for outcomes from the Sample Child file are based on samples that are smaller than those for outcomes from the Person-Core file.[8]

We focus on a set of health outcomes that are relatively common among children and have a reasonable likelihood of exhibiting transitory fluctuations over time. Our outcome variables include three measures of overall health: (i) whether the parent reports that the child is in fair or poor health, (ii) whether the parent reports that the child is in excellent health, and (iii) the number of days in the last year that a child older than five

6. For example, Chay and Greenstone (2003); Currie and Neidell (2005); Currie, Neidell, and Schmieder (2009); Currie and Walker (2011); Currie and Schmieder (2009); Knittel, Miller, and Sanders (2011); and Sanders (2012).

7. The NHIS changed substantially in 1996, making it difficult to include earlier years of the survey due to the survey structure (and many of the outcome variables) not being comparable.

8. Since children are randomly selected within households for the Sample Child file, we do not expect that treatment effects should be heterogeneous across the different samples. However, we have confirmed that results for variables in the Person-Core file are similar when estimated on the sample of children included in the Sample Child file.

has missed school due to illness.[9] The indicators for fair/poor and excellent health status come from a survey question in the Person-Core questionnaire where parents are asked to rank the health of their children on a scale of one to five, with one being excellent and five being poor. Roughly 2 percent of parents report that their child is in fair or poor health, while 55 percent of the sample report that their children are in excellent health.

Using the NHIS child sample, we also examine the effect of labor demand conditions on a set of more narrowly defined health outcomes that are plausibly linked to economic conditions in the short run and unlikely to be subjective or to remain undiagnosed (and thus will not be highly sensitive to changes in respondent mood and/or medical care utilization). Our choice of specific health conditions is further motivated by the Agency of Health Care Research and Quality's (AHRQ) ranking of childhood health conditions by total expenditures (Soni 2014). According to this publication, the five most costly childhood health conditions are: mental disorders, asthma, trauma-related disorders, respiratory infections, and ear infections. As a large share of costs related to these health outcomes is born outside of the household (for example, according to Soni 2014, more than one-half of total expenditures on asthma and mental health were paid for by Medicaid in 2011), changes in the incidence of these conditions may have important policy implications. In our data, we identify (i) whether a child has had an asthma attack in the last year, (ii) whether the child has experienced three or more ear infections in the last year, (iii) whether a child has experienced severe emotional difficulties in the last six months, and (iv) whether the child has experienced an injury in the past three months.[10]

Each of the specific health outcomes that we consider is plausibly linked to labor market conditions through changes in family income, parental time use, and family stress. For example, changes in child mental health may be most related to family stress,[11] while changes in the incidence of ear infections are more likely to result from changes in parents' time use. The incidence of injuries may be associated either with changes in time use, such as changes in daycare attendance or sports participation, or with changes in parental mental health, if injuries reflect child maltreatment.[12]

For asthma in particular, there are a multitude of potential mechanisms linking economic conditions to the incidence of asthma among children. For example, childhood asthma attacks are known to be triggered by air pollution, the level of which varies with aggregate economic activity, and parental stress has been found to enhance the effect of environmental pollution on childhood asthma incidence (Shankardass et al. 2009). Furthermore, exposure to dust, animal hair, cockroaches, and molds is associated with asthma attacks (Institute of Medicine 2000), and such factors are linked to the cleanliness

9. We acknowledge that the number of sick days could be affected by parental employment status, independent of a child's underlying health, and interpret our results accordingly.

10. Unfortunately, we are unable to investigate childhood obesity as an outcome. The NHIS stated in 2008 that they had substantial concerns with how they had been recording the data on child height and weight. In particular, they had not been conducting internal consistency checks for extreme values. In 2008, they improved their survey methodology. However, at that time, they also stopped collecting data on height and weight for children younger than 12 (National Center for Health Statistics 2009).

11. Several existing studies have linked adult mental health to aggregate economic conditions, including Blanchflower and Oswald (2004), Dooley and Catalano (1984), Dooley et al. (1988), and Fenwick and Tausig (1994).

12. Lindo, Schaller, and Hansen (2018) find that overall economic conditions are not strongly related to rates of substantiated child maltreatment, but they find that improvements in labor market conditions for females are associated with increases in maltreatment rates, while improvements in labor market conditions for males are associated with reductions in maltreatment rates.

of a home, possibly becoming more prevalent when parents spend less time at home. Childhood asthma attacks have also been linked with exposure to second-hand smoke (Sabia 2008), and there is evidence that adult smoking also fluctuates with the business cycle (Ruhm 2005b). Finally, the incidence of asthma symptoms may depend on children's level of physical activity, the availability of asthma medication, and whether children and their parents have had counseling on handling medication regimes and dealing with oncoming attacks.

Throughout our analysis we acknowledge that the relative importance of different mechanisms is likely to vary with the condition considered and interpret our findings accordingly. However, because there are many outcome variables, we also create a standardized index of "costly conditions" in the spirit of similar indices put forth by Kling, Liebman, and Katz (2007) and Anderson (2008). The components of the index include: whether the child has experienced severe emotional difficulties, whether the child has had an asthma attack, whether the child has experienced an injury, and whether the child has experienced three or more ear infections. We create a standardized z-score for each variable by subtracting the mean and dividing by the standard deviation.[13] We then create the index by averaging across the standardized z-score versions of each of the individual measures. Using this index as an additional dependent variable improves statistical power (Kling, Liebman, and Katz 2007). Regressing our labor market indicators on this index also serves as a unified hypothesis test for statistical significance across the included outcomes, helping us guard against type-one error due to multiple hypothesis testing (Anderson 2008).

We also use the NHIS to construct a number of variables that help us to explore the mechanisms by which parental employment opportunities affect child health. We are able to identify whether needed medical care was delayed or missed because of cost and whether children are covered by any health insurance coverage. We also use data on parental time use: whether parents were employed last week, the number of hours that they worked, and whether they reported "keeping house" instead of working. Finally, we leverage data on parental mental health, smoking, and drinking behavior.

We merge the NHIS data with state- and time-varying economic and demographic data from other sources. We obtain state monthly unemployment rates from the Bureau of Labor Statistics and construct gender-specific unemployment rates using the basic monthly Current Population Survey (CPS), averaging each over the 12 months preceding the NHIS interview.[14] Predicted employment growth rates—our demand-driven proxies for economic conditions—are created using data from the decennial census and CPS, as described below. State population shares by race/ethnicity and educational attainment are from the Current Population Survey (through 1999) and the American Community Survey (after 1999). Data on housing prices at the state level are from the Federal Housing Finance Agency House Price Index. Data on the number of births in each state–year are obtained from U.S. vital statistics.

13. To calculate the means, we first restrict the sample to individuals in the relevant cohorts for whom there is information on all variables that are included in the z-score, and we then calculate each variable's mean value based on that sample.

14. The pattern and magnitude of the estimates are robust to alternative specifications in which we replace the 12-month average of the unemployment rate with either the six-month average or the unemployment rate in the month of the interview. We also find similar patterns when using the employment to population ratio instead of the unemployment rate.

Table 1
Summary Statistics

Variable	Mean	SD	Observations
Child health outcomes			
Costly conditions index	–0.003	0.519	105,574
Fair/poor health	1.840	13.440	409,983
Excellent health	54.960	49.754	409,983
Sick days from school	3.522	6.552	134,191
Child asthma (past 12 months)	5.474	22.748	194,000
Ear infection	6.111	23.952	193,102
Severe emotional difficulties	1.210	10.934	105,681
Number of injuries	2.750	17.268	194,407
Health insurance and healthcare utilization			
Delayed medical care	3.782	19.076	409,874
Needed medical care, did not get	2.240	14.798	409,836
No insurance coverage	9.480	29.248	408,396
Parental time use			
Mother worked last week	60.190	48.905	166,104
Mother kept house last week	26.500	44.141	166,048
Father worked last week	87.700	32.677	127,457
Father kept house last week	0.855	9.210	127,421
State economic conditions			
Unemployment rate	5.950	2.130	409,983
Male unemployment rate	5.999	2.419	409,983
Female unemployment rate	5.650	1.856	409,983
Predicted employment growth rate	0.584	1.606	409,983
Male predicted employment growth rate	0.319	1.963	409,983
Female predicted employment growth rate	0.898	1.279	409,983

Notes: Data on child health, insurance coverage, healthcare utilization, and parental time use are from the 1997–2012 Person and Child Files of the National Health Interview Survey. State monthly unemployment rates are from the Bureau of Labor Statistics. Construction of the predicted employment growth rates is described in detail in Section IV.B.

Table 1 shows summary statistics for the child health outcomes that we consider, as well as child healthcare utilization and insurance coverage, parental employment in the NHIS sample, and the various measures of state labor market conditions that we employ. Summary statistics for all other variables, including individual demographic controls, state–year control variables, and additional outcomes, are presented in Appendix Table A1.[15]

15. In these and all future tables, the means and coefficient estimates have been multiplied by 100, with the exception of the number of sick days.

IV. Empirical Framework

A. Sample Estimating Equation

We use microlevel data to estimate a model that leverages variation across U.S. states in the timing and severity of labor market shocks. We estimate a variant of a difference-in-differences model that allows us to compare health outcomes among children living in a state that is experiencing a labor market contraction with those living in the same state when employment opportunities are better, while controlling for nationwide shocks. Specifically, we estimate equations like:

$$(1) \quad Y_{iast} = \psi_s + \phi_{at} + \beta U_{st} + \pi Xist + \varepsilon_{iast}$$

where Y_{iast} represents a health outcome for child i, currently age a, living in state s, observed in year t. ψ_s is a vector of state fixed effects, allowing us to control for unobserved differences across states, and ϕ_{at} is a vector of age–year fixed effects, allowing us to control for changes over time in age-specific child health outcomes. U_{st} is the unemployment rate in state s in year t, and X_{ist} is a vector of individual controls including parents' marital status, child race, child gender, mother's age (using ten-year age bins dummies) and education, and month of interview. In some specifications we add controls for state-level factors that may be correlated with both labor market conditions and children's health, including average home prices, the number of births, the fraction of the population in each of four education groups (high school dropout, high school, some college, and college educated), and the fraction of the population in each of three race categories (white, black, other). We also test the robustness of our results to the inclusion of state-specific linear trends to control for unobserved variables correlated with health that change linearly over time within states. Our standard error estimates are clustered at the state level to account for the fact that the error term may be correlated across time periods within each state.

Our estimation strategy harnesses variation in the timing and severity of business cycle fluctuations across states and years. Because the NHIS health data span the period between 1997 and 2012, our estimates are effectively identified off of variation in labor demand driven by two recessions: the dot-com collapse of the early 2000s and the Great Recession, which began in 2007 and peaked in 2009. The extent to which these economic events affected states varied a great deal and depended in part on their industrial composition. For example, states with large financial and information sectors, such as California and New York, experienced large employment declines during the Great Recession. Michigan and Ohio, with strong ties to the automobile industry, were also strongly affected. By contrast, unemployment rates remained relatively low in oil rich states such as North Dakota, Oklahoma, and Wyoming, where the natural resources boom had a substantive buffering effect.

B. Predicted Employment Growth Rates

Though unemployment rates are commonly used as an indicator of local economic conditions in studies of the effects of business cycles on individual and family outcomes, their use is potentially problematic in this setting. Because the denominator of the unemployment rate measures active labor force participation, unemployment rates are

likely to capture changes in labor supply as well as changes in labor demand. This increases the likelihood that changes in unemployment will be correlated with changes in other unobserved variables that may also be related to child outcomes. If exogenous declines in children's health cause a decline in parents' labor force attachment, the denominator of the unemployment rate will decline, and, if total employment remains fixed, the measured unemployment rate will increase. Relatedly, when using the employment to population ratio, labor supply decisions are likely to be correlated with unobservable preferences, attributes, and state-level demographic changes that are related to child health. With both measures, there also may be a direct reverse-causality bias. As a result of all this, OLS coefficients may be biased downward. Another potential source of bias is measurement error: unemployment rates are a noisy measure of actual labor market opportunities. This is especially true in an economic downturn. Because "discouraged workers" (workers who want to be employed but are no longer actively searching for a job) are not counted in measured unemployment rates, the unemployment rate may not be capturing the full extent of the contraction.

As an alternative to unemployment rates, we capture shocks to labor demand by creating an index of predicted employment growth that we use to replace U_{st} in Equation 1. The approach is based on that of Bartik (1991), Katz and Murphy (1992), and Blanchard and Katz (1992). We create a predicted employment growth rate by weighting the national industry-specific employment growth rates by industry shares in each state in a base period and then summing over industries within each state–year as follows:

$$(2) \quad D_{st} = \sum_i G_{it} * \frac{E_{is0}}{E_{s0}}$$

where G_{it} is the growth rate of industry i in year t from the March CPS and E_{is0}/E_{s0} is the ratio of industry i employment in state s to total employment in state s from the 1990 census.[16]

Because variation over time in predicted employment growth is driven by national industry employment growth rates, it will be uncorrelated with state-level supply shocks, as long as there is no industry for which employment is concentrated in a single state (Blanchard and Katz 1992). In order to ensure that this is true, while maintaining sufficient cross-sectional variation in the base-period industry composition, we use data from 17 industry categories. Our estimates are similar when we use fewer (15) or more (21) industry categories.[17]

Cross-sectional variation in state employment shares also helps to identify the effect of demand shocks, since aggregate demand shocks in a particular industry will have

16. The labor demand indices in this paper are identical to those used by Schaller (2016) to estimate the effects of gender-specific labor demand on fertility, except for the choice of base period. The results are robust to using alternative choices of base year, including the average of 1980 and 1990 employment.

17. The 17 industry categories are: (1) agriculture, forestry, and fishing; (2) mining; (3) construction; (4) low-tech manufacturing (lumber, furniture, stone, clay, glass, food, textiles, apparel, and leather; (5) basic manufacturing (primary metals, fabricated metals, machinery, electrical equipment, automobile, other transport equipment [excluding aircraft], tobacco, paper, printing, rubber, and miscellaneous manufacturing); (6) high-tech manufacturing (aircraft, instruments, chemicals, petroleum); (7) transportation; (8) telecommunications; (9) utilities (10) wholesale trade; (11) retail trade; (12) finance, insurance, and real estate; (13) business and repair services; (14) personal services; (15) entertainment and recreation services; (16) professional and related services; and (17) public administration. The division of manufacturing into low-tech and high-tech categories follows Katz and Murphy (1992). Results based on alternative industry groupings are available upon request.

larger employment effects in states where the affected industry makes up a relatively greater share of total employment. There is substantial variation in the industry composition of the workforce across states. For example, agriculture, forestry, and fishing make up less than 1.5 percent of the workforce in states like New Jersey, New York, Massachusetts, Rhode Island, Connecticut, and Maryland, while these sectors make up more than 8 percent of total employment in Nebraska, Idaho, Montana, North Dakota, and South Dakota. Similarly, the share of the workforce employed in basic manufacturing ranges from less than 3 percent in Alaska and Wyoming to approximately 20 percent in Indiana and Michigan.

Because the time variation in this predicted employment growth measure is driven by national industry employment growth from March of the previous year to March of the current year (as it is based on March CPS employment estimates), the annual measure will be less accurate the further from March the interview month is. To correct for this, we adjust the timing of the index by weighting the predicted employment growth rates differently depending on the month of interview. For March, we use the current-year index, as it represents predicted employment growth from last March to this March. For February, we put 11/12 weight on this year's index and 1/12 weight on last year's index, since the first month of the reference period would have fallen prior to the previous March CPS. For April, we put 11/12 weight on this year's index and 1/12 weight on next year's index, and so on.

Variation over time in the average of the predicted employment growth rates (across states) is shown in Appendix Figure A1, along with an average of state unemployment rates. In each of the two recessionary periods, the average predicted employment growth rate declines sharply just before the unemployment rate increases and increases again prior to the recovery. We illustrate geographic variation in the magnitude of the economic downturn in the top panel of Appendix Figure A2, which shows peak-to-trough changes in the predicted employment growth rate in each state during the Great Recession. The map shows the largest declines in predicted employment growth rates in Tennessee, Vermont, Massachusetts, and states in the upper Midwest.

In order to estimate separately the effects of shocks to labor demand facing fathers and mothers, we create analogous predicted employment growth rates that reflect gender-specific labor demand conditions. Specifically, rather than weighting national industry employment growth rates by the base-period share of total state employment in each industry, we weight by the base-period share of males or females employed in a given state in each industry, summing across industries, by gender, within the state as follows:

$$(3) \quad D_{stg} = \sum_i G_{it} * \frac{E_{isg0}}{E_{sg0}}$$

where g indexes the group (male, female).[18] These indices, which are similar to those used by Schaller (2016) and to the predicted earnings indices used by Aizer (2010) and Bertrand, Kamenica, and Pan (2015) to construct male to female earnings ratios, can be

18. It would theoretically be possible to construct these indices based on base-period industry employment shares for the subgroup of men and women who are, in fact, fathers and mothers. However, we are concerned about power in the already-small state CPS samples. There are also potential selection issues. In particular, the distribution of employment across industries among all employed women will arguably generate a better proxy for potential labor market opportunities than the employment distribution among the (selected) sample of working mothers.

interpreted as gender-specific predicted employment growth rates. As with the overall labor demand index, adjacent March–March employment growth rates are weighted depending on the month of interview. We include the male and the female indices in the same regression, so the coefficient on the male index represents the effect of a one percentage point increase in the predicted employment growth rate for males, holding predicted female employment growth constant, and vice versa.

Within states, the differences between the male and female predicted employment growth rates are driven by differences in the industry compositions of the male and female workforces. On average, men are more likely to be employed in agriculture, forestry and fishing, mining, construction, basic and high-tech manufacturing, utilities, wholesale trade, and business and repair services, while women are about as likely or more likely to be employed in low-tech manufacturing, telecommunications, entertainment and recreation services, retail trade, finance, insurance, and real estate, public administration, and personal and professional services.

Across states, in addition to the variation in overall industry composition of employment described that helps to identify the effects of the overall predicted employment growth index, there is substantial variation in the *relative* employment shares of men and women in each industry. For example, while women are about as likely as men to be employed in the finance, insurance, and real estate sector in Washington, DC, they are more than twice as likely to be employed in that sector in Delaware, Michigan, and Idaho. Overall, the idea is that the growth of an industry that is generally male-intensive will increase predicted employment growth for men more than for women, and that the relative size of the increase will be the greatest in states where the male share of employment in that industry is high, both overall and relative to the female share. State variation in peak-to-trough changes in the male and female predicted employment growth rates during the Great Recession is shown in the bottom two panels of Appendix Figure A2.

Later in the paper (in Section VI.C), we will show that the predicted male and female employment growth indices are correlated with paternal and maternal employment and time use in our NHIS sample. As shown in Appendix Table A2, our male and female shift-share indices are also correlated in predictable ways with more common, but less exogenous, gender-specific measures of labor market conditions from the Current Population Survey's Merged Outgoing Rotation Groups. For example, the within-gender correlation between predicted employment growth and actual employment growth is 0.67 for women and 0.54 for men, while the cross-gender correlations are not statistically significant. As would be expected, less striking but similar correlations exist between gender-specific measures of predicted employment growth and gender-specific measures of the employment rate. Also of interest is the relationship between our gender-specific indices and gender-specific measures of the unemployment rate. Relative to the female index, the male index is a much stronger predictor of *both* male and female unemployment rates. This is not surprising as, relative to male unemployment, variation in the female unemployment rate is more likely to reflect variation in labor force participation, which increases among women when there is a decline in male labor market opportunities.[19]

19. While the employment results in Table A2 reassure us that our male and female predicted employment growth indices are indeed associated with measurable changes in labor market opportunities for men and women, the results for the unemployment rate raise the possibility that the two indices may be capturing

V. Results

A. Effects of General Labor Market Conditions on Children's Health

We begin by estimating the relationship between aggregate employment conditions and children's health outcomes. Table 2 follows the adult health literature and focuses on the unemployment rate as the regressor of interest. We see that although many of the point estimates suggest that labor market contractions are negatively associated with children's health outcomes, most of the results are statistically insignificant. In particular, unemployment rates do not appear to be correlated with parent-reported general health, asthma attacks, ear infections, or the number of sick days a child takes from school. There are, however, two specific health measures for which the association with unemployment rates is positive and statistically significant: injuries and severe emotional difficulties.

The coefficients indicate that a one percentage point increase in the state unemployment rate is associated with a 4.5–6.5 percent increase (relative to the mean) in the number of injuries (depending on the specification) and a 10.2–11.1 percent increase in the likelihood that a child experiences severe emotional difficulties (relative to the mean of these outcomes reported in Table 1). In the specification that includes state–year controls but no time trends, the magnitudes of the estimated effects imply that an increase in the unemployment rate from 5 percent to 10 percent (the size of the increase in the U.S. unemployment rate during the Great Recession) is predicted to increase the incidence of injuries and the incidence of emotional difficulties among children by approximately eight per 1000 children and six per 1000 children, respectively.

Notably, these findings contrast both with the literature on changes in adult health over the business cycle, which has generally shown that increased unemployment rates are associated with improvements in adult health, and with the literature on the relationship between unemployment rates and infant health, which has found that economic downturns are associated with reductions in infant mortality and the incidence of low birth weight. On the other hand, they are consistent with recent work looking at the direct effects of parental job displacement on child health: Schaller and Zerpa (2017) find that paternal job loss is associated with worse mental health among children and leads to increases in injuries among children in families with low socioeconomic status.

Because it is not obvious whether the impacts of labor market conditions on child health should be seen immediately or whether it takes time before they are observed, we have also estimated regressions that include both the unemployment rate averaged over the preceding 12 months, and the average unemployment rate 12–24 months prior to the interview month (for example, the one year lag of the unemployment rate). The results of these analyses, which are available in the Online Appendix (available at http://jhr.uwpress.org/), are largely consistent with those in Table 2. For most outcomes, inclusion of the lagged unemployment rate has a negligible effect on the coefficient estimates, but slightly increases the estimated standard errors. Most of the coefficient estimates on the lagged unemployment rate are also not statistically distinguishable from zero.

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different marginal changes in actual employment, hours, and earnings among their respective populations. We interpret our results with this limitation in mind. We additionally test, in Section VI.A, whether the results are robust to the inclusion of a control for the overall state unemployment rate and find that they are.

Table 2
Unemployment Rates and Child Health

Outcome	(1)	(2)	(3)
General measures of child health			
Costly conditions index	0.005**	0.005	0.002
	(0.002)	(0.003)	(0.004)
Fair/poor health	0.058	0.056	0.023
	(0.036)	(0.043)	(0.062)
Excellent health	–0.427	–0.461	–0.663
	(0.336)	(0.309)	(0.451)
Sick days from school	0.027	0.037	0.055
	(0.033)	(0.039)	(0.050)
Specific child health outcomes			
Asthma attack in 12 months	0.072	0.084	–0.033
	(0.088)	(0.087)	(0.111)
Ear infections	0.03	0.122	0.034
	(0.010)	(0.101)	(0.133)
Severe emotional difficulties	0.131**	0.124**	0.134*
	(0.042)	(0.057)	(0.072)
Number of injuries	0.178***	0.165**	0.123
	(0.0485)	(0.0713)	(0.103)
State and age–year FE	Yes	Yes	Yes
State–year controls	No	Yes	Yes
State trends	No	No	Yes

Notes: Each coefficient is from a separate regression. Standard errors (in parentheses) are clustered at the state level. All specifications include controls for parents' marital status, child race, child gender, mother's age, and mother's education. State–year controls include the state average home price, the number of births, the fraction of the population in each of three education groups, and the fraction of the population in each of three race groups. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 3 shows results from regressions in which we replace the unemployment rate with an exogenous index of predicted employment growth (as a reminder, an increase in the right hand side variable now represents a positive shock to economic conditions rather than a negative one). We use this alternate measure of overall economic conditions for two reasons. First, as discussed in the previous section, to the extent that movements in the unemployment rate represent changes in labor supply as well as labor demand, the estimates in Table 2 will be biased if changes in labor supply are related to changes in child health. Second, we estimate the effects of aggregate predicted employment growth rates in order to generate estimates that are more easily compared to the corresponding estimates using gender-specific labor demand indices that are presented in the next section. When we replace unemployment rates with predicted employment growth rates, the statistically significant relationships between labor

Table 3
Predicted Employment Growth Rates and Child Health

Outcome	(1)	(2)	(3)
General measures of child health			
Costly conditions index	0.001	0.001	0.001
	(0.004)	(0.004)	(0.004)
Fair/poor health	0.047	0.043	0.060
	(0.048)	(0.050)	(0.051)
Excellent health	–0.401	–0.354	–0.386
	(0.331)	(0.339)	(0.338)
Sick days from school	0.042	0.037	0.037
	(0.039)	(0.039)	(0.039)
Specific child health outcomes			
Asthma attack in 12 months	–0.123	–0.154	–0.133
	(0.139)	(0.140)	(0.140)
Ear infections	0.062	0.048	0.065
	(0.169)	(0.163)	(0.160)
Severe emotional difficulties	0.110	0.109	0.116
	(0.080)	(0.080)	(0.082)
Number of injuries	0.004	0.006	0.009
	(0.110)	(0.109)	(0.108)
State and age–year FE	Yes	Yes	Yes
State–year controls	No	Yes	Yes
State trends	No	No	Yes

Notes: Each coefficient is from a separate regression. Standard errors (in parentheses) are clustered at the state level. All specifications include controls for parents' marital status, child race, child gender, mother's age and mother's education. State–year controls include the state average home price, the number of births, the fraction of the population in each of three education groups, and the fraction of the population in each of three race groups. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

market conditions and injuries and emotional difficulties disappear. In other words, we find that the state-level aggregate predicted employment growth rate is *not* significantly associated with any of our child health outcomes.

B. Effects of Gender-Specific Labor Market Conditions on Children's Health

The estimated overall effects shown in Tables 2 and 3 may mask very different relationships between children's health and contemporaneous male and female labor market opportunities. Aggregate measures of labor market conditions capture changes in labor market opportunities for both men and women, and as discussed in Section II, there are many reasons to believe that male and female labor market conditions potentially have different influences on child health.

A natural extension of the analysis in the previous section is to examine the effects of male and female unemployment rates on child health. For the sake of comparison, we do this in Table 4. However, we have reason to be cautious in our interpretation of these results. In particular, because female labor supply is likely more responsive to child health and family circumstances, the coefficients on female unemployment rates may be more likely to suffer bias from the correlation between child health and labor supply than the coefficients on overall unemployment rates or on male unemployment rates. The estimated effects of the male unemployment rate in Table 4 are similar to the effects of the overall unemployment rate seen in Table 2. However, we find no statistically significant associations between the female unemployment rate and child health.

In Table 5, we switch to our preferred explanatory variables—our gender-specific predicted employment growth rates. In these results, the pattern of the estimates is striking: across all outcomes, positive labor demand shocks for females are associated with decreases in child health, while positive labor demand shocks for males are associated with improvements in child health. Many of the estimates are substantial and statistically different from zero, and the magnitudes of the coefficients are similar across all three specifications. In general, the estimates on the female index are larger in absolute magnitude than the estimates on the male index.

We first focus on the summary index of costly conditions. Here, the estimated coefficients on male employment growth are between –0.008 and –0.009, depending on the regression specification, while the estimated coefficients on female employment growth are between 0.013 and 0.014. Both estimates are statistically significant across all three specifications. The magnitude of the coefficient estimates implies that, holding male labor market conditions constant, an increase in female predicted employment growth of one percentage point increases costly conditions by approximately 0.014 standard deviations, while the same increase in male predicted employment growth reduces costly conditions by approximately 0.009 standard deviations. Moving on to the other general measures of child health, we see the same patterns. In particular, we see that increases in female labor demand result in reductions in the likelihood that a child is reported to be in excellent health and increases in the number of sick days, while the coefficients on male labor demand in the same regressions are statistically insignificant and opposite-signed.[20]

The right-hand side of Table 5 shows the results from regressions using the specific child health outcomes that make up the costly conditions index. Again, the contrast between the point estimates for the male and female indices, which is apparent across all specifications and health outcomes, suggests that improvements in labor market opportunities for fathers are associated with improvements in child health, while improvements in labor market opportunities for mothers are associated with worse child health. In particular, a one percentage point increase in male predicted employment growth is associated with a statistically significant decline of approximately 0.28 percentage points in the probability that a child has an asthma attack, whereas a one percentage point increase in female predicted employment growth is associated with a comparable (but statistically insignificant) increase. The magnitude of these estimates

20. Note that the potential bias resulting from an independent effect of maternal employment on sick days, holding health constant, should work in the opposite direction from the estimated effect of female labor demand conditions.

Table 4
Male and Female Unemployment Rates and Child Health

	(1)	(2)	(3)		(1)	(2)	(3)
Costly Conditions Index				**Asthma**			
Male Unemployment rate	0.003 (0.003)	0.002 (0.003)	0.000 (0.003)	Male Unemployment rate	–0.059 (0.127)	–0.057 (0.117)	–0.069 (0.110)
Female Unemployment rate	0.003 (0.004)	0.003 (0.005)	0.002 (0.005)	Female Unemployment rate	0.163 (0.181)	0.178 (0.183)	0.072 (0.190)
Fair/Poor Health				**Ear Infections**			
Male Unemployment rate	0.032 (0.051)	0.032 (0.050)	0.030 (0.051)	Male Unemployment rate	–0.069 (0.118)	–0.052 (0.110)	–0.113 (0.108)
Female Unemployment rate	0.036 (0.066)	0.036 (0.074)	0.011 (0.076)	Female Unemployment rate	0.125 (0.146)	0.212 (0.142)	0.185 (0.137)
Excellent Health				**Severe Emotional Difficulties**			
Male Unemployment rate	–0.586* (0.346)	–0.566 (0.349)	–0.598* (0.354)	Male Unemployment rate	0.087 (0.069)	0.072 (0.072)	0.087 (0.089)
Female Unemployment rate	0.298 (0.444)	0.288 (0.426)	0.129 (0.464)	Female Unemployment rate	0.047 (0.098)	0.056 (0.110)	0.049 (0.118)
Sick Days				**Injuries**			
Male Unemployment rate	–0.024 (0.051)	–0.021 (0.051)	–0.008 (0.060)	Male Unemployment rate	0.196** (0.068)	0.199** (0.072)	0.161* (0.086)
Female Unemployment rate	0.057 (0.055)	0.065 (0.053)	0.060 (0.059)	Female Unemployment rate	–0.035 (0.085)	–0.057 (0.090)	–0.046 (0.104)
State and age–year FE	Yes	Yes	Yes	State and Age–Year FE	Yes	Yes	Yes
State–year controls	No	Yes	Yes	State–year controls	No	Yes	Yes
State trends	No	No	Yes	State trends	No	No	Yes

Notes: Standard errors (in parentheses) are clustered at the state level. Male and female unemployment rates are included together in the same regression. All specifications include controls for parents' marital status, child race, child gender, mother's age, and mother's education. State–year controls include the state average home price, the number of births, the fraction of the population in each of three education groups, and the fraction of the population in each of three race groups. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table 5
Male and Female Predicted Employment Growth Rates and Child Health

	(1)	(2)	(3)		(1)	(2)	(3)
Costly Conditions Index				**Asthma**			
Predicted male Employment growth	–0.009** (0.004)	–0.009** (0.004)	–0.008* (0.004)	Predicted male Employment growth	–0.265* (0.139)	–0.282** (0.140)	–0.269* (0.138)
Predicted female Employment growth	0.014** (0.005)	0.014** (0.005)	0.013** (0.005)	Predicted female Employment growth	0.236 (0.167)	0.221 (0.166)	0.225 (0.159)
Fair/Poor Health				**Ear Infections**			
Predicted male Employment growth	–0.027 (0.060)	–0.033 (0.064)	–0.006 (0.065)	Predicted male Employment growth	–0.050 (0.149)	–0.092 (0.143)	–0.069 (0.140)
Predicted female Employment growth	0.102 (0.067)	0.105 (0.069)	0.085 (0.072)	Predicted female Employment growth	0.154 (0.198)	0.198 (0.196)	0.182 (0.194)
Excellent Health				**Severe Emotional Difficulties**			
Predicted male Employment growth	0.142 (0.358)	0.212 (0.377)	0.208 (0.393)	Predicted male Employment growth	–0.023 (0.084)	–0.023 (0.086)	–0.020 (0.090)
Predicted female Employment growth	–0.740** (0.348)	–0.782** (0.372)	–0.809* (0.404)	Predicted female Employment growth	0.176* (0.102)	0.175* (0.104)	0.176 (0.108)
Sick Days				**Injuries**			
Predicted male Employment growth	–0.049 (0.042)	–0.053 (0.045)	–0.062 (0.043)	Predicted male Employment growth	–0.121 (0.0838)	–0.121 (0.0832)	–0.109 (0.0829)
Predicted female Employment growth	0.126* (0.067)	0.125* (0.071)	0.137** (0.067)	Predicted female Employment growth	0.187* (0.105)	0.189* (0.106)	0.173 (0.104)
State and age–year FE	Yes	Yes	Yes	State and age–year FE	Yes	Yes	Yes
State–year controls	No	Yes	Yes	State–year controls	No	Yes	Yes
State trends	No	No	Yes	State trends	No	No	Yes

Notes: Standard errors (in parentheses) are clustered at the state level. Male and female predicted employment growth indices are included together in the same regression. All specifications include controls for parents' marital status, child race, child gender, mother's age, and mother's education. State–year controls include the state average home price, the number of births, the fraction of the population in each of three education groups, and the fraction of the population in each of three race groups. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

represents a 5 percent change in a child's probability of having an asthma attack. The estimated effects of predicted female employment growth on the likelihood of injuries and severe emotional difficulties are also positive and weakly significant, representing increases of 7 percent (injuries) and 14.5 percent (emotional difficulties) relative to the sample means.

VI. Discussion

A. Heterogeneity

An important source of potential heterogeneity in our results is differences in family structure. In particular, we might expect the estimated relationships between our gender-specific indices and children's health to vary depending on whether there are one or two adults in the household. If the mechanisms we propose are salient, then we would expect the coefficients on the male indices to fall when we focus our analysis on children who are living in single-mother families.[21]

To consider this, we reestimate Equation 1 separately for samples of children living in households that do not contain a male older than 25 and those that do include an adult male older than 25. These results are presented in Table 6. Consistent with our hypothesis, the estimated effects of the male index are substantially attenuated when we focus on single-mother families, but are similar to those for the full sample in families where there is an adult male.

We have also investigated heterogeneous effects by reestimating Equation 1 for subsamples defined by maternal education (high school dropout, high school graduate, any college) and child's age (0–5, 6–12, or 13–17). When we analyze subsamples, however, the number of observations in each cell falls. This substantially reduces the precision of the estimates and makes it difficult to discern patterns with accuracy. For brevity, we relegate the results of these analyses to Appendix Tables A3 and A4. We note that gender-specific employment patterns appear to be somewhat stronger for school-aged children. This makes sense, as some child health conditions (for example, asthma and mental health) are more likely to become evident at older ages. Also, the NHIS does not survey parents about their children's emotional difficulties or sick days from school unless they are over the age of four for emotional difficulties and five for sick days. It is also worth noting that in our sample, mothers of school-aged children are more likely to be employed than mothers of younger children.[22] Across all of the subgroup analyses, however, few patterns stand out.

21. It is much more difficult to predict how the effects of female labor market conditions should vary across family types. In mother-only families, mothers are likely to be both the main provider of childcare and the main source of income. Therefore, when female labor market opportunities improve, it is not clear whether the income effects versus time effects should dominate (relative to two parent families). It is also not clear whether having an employed (absent) mother or an unemployed (no income) mother should be more stressful for children in single-mother families, or whether single parents' outside childcare options would be relatively better or worse for child health.

22. For mothers of children ages 6–12, 62 percent are employed, relative to 52 percent of mothers of younger children.

Table 6
Male and Female Predicted Employment Growth Rates and Child Health, by Presence of Adult Male in Household

	No Man in House	Man in House		No Man in House	Man in House
Costly Conditions Index			**Asthma**		
Predicted male Employment growth	–0.001 (0.009)	–0.010** (0.005)	Predicted male Employment growth	–0.118 (0.329)	–0.335** (0.160)
Predicted female Employment growth	0.875 (1.148)	0.015** (0.006)	Predicted female Employment growth	0.216 (0.380)	0.238 (0.181)
N	25,402	80172	*N*	48,560	145,440
Y mean	0.05026	–0.01680	*Y* mean	7.489	4.911
Fair/Poor Health			**Ear Infections**		
Predicted male Employment growth	0.088 (0.167)	–0.067 (0.062)	Predicted male Employment growth	0.329 (0.289)	–0.205 (0.182)
Predicted Female Employment growth	0.118 (0.180)	0.107 (0.071)	Predicted Female Employment growth	–0.412 (0.385)	0.375 (0.251)
N	97,181	312,802	*N*	48,326	144,776
Y mean	3.337	1.422	*Y* mean	7.206	5.804

Excellent Health			**Severe Emotional Difficulties**		
Predicted male Employment growth	–0.216 (0.624)	0.328 (0.381)	Predicted male Employment growth	0.0468 (0.232)	–0.0153 (0.081)
Predicted female Employment growth	–0.260 (0.855)	–0.938** (0.404)	Predicted female Employment growth	0.295 (0.334)	0.121 (0.106)
N	97,181	312,802	*N*	25,434	80,247
Y mean	47.300	57.090	*Y* mean	2.206	0.945
Sick Days			**Injuries**		
Predicted male Employment growth	–0.049 (0.111)	–0.053 (0.038)	Predicted male Employment growth	0.0428 (0.209)	–0.155 (0.105)
Predicted female Employment growth	0.145 (0.221)	0.126** (0.057)	Predicted female Employment growth	0.153 (0.265)	0.191 (0.133)
N	31,795	102,396	*N*	48,577	145,470
Y mean	4.310	3.316	*Y* mean	2.708	2.760

Notes: Standard errors (in parentheses) are clustered at the state level. "Man in House" is an indicator for the presence of any male older than 25 in the household. Male and female predicted employment growth indices are included together in the same regression. All specifications include individual and state–year controls. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

B. Mechanisms

Our results echo those of recent studies that document differential impacts of individual maternal and paternal job loss on children's health and achievement (Schaller and Zerpa 2017; Liu and Zhao 2011; Kalil and Ziol-Guest 2008). Our analyses differ from the previous research, however, because we focus on the impact of aggregate demand conditions, rather than individual job loss. As described in Section II, there are a number of reasons that the impacts of parental job loss may differ from the impacts of community-level employment opportunities. For example, some researchers have argued that because pollution moves countercyclically, it might contribute to the procyclical variation in mortality. Our estimates are not consistent with pollution playing an important role, however, as men are more likely than women to be employed in industries that produce high levels of pollution. We find no evidence that male employment opportunities are associated with worse children's health outcomes, which suggests that pollution is unlikely to be a leading mechanism for our findings, at least in the short run. Similarly, it is unlikely that the estimates reflect variation in the provision of social services over the business cycle, as such variation would be tied to variation in tax revenues and should produce positive coefficients on both the male and female employment indices.

Our estimates do line up well with several well-known empirical facts. First, in most married-couple households, husbands work more hours than wives, are more likely to be employed full time, and have higher wages.[23] This suggests that compared to changes in women's labor market opportunities, improvements in men's opportunities should have larger effects on family income and health insurance coverage. To the extent that income and insurance coverage are associated with better child health, improvements in men's employment opportunities should therefore have a relatively larger positive effect. We investigate this hypothesis by estimating regressions with measures of insurance coverage and underutilization of healthcare as dependent variables. We examine the relationship between our male and female employment growth indices and (i) whether medical care was delayed in the past 12 months due to concerns about costs, (ii) whether the child needed medical care in the past 12 months but did not get it due to costs, and (iii) whether the child currently has no insurance coverage.

The results of this exercise are shown in Table 7. The pattern of estimates lines up well with our expectations: while the point estimates associated with the male and female employment indices in the first three columns are all negative (as expected), the estimates on the male index are substantively larger. Moreover, the estimated effects of predicted male employment growth on whether medical care was delayed due to costs, or whether the child did not get medical care due to costs, are both substantial and statistically different from zero. The estimated effect of a one percentage point increase in male employment growth is associated with a 5 percent decline in the probability that a parent reports that his/her child's medical care is delayed due to costs, and an 8 percent decline in the probability that a parent reports his/her child did not receive medical care

23. Recently Bertrand, Kamenica, and Pan (2015) documents that for 2008–2011, wives earn more than their husbands in only 27 percent of households.

Table 7
Potential Mechanisms

Panel 1: Healthcare Utilization and Insurance Coverage

	Delayed Care	Needed Care, Did Not Get	No Health Insurance
Predicted male Employment growth	–0.305** (0.140)	–0.173** (0.069)	–0.202 (0.196)
Predicted female Employment growth	–0.085 (0.193)	–0.030 (0.092)	–0.065 (0.200)

Panel 2: Parents' Employment and Time Use

	Father			Mother		
	Employed Last Week	Work Hours Last Week	Kept House Last Week	Employed Last Week	Work Hours Last Week	Kept House Last Week
Predicted male Employment growth	0.589* (0.309)	0.310** (0.097)	–0.019 (0.060)	–0.152 (0.319)	0.148 (0.137)	0.586** (0.266)
Predicted female Employment growth	–0.407 (0.383)	–0.278** (0.121)	–0.005 (0.079)	0.706* (0.354)	–0.003 (0.187)	–0.697* (0.385)

(*continued*)

Table 7 (*continued*)

Panel 3: Parents' Mental Health and Health Behaviors

	Father			Mother		
	Any Mental Problem	Any Smoking	Heavy Drinking	Any Mental Problem	Any Smoking	Heavy Drinking
Predicted male Employment growth	0.237 (0.292)	0.524 (0.532)	–0.425 (0.674)	–0.221 (0.364)	0.635* (0.363)	0.0708 (0.217)
Predicted female Employment growth	–0.153 (0.500)	–0.235 (0.693)	0.524 (0.724)	0.409 (0.412)	–0.460 (0.415)	–0.139 (0.299)

Panel 4: Family Structure

	Unmarried	Man in the House	Biological Father in Household	Father Missing
Predicted male Employment growth	–0.000 (0.002)	–0.002 (0.001)	0.004* (0.002)	–0.002 (0.001)
Predicted female Employment growth	0.001 (0.002)	0.001 (0.002)	–0.004 (0.003)	0.003** (0.001)

Notes: Standard errors (in parentheses) are clustered at the state level. Male and female predicted employment growth indices are included together in the same regression. All specifications include individual and state–year controls. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

due to costs. The pattern and relative magnitudes of the estimates are consistent with our expectations given that husbands are typically the primary earners in the household.[24]

Another possible reason for differences between coefficients on the male and female indices is differences in time use within the household in response to labor market shocks. On average, employed women spend more time in housework and childcare than employed men, even conditional on hours of paid work. For example, among married parents who are full-time workers, 71 percent of mothers spend some time caring for their children, whereas only 54 percent of fathers do so (Bureau of Labor Statistics 2008). Notably, recent research has found that among parents who have recently become unemployed, mothers are more likely than fathers to reallocate their time to parenting tasks (Aguiar, Hurst, and Karabarbounis 2013; Lindo, Schaller, and Hansen 2018; Pailhé and Solaz 2012).[25] Similarly, during periods of economic expansion, it is possible that even employed mothers will devote more hours in work on the intensive margin. This suggests that if parental care is an important contributor to children's health, improvements in female labor market opportunities will have a relatively greater (negative) impact on children's health, which is consistent with our findings.

We conduct several exploratory analyses using data on work and time use in the NHIS to provide suggestive support for this hypothesis. In the second panel of Table 7, we show effects of male and female labor market conditions on whether each parent worked last week, each parent's work hours last week, and whether each parent "kept house" last week. We find that increases in female predicted employment growth are associated with an increase in mothers' probability of working in the last week. This increase is accompanied by a corresponding decrease of approximately the same magnitude, in their probability of having "kept house" last week, which suggests that mothers are directly substituting time in the labor market for time at home with children.

Meanwhile, increases in predicted male employment growth have a positive effect on fathers' labor market outcomes, but no effect on their probability of having recently engaged in housework. In addition, we find evidence of cross-gender effects that

24. Interestingly, when we conduct analyses of the relationship between our labor demand indices and receipt of medical care separately for households with and without an adult male in the household, we also find that the impact of the gender-specific indices differs depending on family type in predictable ways. Specifically, in female-headed families, an improvement in female labor market conditions is associated with an improvement in healthcare access, whereas an improvement in male labor market conditions has no statistically significant effect. On the other hand, in families containing an adult male, we find that better employment conditions for males are associated with improvements in healthcare access, and that better employment conditions for females have no statistically significant effect. These results are available from the authors upon request.

25. For example, using the data from the American Time Use Survey, Aguiar, Hurst, and Karabarbounis (2013) find that women reallocate nearly twice as many of their foregone market work hours in a recession to childcare as men do, and Lindo, Schaller, and Hansen (2013) find that maternal nonemployment is associated with an 80 percent larger increase in minutes alone with children than paternal nonemployment, controlling for employment status in an earlier period. While we did try to investigate the correlations between our key explanatory variables and parental time use using the ATUS, we found that the ATUS sample was both too short (it doesn't begin until 2003) and too small, in terms of numbers of observations per state, to generate precise estimates of these associations with our identification strategy. For similar reasons, we have estimated but do not to report associations between economic conditions and parental activity variables from the child welfare modules of the Survey of Income and Program Participation.

suggest that there may be some degree of substitution between fathers' and mothers' employment within families: improvements in male labor market conditions are associated with increases in the likelihood that mothers "kept house" and improvements in female labor market conditions are associated with reductions in fathers' work hours. Overall, these time use patterns are consistent with our hypothesis that the differences in the estimated effects of the male and female indices on children's health reflect differences in parental time use and how it responds to labor market shocks.

Another possibility is that the differential impacts of male and female employment opportunities on children's health reflect differences in how mothers' and fathers' own health, and health behaviors, vary with changes in labor market demand. For example, the probability that a child has an asthma attack might fall when male employment opportunities improve because working fathers may smoke less, but the reverse might be true for mothers. It also may be that male and female labor market shocks have different effects on parents' mental health. To investigate these possibilities, we have estimated regressions in which we replace the child health outcomes with indicators of maternal and paternal mental health, smoking, and drinking. As shown in the third panel of Table 7, we find no evidence that these potential pathways are driving our estimates: across the regressions there are no consistent patterns, and virtually none of the estimates are statistically significant.

Following Schaller (2016) and Shenhav (2016), we consider whether the effects of gender-specific labor market conditions on child health operate through their impact on family structure. The bottom panel of Table 7 shows the estimated effects of male and female employment opportunities on the probabilities that (i) the child's parents are unmarried, (ii) there is a male older than 26 in the household, (iii) the biological father is present (relative to either no father present or a nonbiological father), and (iv) that the father is not in the household, or his information is missing. For the latter two outcomes we find suggestive evidence that improvements in male labor demand conditions increase the probability that the father is present, while improvements in female labor demand conditions reduce the probability that the father is present. The magnitude of the coefficient estimates implies that, holding female labor market conditions constant, an increase in male predicted employment growth of one percentage point increases the probability that the biological father is present by about 0.6 percent (relative to the mean). Similarly, holding male labor market conditions constant, an increase in female predicted employment growth of one percentage point reduces the probability that there is information on the father by approximately 1 percent. Overall these results suggest that there may be some disruptive (beneficial) effects of female (male) employment growth on family life. However, these impacts are small relative to both the mean and to our documented child health impacts of gender-specific employment growth.

C. Potential Confounding Factors

Finally, it is important to discuss and rule out a number of potential confounding factors that might cause us to observe differing effects of male and female labor demand indices on children's health outcomes. In particular, we might be concerned that the male and female labor demand indices are differentially associated with (i) the gender of the reporting parent in the NHIS survey, (ii) the composition of the NHIS sample (due to

changes in fertility, marriage and divorce, migration, or nonresponse), or (iii) unobservable economic factors.

First, if the gender or the mental state of the reporting parent is associated with the male or female labor demand index, we might be concerned about differential reporting bias. In other words, it may be that reported child health responds differently to the two indices, when true underlying health does not. As discussed in the previous section, we find no significant association between male and female labor demand and parents' observed mental health.[26] In Appendix Table A5, we also confirm that there is no association between the gender of the responding parent and the male and female labor demand indices.

We also might be concerned that the male and female labor demand indices have differing associations with the composition of the NHIS sample. This would occur if the two indices had asymmetrical effects on migration (for example, if families are more likely to relocate in response to fathers' job opportunities) or survey nonresponse (for example, if maternal employment leads to a reduction in the likelihood of completing the survey). To address this issue, we estimate correlations between our male and female labor demand indices and indicators for child gender, race/ethnicity, and mother's educational attainment in our NHIS sample. These results, also shown in Appendix Table A5, reassuringly suggest that our results are not driven by asymmetrical changes in sample composition associated with the male and female indices.

Since we know that labor market conditions are associated contemporaneously with both fertility and infant health (Schaller 2016; Dehejia and Lleras-Muney 2004), we also might be concerned that serial correlation in unemployment rates might be causing us to confound the effects of current unemployment rates with the effects of unemployment rates in the year of conception or birth. To address this issue, we check that our results are robust to dropping children who are under two years old. We also confirm that controlling for the unemployment rate in the year of conception does not affect the coefficients on recent labor market conditions.

Finally, it is possible that the male and female labor market indices are associated with different states of the aggregate economy. In particular, since male labor market conditions tend to decline more in a recession than female labor market conditions (Hoynes, Miller, and Schaller 2012), an increase in the male labor demand index, holding the female labor demand index constant, might be proxying for some unobservable factor associated with a weaker economy in general. We roughly test for this by including a control for the state unemployment rate in the regressions on the gender-specific indices. The observed patterns in the effects of male and female labor demand conditions on child health hold, even when controlling for the underlying state of the economy. Results from these analyses are available in the Online Appendix.

26. As discussed in the previous section, parents' mental health is also a potential mechanism by which labor market conditions may affect child health. Thus, it would not be surprising if we were to find that male and female labor demand were each associated with significant changes in these outcomes. However, here we use these estimates in the spirit of a placebo test, with the idea that if the respondent's mental state were causing him or her to *misreport* a child's health, that it is likely that we would see this same pattern of misreporting in the respondent's own outcomes and in those of the other parent. As we find no consistent patterns in the effects of the male and female labor demand indices on parents' mental health outcomes, we are less worried about the possibility of differential misreporting.

VII. Conclusions

This paper examines the link between labor market conditions and children's health. An extensive literature documents that adult health declines when labor market opportunities improve, but we know very little about the extent to which this relationship translates to children's health outcomes. Economic theory does not provide clear predictions about the sign of the relationship. Moreover, existing research hints that changes in labor demand for mothers and fathers may affect the production of children's health very differently.

We are among the first to examine the relationship between cyclical changes in labor market opportunities and children's health and the first to address the potential endogeneity that is inherent in related empirical analyses that rely on common measures of employment opportunities, such as the unemployment rate. We do this by developing a predicted employment growth rate that exploits state-specific industry employment shares in a base period together with national, industry-specific, employment growth. We then take this approach to analyses of labor demand conditions and gender-specific influences on children's health.

Unlike most studies of adult health, we find no evidence that general labor demand conditions are associated with improvements in contemporaneous measures of children's health outcomes. Instead, we find that increases in local unemployment rates are associated with small but significant increases in the incidence of injuries and severe emotional difficulties among children. This empirical result also contrasts with previous studies that have documented a negative correlation between the unemployment rate and infant health outcomes.

We also find consistent evidence that focusing on a broad measure of employment opportunities masks important underlying relationships. Specifically, we find that improvements in male labor market conditions are associated with decreases in injuries among children, while improvements in labor market conditions facing women are associated with declining parent-reported child health and increases in the likelihood that children experience severe emotional difficulties. To understand this finding, we provide supporting evidence that income effects may dominate time-use effects when it comes to fathers' employment, while maternal time use plays a more important role in mediating the effects of maternal employment on children's health outcomes.

Appendix

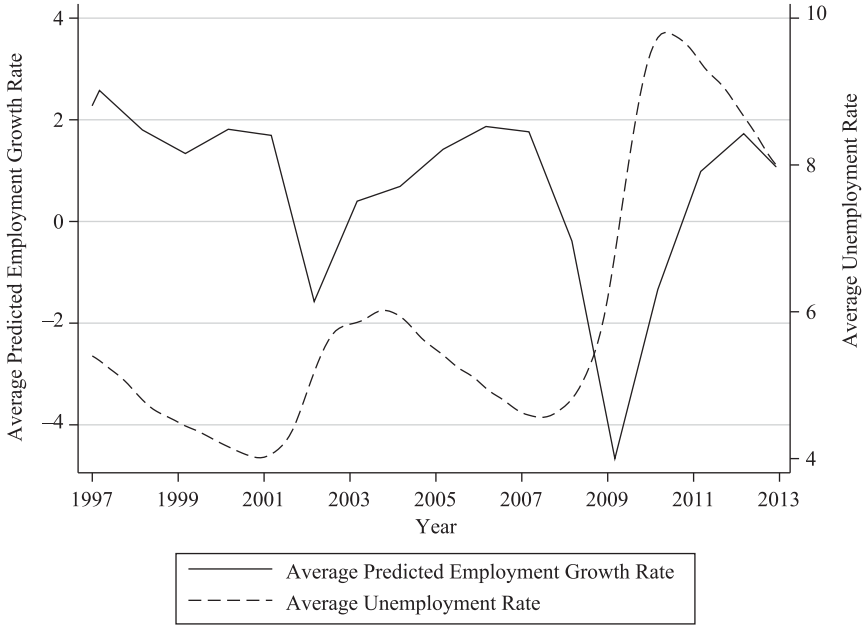
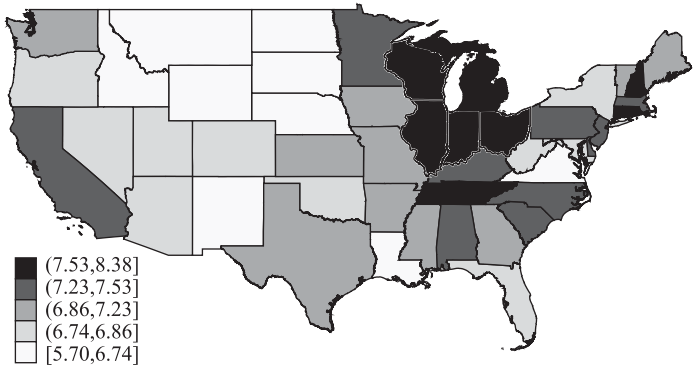


Figure A1

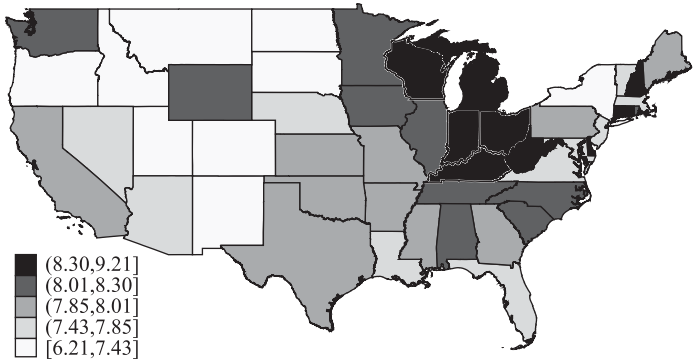
Predicted Employment Growth Rate and the Unemployment Rate

Notes: The predicted employment growth rate and the unemployment rate shown above are population-weighted averages of state-specific values in each month. In addition to being averages across states, both variables represent economic conditions *averaged over the last 12 months*, to match the explanatory variables in our regressions. The predicted employment growth rate is a weighted average of two adjacent March values, depending on the month in question, as described in Section IV. The unemployment rate is averaged over the 12 months prior, as described in Section III.

Panel A: Change in Predicted Total Employment Growth Rate



Panel B: Change in Predicted Male Employment Growth Rate



Panel C: Change in Predicted Female Employment Growth Rate

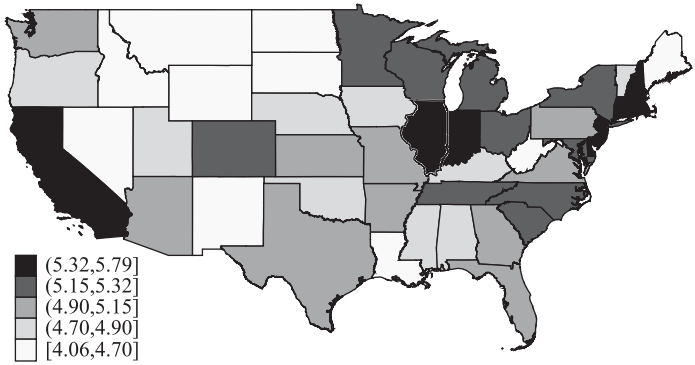


Figure A2

Changes in Predicted Employment Growth Rates

Notes: For each state, the change in each predicted employment growth rate is calculated as the difference between the maximum and minimum values experienced between 2005 and 2012. Shading indicates quintiles, with darker shades representing larger swings in predicted employment growth.

Table A1
Additional Summary Statistics

Variable	Mean	SD	Observations
Additional outcomes			
Adult male (>26) in household	0.782	0.413	409,983
Mother's work hours last week	36.46	12.046	203,525
Father's work hours last week	45.363	11.91	231,526
Mother mental health problems	12.662	33.255	159,000
Father mental health problems	8.203	27.449	91,202
Father smokes at all	22.555	41.795	91,408
Father drinks heavily	13.608	43.499	64,364
Mother smokes at all	21.367	40.990	159,206
Mother drinks heavily	3.580	19.472	88,795
Father is survey respondent	0.248	0.432	409,983
Biological dad in household	0.625	0.484	409,014
Dad missing	0.303	0.460	410,981
Individual controls			
Female	0.489	0.500	409,983
White	0.725	0.447	409,983
Black	0.154	0.361	409,983
Hispanic	0.193	0.395	409,983
Mother's age	35.906	7.816	409,983
Mother high school dropout	0.139	0.346	409,983
Mother high school or GED	0.226	0.418	409,983
Mother some college	0.497	0.500	409,983
Married mother	0.698	0.459	409,983
State–year controls			
Fraction white	0.810	0.138	409,983
Fraction black	0.110	0.110	409,983
Fraction other race	0.078	0.103	409,983
Number of births	79,977	94,683	409,983
Fraction high school dropout	0.141	0.048	409,983
Fraction high school graduate	0.306	0.048	409,983
Fraction some college	0.281	0.044	409,983
House price index	296.436	107.994	409,983

Notes: Additional outcome variables and individual control variables are from the NHIS. State population shares by race/ethnicity and educational attainment are from the Current Population Survey (before 1999) and the American Community Survey (after 1999). The house price index is from the Federal Housing Finance Agency.

Table A2
Predicted Employment Growth Rates and Labor Market Conditions Measured in CPS-MORG

	Male			Female		
	Employment Growth Rate	Employment Rate	Unemployment Rate	Employment Growth Rate	Employment Rate	Unemployment Rate
Predicted male Employment growth	0.539** (0.221)	0.363*** (0.098)	–0.465*** (0.059)	–0.037 (0.203)	–0.024 (0.098)	–0.129* (0.065)
Predicted female Employment growth	0.396 (0.388)	–0.060 (0.133)	0.092 (0.066)	0.671** (0.291)	0.141 (0.098)	–0.071 (0.081)
Y mean	0.834	79.498	6.104	1.243	68.671	5.637

Notes: Standard errors (in parentheses) are clustered at the state level. Monthly state-level employment growth rates, employment rates, and unemployment rates by gender are calculated from the 1997–2012 Current Population Survey Merged Outgoing Rotation Group samples. Male and female predicted employment growth indices are included together in the same regression. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A3
Male and Female Predicted Employment Growth Rates and Child Health, by Mother's Educational Attainment

	High School Dropout	High School Graduate	Some College		High School Dropout	High School Graduate	Some College
Costly Conditions Index				**Asthma**			
Predicted male Employment growth	–0.022 (0.015)	–0.003 (0.006)	–0.008* (0.005)	Predicted male Employment growth	–0.330 (0.361)	–0.296 (0.315)	–0.126 (0.176)
Predicted female Employment growth	0.042* (0.023)	–0.004 (0.012)	0.014** (0.005)	Predicted female Employment growth	0.697 (0.518)	0.148 (0.413)	0.130 (0.254)
N	17,720	25,018	53,380	*N*	31,548	30,468	90,157
Y mean	–0.002	–0.004	–0.002	*Y* mean	4.954	3.692	5.693
Fair/Poor Health				**Ear Infections**			
Predicted male Employment growth	–0.135 (0.240)	–0.053 (0.122)	0.058 (0.0673)	Predicted male Employment growth	–0.235 (0.425)	–0.102 (0.251)	–0.120 (0.230)
Predicted female Employment growth	0.579** (0.258)	0.100 (0.154)	–0.030 (0.090)	Predicted female Employment growth	0.227 (0.589)	0.170 (0.319)	0.345 (0.335)
N	75,949	91,954	180,516	*N*	31,392	43,367	89,742
Y mean	3.810	2.003	1.111	*Y* mean	6.649	6.008	5.935

(*continued*)

Table A3 (*continued*)

	High School Dropout	High School Graduate	Some College		High School Dropout	High School Graduate	Some College
Excellent Health				**Severe Emotional Difficulties**			
Predicted male Employment growth	0.545 (0.676)	0.597 (0.691)	–0.374 (0.446)	Predicted male Employment growth	–0.378 (0.381)	0.139 (0.182)	–0.024 (0.0727)
Predicted female Employment growth	–1.185 (1.086)	–0.838 (0.808)	–0.317 (0.376)	Predicted female Employment growth	0.985* (0.584)	–0.028 (0.238)	0.046 (0.117)
N	75,949	91,954	180,516	*N*	17,728	25,041	53,429
Y mean	41.55	50.37	62.27	*Y* mean	1.690	1.282	0.976
Sick Days				**Injuries**			
Predicted male Employment growth	–0.0611 (0.184)	0.056 (0.083)	–0.092 (0.061)	Predicted male Employment growth	–0.193 (0.246)	–0.099 (0.219)	–0.147 (0.125)
Predicted female Employment growth	0.327 (0.227)	0.101 (0.096)	0.111 (0.074)	Predicted female Employment growth	0.243 (0.305)	0.222 (0.280)	0.208 (0.180)
N	21,039	30,468	61,959	*N*	31,550	43,577	90,179
Y mean	3.657	3.692	3.396	*Y* mean	1.805	2.453	3.187

Notes: Standard errors (in parentheses) are clustered at the state level. Male and female predicted employment growth indices are included together in the same regression. All specifications include individual and state–year controls. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A4
Male and Female Predicted Employment Growth Rates and Child Health, by Child's Age

	Age 0–5	Age 6–12	Age 13–17		Age 0–5	Age 6–12	Age 13–17
Costly Conditions Index				**Asthma**			
Predicted male Employment growth		–0.015** (0.006)	–0.004 (0.005)	Predicted male Employment growth	–0.216 (0.169)	–0.371 (0.304)	–0.239 (0.241)
Predicted female Employment growth		0.017** (0.008)	0.012* (0.007)	Predicted female Employment growth	0.118 (0.238)	0.490 (0.309)	–0.0404 (0.340)
N		49,617	41,255	*N*	66,698	70,048	57,254
Y mean		–0.002	–0.018	*Y* mean	4.740	6.116	5.456
Fair/Poor Health				**Ear Infections**			
Predicted male Employment growth	–0.046 (0.092)	0.001 (0.069)	–0.073 (0.130)	Predicted male Employment growth	0.325 (0.237)	–0.576** (0.245)	0.086 (0.162)
Predicted female Employment growth	0.151 (0.119)	0.0563 (0.110)	0.123 (0.139)	Predicted female Employment growth	0.0369 (0.451)	0.347 (0.294)	0.187 (0.235)
N	134,628	162,503	112,852	*N*	65,902	69,980	57,220
Y mean	1.533	1.891	2.136	*Y* mean	11.010	4.689	2.316

(*continued*)

Table A4 (*continued*)

	Age 0–5	Age 6–12	Age 13–17		Age 0–5	Age 6–12	Age 13–17
Excellent Health				**Severe Emotional Difficulties**			
Predicted male Employment growth	–0.0509 (0.497)	0.615 (0.451)	–0.091 (0.401)	Predicted male Employment growth		–0.179 (0.130)	0.101 (0.124)
Predicted female Employment growth	–0.710 (0.613)	–0.900* (0.470)	–0.640 (0.498)	Predicted female Employment growth		0.381** (0.178)	0.0387 (0.152)
N	13,4628	162,503	112,852	*N*		49,663	41,299
Y mean	58.170	54.46	51.81	*Y* mean		1.246	1.371
Sick Days				**Injuries**			
Predicted male Employment growth		–0.088* (0.052)	–0.005 (0.078)	Predicted male Employment growth	–0.144 (0.136)	–0.0795 (0.168)	–0.145 (0.229)
Predicted female Employment growth		0.210** (0.066)	0.024 (0.145)	Predicted female Employment growth	0.0561 (0.225)	0.0896 (0.154)	0.446* (0.241)
N		68,845	55,863	*N*	66,711	70,060	57,276
Y mean		3.340	3.905	*Y* mean	1.905	2.613	3.942

Notes: Standard errors (in parentheses) are clustered at the state level. Male and female predicted employment growth indices are included together in the same regression. The NHIS does not survey parents about their children's emotional difficulties or sick days from school unless they are over the age of four (emotional difficulties) or five (sick days) so we omit results for the youngest age group for these outcomes. All specifications include individual and state–year controls. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A5
Correlations between Male and Female Predicted Employment Growth Rates and Sample Composition

		Child			Mother	
	Respondent is Father	Female	Black	Hispanic	High School Dropout	Any College
Predicted male Employment growth	0.003 (0.003)	–0.000 (0.002)	–0.000 (0.002)	–0.003 (0.002)	0.003 (0.003)	–0.005 (0.003)
Predicted female Employment growth	–0.003 (0.004)	–0.027 (0.200)	0.0000 (0.003)	0.001 (0.003)	–0.003 (0.003)	–0.000 (0.004)
Y mean	0.248	0.489	0.154	0.193	0.139	0.496

Notes: Standard errors (in parentheses) are clustered at the state level. Male and female predicted employment growth indices are included together in the same regression. All specifications include individual and state–year controls. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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