

Economic Security and the Birth of a Child:
Three Essays on Employment, Income, and Paid Leave Among Parents of Newborns

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Abstract

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This dissertation focuses on parents of newborns around the time a child is born, examining the economic conditions of parents around a birth and exploring the potential of public policies to promote economic stability for families around this time. The first chapter uses administrative microdata from birth certificate and earnings records to analyze patterns of earnings and employment among parents who welcomed a new baby between 2010 and 2016 in Washington State. I present a detailed analysis of parental earnings patterns around childbirth, tracking employment rate, earnings and hours levels, employer continuity, and earnings volatility in the two-year period around a birth for all parents and for mothers disaggregated by racial and ethnic identity, educational attainment, and wage rate quintile. Next, I examine household-level measures of earnings and safety net program income in the time around a birth. I find that parents in Washington State experience substantial earnings volatility when a child is born. Aggregating earnings of both parents listed on a given birth certificate to calculate household-

level income measures does attenuate the volatility faced by individual parents, but substantial economic instability still remains. For example, over half of Washington households see their income fall by half or more during the year around a birth. Use of means-tested programs increases in the perinatal period, which offsets earnings volatility slightly (especially for single mother households) – but household earnings remain volatile even with the addition of these sources of income.

The second chapter studies paid leave programs, which many states have recently enacted. Paid leave policies differ significantly across states, and the implications of these policy differences remain under-studied. This paper assesses the implications of state policy design features for the share of parents eligible for paid leave, as well as for disparities in eligibility across parent demographic, socioeconomic, and employment characteristics. I use administrative microdata from Washington State to simulate working parents' eligibility for claiming paid leave under ten different states' policies. State policy designs differ dramatically in terms of overall generosity and disparities in eligibility across subgroups. In general, policies that are less restrictive and allow more parents to access paid leave also significantly narrow disparities in who is eligible. State policies with more stringent employment requirements disproportionately exclude mothers (versus fathers); mothers working in low-wage jobs; mothers with lower educational attainment; and Black, Indigenous, and Latina mothers from qualifying for paid leave.

Finally, the third chapter focuses on one such paid leave policy, Washington State's Paid Family and Medical Leave (PFML) program. Starting in 2020, parents who worked at least 820 hours in the year before a birth qualify for up to twelve weeks of paid leave to bond with a new child, and mothers can take additional leave for pregnancy and related health conditions. I

describe use of the policy in its first few years, using multiple sources of administrative microdata: health insurance data on birth-related insurance claims from the Washington State All Payer Claims Database and employment and paid leave records from the state's Employment Security Department. These records enable me to identify a population of potential policy users, precisely estimate policy eligibility and take-up, and estimate how PFML use affected employment.

I find that a majority of eligible Washington mothers who gave birth between 2020 and 2022 use PFML at some point during the perinatal period. Take-up increases between 2020 and 2022 as the policy rolls out, especially for medical leave. Analysis of policy take-up by mother characteristics reveals some important disparities. For example, results suggest that eligible Native Hawaiian/Pacific Islander and American Indian/Alaska Native mothers are less likely to take up paid bonding and medical leave than mothers identifying with other racial and ethnic groups. Mothers in more urban areas are more likely to take up both types of leave. There are also sharp disparities by wage rate; for example, only 30 percent of eligible mothers in the lowest-wage jobs took up bonding leave compared to 67 percent of mothers in the highest-wage jobs.

Regression discontinuity analyses of the local average treatment effect of PFML eligibility on employment among mothers around the eligibility threshold find mixed results. There is some evidence that eligibility for PFML has small negative effects on employment status and intensity (i.e., hours worked) in the short term. However, this largely does not translate into significant reductions in total earnings (including wages plus PFML benefits), suggesting that mothers who are just eligible for the policy, on average, are able to spend more paid time off with their children without seeing reductions in overall income. Among mothers who worked

following a birth, PFML eligibility led to an increase in continuity of work with the same employer.

Table of Contents

<i>List of Tables</i>	1
<i>List of Figures</i>	1
<i>List of Appendix Tables</i>	4
<i>List of Appendix Figures</i>	4
<i>Acknowledgments</i>	5
<i>Introduction</i>	7
Overview.....	9
Summary of Chapter 1.....	11
Summary of Chapter 2.....	12
Summary of Chapter 3.....	13
Chapter 1 : Parental Employment and Income Instability Around the Birth of a Child: Prevalence, Disparities, and the Role of Means-Tested Programs	15
Introduction	15
Research on employment and income around a birth	18
Parental employment	18
Household income and poverty	20
Earnings and income volatility	22
The role of means-tested programs	23
The current study	25
Policy context: Births in Washington State, 2010-2016	28
Data and measures	30
DOH birth records	30
ESD Unemployment Insurance wage reports.....	31
DSHS program records.....	32
Study population.....	32
Household-level analyses	32
Parent demographic and socioeconomic characteristics	34
Employment and income measures	34
Analytic approach	37
Results	37
Employment around a birth: all mothers and fathers	37
Heterogeneity by mother characteristics	40
Household earnings levels and volatility	42
Use of means-tested programs around a birth	43
Household income levels and volatility	46
Discussion and conclusion	47
Limitations.....	49
Implications for policy	50
Tables and figures	51
Appendix: Supplemental analyses	73

<i>Chapter 2 : How state policy design shapes eligibility for paid family leave: Evidence from a simulation with administrative data</i>	88
Introduction	88
Policy context: Paid family leave in the United States	91
Policy design and inequality	93
The current study	94
Data and measures	95
Department of Health birth certificate records	95
Employment Security Department Unemployment Insurance wage records	96
Study population	96
Parent demographic and socioeconomic characteristics	98
Estimating paid leave eligibility	99
Results	100
Discussion and conclusion	108
Limitations	109
Research implications	111
Policy implications	112
Tables and figures	113
<i>Chapter 3 : Paid leave and maternal employment: Evidence from Washington State</i>	127
Introduction	127
Background: Paid family and medical leave in the United States and in Washington State	130
Research on paid leave and its effects on maternal employment	132
Effects on leave taking	132
Effects on employment	133
Effects on household income & poverty	134
The current study	136
Data and measures	137
Washington All-Payer Claims Data	137
ESD Wage Reports	139
ESD PFML Program Records	140
Measures	140
Analytic approach	142
Results	143
Descriptive statistics of analytic sample	143
PFML take-up	148
Regression discontinuity results	151
Discussion and conclusion	162
Limitations	165
Implications for research	166
Implications for policy	167
Tables and figures	169
Appendix: Supplemental methodological information	217
Health insurance claims data	217
Differences between Employment Security Department wage report data sources	217

Appendix tables and figures	218
Conclusion	224
Works Cited	229

List of Tables

Table 1.1. Sample size and share of parents included in sample	51
Table 2.1. Descriptive statistics of analytic sample compared to nationwide estimates	113
Table 2.2. Eligibility Requirements for State Paid Family and Medical Leave Laws.....	114
Table 2.3. Parent population by perinatal employment status	115
Table 3.1. Number of individuals giving birth: APCD sample compared to statewide data.....	169
Table 3.2. Births by mother characteristics, APCD vs. other state data sources	170
Table 3.3. Perinatal employment statistics of mothers in APCD sample	172
Table 3.4. Take-up of PFML, all mothers regardless of eligibility	175
Table 3.5. Take-up of PFML, eligible mothers	176
Table 3.6. Take-up of PFML among eligible mothers, by mother characteristics	177
Table 3.7. Estimates of differences in mother characteristics around cutoff point.....	180
Table 3.8. Take-up of PFML by hours worked in qualifying period.....	181
Table 3.9. Estimates of the effect of threshold crossing on use of PFML	182
Table 3.10. Estimates of the effect of threshold crossing on quarterly employment outcomes (using UI wage reports)	189
Table 3.11. Estimates of the effect of threshold crossing on quarterly employment outcomes (using PFML wage reports)	191
Table 3.12. Estimates of the effect of threshold crossing on multiple-quarter employment outcomes (using UI wage reports)	209
Table 3.13. Estimates of the effect of threshold crossing on multiple-quarter employment outcomes (using PFML wage reports)	210
Table 3.14. Characteristics of mothers by selection into the bandwidth	213

List of Figures

Figure 1.1. Employment status and intensity among parents in the quarters around a birth	52
Figure 1.2. Mean earnings and hours worked among parents in the quarters around a birth	53
Figure 1.3. Rate of returning to the same employer following a birth.....	54
Figure 1.4. Earnings volatility among parents in the quarters around a birth.....	55
Figure 1.5. Employment patterns of mothers in the quarters around a birth: By race/ethnicity ...	56
Figure 1.6. Employment patterns of mothers in the quarters around a birth: By educational attainment.....	57
Figure 1.7. Employment patterns of mothers in the quarters around a birth: By wage rate	58

Figure 1.8. Mean household earnings in the quarters around a birth, all households	59
Figure 1.9. Volatility of household earnings in the quarters around a birth, all households	60
Figure 1.10. Mean household earnings in the quarters around a birth, by household type	61
Figure 1.11. Volatility of household earnings in the quarters around a birth, by household type	62
Figure 1.12. Receipt of means-tested benefits in the quarters around a birth, all households	63
Figure 1.13. Benefit amounts in the quarters around a birth, all households	64
Figure 1.14. Receipt of means-tested benefits in the quarters around a birth, by household type	65
Figure 1.15. Benefit amounts in the quarters around a birth, by household type: all households	66
Figure 1.16. Benefit amounts in the quarters around a birth, by household type: among recipient households.....	67
Figure 1.17. Household-level income around a birth, all households	68
Figure 1.18. Volatility of household income around a birth, all households	69
Figure 1.19. Household income in quarters around a birth, by household type	70
Figure 1.20. Volatility in household income around a birth, by household type: Standard deviation of arc percent change in income	71
Figure 1.21. Volatility in household income around a birth, by household type: Share of households experiencing income drop of 25% or more.....	72
Figure 2.1. Estimated eligibility for paid leave among mothers vs. fathers	116
Figure 2.2. Estimated eligibility for paid leave among mothers, by wage quintile in primary pre-birth job.....	117
Figure 2.3. Estimated eligibility for paid leave among mothers, by industry of employment ...	118
Figure 2.4. Estimated eligibility for paid leave among mothers, by educational attainment.....	119
Figure 2.5. Estimated eligibility for paid leave among mothers, by race and ethnicity	120
Figure 2.6. Effects of hypothetical earnings cutoffs on mothers' PFL eligibility	121
Figure 2.7. Effects of hypothetical hours cutoffs on mothers' PFL eligibility	124
Figure 3.1. Density of assignment variable (hours worked in PFML qualifying period) along eligibility threshold	179
Figure 3.2. Any PFML take-up by hours worked in qualifying period (using UI wage reports)	183
Figure 3.3. Any PFML take-up by hours worked in qualifying period (using PFML wage reports)	184
Figure 3.4. Bonding leave take-up by hours worked in qualifying period (using UI wage reports)	185
Figure 3.5. Bonding leave take-up by hours worked in qualifying period (using PFML wage reports)	186

Figure 3.6. Medical leave take-up by hours worked in qualifying period (using UI wage reports)	187
Figure 3.7. Medical leave take-up by hours worked in qualifying period (using PFML wage reports)	188
Figure 3.8. Employment status by hours worked in qualifying period (using UI wage reports)	193
Figure 3.9. Employment status by hours worked in qualifying period (using PFML wage reports)	194
Figure 3.10. Hours worked by hours worked in qualifying period (using UI wage reports)	195
Figure 3.11. Hours worked by hours worked in qualifying period (using PFML wage reports)	196
Figure 3.12. Earnings from work by hours worked in qualifying period (using UI wage reports)	197
Figure 3.13. Earnings from work by hours worked in qualifying period (using PFML wage reports)	198
Figure 3.14. Earnings from work plus PFML payments by hours worked in qualifying period (using UI wage reports)	199
Figure 3.15. Earnings from work plus PFML payments by hours worked in qualifying period (using PFML wage reports)	200
Figure 3.16. Worked for same employer (specification 1) by hours worked in qualifying period (using UI wage reports)	201
Figure 3.17. Worked for same employer (specification 1) by hours worked in qualifying period (using PFML wage reports)	202
Figure 3.18. Worked for same employer (specification 2) by hours worked in qualifying period (using UI wage reports)	203
Figure 3.19. Worked for same employer (specification 2) by hours worked in qualifying period (using PFML wage reports)	204
Figure 3.20. Worked for same employer (specification 3) by hours worked in qualifying period (using UI wage reports)	205
Figure 3.21. Worked for same employer (specification 3) by hours worked in qualifying period (using PFML wage reports)	206
Figure 3.22. Worked for same employer (specification 4) by hours worked in qualifying period (using UI wage reports)	207
Figure 3.23. Worked for same employer (specification 4) by hours worked in qualifying period (using PFML wage reports)	208
Figure 3.24. Multi-quarter employment outcomes across hours worked in qualifying period (using UI wage reports)	211
Figure 3.25. Multi-quarter employment outcomes across hours worked in qualifying period (using UI wage reports)	212

List of Appendix Tables

Appendix Table 3.1. Diagnosis and procedure codes used to identify births in All-Payer Claims Data.....	218
Appendix Table 3.2. Comparison of UI and PFML wage reports: Quarterly wages	222
Appendix Table 3.3. Comparison of UI and PFML wage reports: Quarterly hours	223

List of Appendix Figures

Appendix Figure 1.1. Hours worked by mothers, by race and ethnicity	73
Appendix Figure 1.2. Mothers' earnings, by race and ethnicity.....	74
Appendix Figure 1.3. Standard deviation of arc percent change in mothers' earnings, by race and ethnicity.....	75
Appendix Figure 1.4. Hours worked by mothers, by educational attainment	76
Appendix Figure 1.5. Mothers' earnings, by educational attainment.....	77
Appendix Figure 1.6. Standard deviation of arc percent change in mothers' earnings, by educational attainment	78
Appendix Figure 1.7. Hours worked by mothers, by wage quintile	79
Appendix Figure 1.8. Mothers' earnings, by wage quintile	80
Appendix Figure 1.9. Standard deviation of arc percent change in mothers' earnings, by wage quintile	81
Appendix Figure 1.10. Employment rates of mothers, by industry of employment	82
Appendix Figure 1.11. Hours worked by mothers, by industry of employment	83
Appendix Figure 1.12. Mothers' earnings, by industry of employment.....	84
Appendix Figure 1.13. Share of mothers returning to pre-birth employer, among those working in year following birth, by industry of employment	85
Appendix Figure 1.14. Standard deviation of arc percent change in mothers' earnings, by industry of employment	86
Appendix Figure 1.15. Share of mothers experiencing earnings drop of 25% or more, by industry of employment	87

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Introduction

When a child is born, parents—especially mothers—often experience changes to employment. Parents may take unpaid leave from work, work fewer hours, voluntarily leave a job, or even be fired (Laughlin, 2011). As a result, households frequently face reduced or less predictable income around the birth of a child—precisely the time increased resources are needed to cover expenses for the new child’s needs (Brandrup & Mance, 2011; Stanczyk, 2020). Employment and income instability around the time of a child’s birth has important short- and long-term consequences for parents and children. Earnings changes around birth are associated with health insurance coverage changes and gaps (Daw et al., 2017), increases in poverty (Bane & Ellwood, 1986; McKernan & Ratcliffe, 2005), financial planning challenges (Hacker et al., 2014; Morduch & Schneider, 2017), increased parent and child stress (Hardy, 2014; Sandstrom & Huerta, 2013), and adverse downstream effects on child development (Gennetian et al., 2015, 2018; Hardy, 2014; Hardy et al., 2019). In the longer term, employment instability around a birth may also be associated with permanent changes in the trajectory of parents’ future earnings, particularly for mothers (Altonji et al., 2013; Glauber, 2018; Lundberg & Rose, 2000; Yu & Kuo, 2017).

Household economic conditions around a birth are shaped by a broad array of public policies, including those that regulate the labor market, child care, health care, taxation, and public benefit provision. For example, several means-tested benefit programs are targeted at families with young children, and may provide additional resources to support household incomes in the perinatal period (Hill, 2012; Stanczyk, 2020). In addition, paid family and medical leave is discussed as a potentially promising way to smooth perinatal income disruptions, reduce employment instability, and support caregiving (Rossin-Slater, 2018). In the

absence of a federal paid leave mandate, researchers and policy decisionmakers are looking to the handful of states that have innovated in this area in the last decade or so for lessons on the effects of such policies (Jacobs, 2018).

Research suggests that employment changes related to childbirth affect parents and households unequally (Hill et al., 2021). For example, single-mother households without other adults present experience significantly larger percentage reductions in household income around a birth (Stanczyk, 2020). Mothers with lower educational attainment reduce work earlier in pregnancy, return to work less quickly after a birth, and experience larger declines in household income (Laughlin, 2011; Stanczyk, 2020). Poverty rates around a birth are significantly higher for Black and Latina mothers than for White mothers (Hamilton et al., 2023). Mothers who have recently immigrated to the U.S. are less attached to the labor force than U.S.-born women (Lu et al., 2017). While either parent may experience a spell of not working around the time of a birth, having children disproportionately affects the earnings of mothers more than fathers. Women with children tend to earn less than women without children, while the opposite is true for fathers (Budig & England, 2001; Glauber, 2018; Lundberg & Rose, 2000; Yu & Kuo, 2017); disparities emerging from employment disruptions around the time of a birth are a likely contributor to the overall gender wage gap (Waldfogel, 1998).

Policy responses could ameliorate or exacerbate these inequalities. In the case of paid leave, working parents of color, particularly Latinx parents, and parents working in lower-wage jobs are less likely to report having access to paid parental leave compared to White working parents and working parents earning higher wages (Gault et al., 2014). These findings suggest that state paid leave mandates, which apply to a broader group of parents, could make access to leave more equitable. Public assistance programs that target lower-income and/or single-parent

households may also narrow perinatal income inequalities by helping families most likely to experience income reductions and poverty around a birth (Stanczyk, 2020). However, inequalities remain in parents' ability to access paid leave programs, suggesting that it is not clear whether they would reduce inequalities in perinatal economic conditions (Goodman et al., 2020, 2021; National Partnership for Women & Families, 2018; Setty et al., 2016).

Despite the prevalence of perinatal income disruptions and significant interest in work-care reconciliation policies, research on these topics has had gaps and limitations. In response, this dissertation contributes new evidence on the economic conditions of parents of newborns and the potential of paid leave policies to equitably support new parents.

Overview

This dissertation consists of three empirical studies that all use administrative microdata from Washington State to study employment, income, and the implications of paid leave policies among parents of newborns. My first chapter aims to better describe the employment and income trajectories of households that welcome a new child. I report trends in employment and income levels and volatility among Washington parents in a two-year period around a birth. The study uses multiple measures to explore trends in parental employment instability for all Washington State parents, and across racial groups, educational attainment, and wage rate quintile. Then, the study assesses trends in income from earnings as well as means-tested safety net programs at the household level around a birth. Next, the second chapter studies differences across state paid leave policies in the U.S. Leveraging Washington State data, I simulate working parents' eligibility for claiming paid leave under ten different states' policies. This study aims to assess how state policy design affects overall eligibility rates and disparities in eligibility for these programs. Finally, the third chapter examines Washington State's Paid Family and Medical Leave policy in greater detail. This study aims to describe use of this policy in its first two years

among mothers who gave birth. Then, I use a regression discontinuity design to estimate the causal effects of the policy on employment around a birth.

Taken together, these studies move forward the research literature in several ways. I discuss the contribution of each chapter in more detail below, but first highlight a few main points here. First, there is a need for research that explores employment instability around a birth with more nuance – to understand heterogeneity in which parents experience various forms of instability, and what role means-tested safety net programs play. Heterogeneity in parent experiences of employment disruption around birth has been less studied in the prior literature compared to overall trends, partly due to data limitations (Stanczyk, 2020). This dissertation also addresses a limitation of the literature on earnings volatility, which has tended to focus more on male earnings in part because of analytic complexities with studying mothers' employment in the early years of a child's life; instead, the studies in this dissertation address the time around a birth directly. The literature on state paid family leave policies has typically estimated the effect of specific state policies and has not compared across states; Chapter 2 works towards addressing that limitation by directly comparing features of the state policies. It can be difficult to estimate take-up rates for any policy, including paid leave, but Chapter 3 uses merged administrative data to overcome this challenge by identifying a population with both a potential need for the policy (i.e., the birth of a child) and the employment history to qualify them for the state's program. Finally, Chapter 3 presents the first causal study of the effects of Washington State's paid leave policy.

Each paper uses administrative microdata in novel ways. Chapters 1 and 2 leverage the Washington Merged Longitudinal Administrative Data, a collection of administrative records from seven Washington State agencies generally covering the period between 2010 and 2017

(Romich et al., 2018). Chapter 3 incorporates separately requested records from the state's All-Payer Claims Database and Employment Security Department. In each of these projects, collaborations with state policy and research staff made the work possible and significantly enriched the final products. The use of administrative data offers several advantages. Researchers studying parental employment and paid leave have often relied on survey data (Baum & Ruhm, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019; Ybarra et al., 2019), using self-reported earnings and employment information. Survey data is subject to recall bias, social desirability bias, and non-response bias, problems that have been shown to be increasing in recent years (Meyer et al., 2015). There is evidence that these issues disproportionately bias earnings data on low-income respondents. Survey bias has become especially acute during the Covid-19 pandemic, posing serious problems for the study of employment and economic wellbeing during this time period (Rothbaum & Hokayem, 2021). Surveys also have smaller sample sizes that can prevent researchers from identifying precise time trends and conducting sub-group analyses, and they are often limited in the ability to follow individuals over time. I discuss the specific advantages of each administrative data resource throughout the papers.

Summary of Chapter 1

In Chapter 1, I analyze patterns of earnings and employment among parents who were listed on birth certificates in Washington State between 2010 and 2016. First, I present a detailed analysis of parental earnings patterns around childbirth. Using birth certificate records merged to quarterly employment records, I track multiple metrics that capture parents' employment and earnings in a two-year period surrounding a birth: employment rate, earnings and hours levels, employer continuity, and earnings volatility. I present results for all mothers and fathers and then report results for mothers disaggregated by racial and ethnic identity, educational attainment, and wage rate quintile. Next, I use the linking of parents on the same birth certificate to approximate

household-level measures of earnings and income in the perinatal period. I merge data on means-tested safety net programs to also assess the role that these public assistance programs play in the time around a birth. I report trends in program use in the two-year period surrounding a birth. Finally, I report on household earnings plus program benefits. Household-level analyses explore how perinatal earnings and income differ between single- and two-parent households.

I find that parents in Washington State experience substantial earnings volatility when a child is born. Results also demonstrate inequalities in experiences of economic volatility around a birth. Aggregating earnings of both parents listed on a given birth certificate to calculate household-level measures does attenuate the volatility faced by individual parents, but substantial instability still remains. For example, over half of Washington households see their income fall by half or more during the year around a birth. Use of means-tested programs does increase in the perinatal period, which offsets earnings volatility slightly (especially for single mother households).

Summary of Chapter 2

Chapter 2 uses Washington State data to better understand differences across state paid leave policy designs in ten states. This paper assesses the implications of paid leave eligibility requirements for the share of parents of newborns who would be eligible for paid leave. I also examine whether the eligibility requirements generate disparities in eligibility across parent demographic, socioeconomic, and employment characteristics. State policies determine eligibility for paid leave based on employment histories in a qualifying period – usually approximately a one-year period before a qualifying event. Like in Chapter 1, I use birth certificate records merged to employment records. I use these records to capture parents’ work histories in the qualifying period relative to a birth, then simulate the rate of Washington parents who would have been eligible for claiming paid leave under ten different states’ policies.

I find that state policy designs differ dramatically both in terms of overall generosity and disparities in eligibility across subgroups. In general, policies that are less restrictive and allow more parents to access paid leave also significantly narrow disparities in who is eligible. State policies with more stringent employment requirements disproportionately exclude mothers (versus fathers); mothers working in low-wage jobs; mothers with lower educational attainment; and Black, Indigenous, and Latina mothers from qualifying for paid leave.

Summary of Chapter 3

Finally, I analyze Washington State's new Paid Family and Medical Leave (PFML) program. Starting in 2020, parents who worked at least 820 hours in Washington in the year before a birth qualify for up to twelve weeks of paid leave to bond with a new child. In addition, mothers can take additional leave for pregnancy and related health conditions. I describe use of the policy in its first few years. I address two research questions: First, what share of mothers of newborns use PFML around the time of a birth, and how does access to the policy vary across demographic and employment characteristics? Second, what is the causal effect of the PFML policy on maternal employment around a birth – including employment status, earnings and hours levels and volatility, and employer continuity? To answer these questions, I integrate records from two administrative data sources. Health insurance data on birth-related insurance claims from the Washington State All Payer Claims Database identify a population of potential policy users: mothers who gave birth. Employment and paid leave records from the state's Employment Security Department provide detailed quarterly data on hours worked, wages earned, employer characteristics, and paid family and medical leave claims. These records enable me to identify a population of potential policy users, precisely estimate policy eligibility and take-up, and assess how PFML access affected employment.

I use these data to estimate the percentage of mothers of newborns who took paid leave, then calculate take-up rates disaggregated by mother demographic and socioeconomic characteristics to analyze how equitable access to the program was. This analysis reveals that a majority of eligible Washington mothers who give birth between 2020 and 2022 use PFML at some point during the perinatal period. Take-up increases between 2020 and 2022 as the policy rolls out, especially for medical leave. Analysis of policy take-up by mother characteristics reveals some important disparities. For example, results suggest that eligible Native Hawaiian/Pacific Islander and American Indian/Alaska Native mothers are less likely to take up paid bonding and medical leave than mothers identifying with other racial and ethnic groups. Mothers in more urban areas are more likely to take up both types of leave. There are sharp disparities by wage rate; for example, only 30 percent of eligible mothers in the lowest-wage jobs took up bonding leave compared to 67 percent of mothers in the highest-wage jobs.

Regression discontinuity estimates of the local average treatment effect of PFML eligibility on mothers around the eligibility threshold found mixed and somewhat inconclusive results. There is some evidence that eligibility for PFML has small negative effects on employment status and intensity (i.e., hours worked) in the short term. However, this largely does not translate into significant reductions in total earnings (including wages plus PFML benefits), suggesting that mothers, on average, are able to spend more paid time off with their children without experiencing income reductions. There is relatively consistent evidence that PFML eligibility is associated with an increase in continuity of work with the same employer.

Chapter 1 : Parental Employment and Income Instability Around the Birth of a Child: Prevalence, Disparities, and the Role of Means-Tested Programs

Introduction

Earnings volatility is prevalent over the life course, and large drops in earnings are a relatively common experience for individuals and households. In 2016, for example, 39% of working-age adults in the U.S.—and 56% of low-income working-age adults—lived in a household where income fell 25% relative to the overall yearly average in one or more months (Maag et al., 2017). Among the low- and moderate-income families included in the U.S. Financial Diaries project, families tended to have between two and three months of the year when their income was 25% or more below their annual average (Morduch & Schneider, 2017). The time around when a child is born can be particularly economically volatile for families, due largely to parental employment changes around a birth. Parents, especially mothers, may take unpaid leave from work, work fewer hours, voluntarily leave a job, or even be fired (Laughlin, 2011). As a result, households frequently face reduced or less predictable income around the birth of a child – precisely the time increased resources are needed to cover expenses for the new child’s needs (Brandrup & Mance, 2011; Stanczyk, 2020).

This employment and income instability around the time of a child’s birth has the potential to have short- and long-term consequences for parents and children. In the short term, earnings changes around birth are associated with health insurance coverage changes and gaps (Daw et al., 2017), increases in poverty (Bane & Ellwood, 1986; McKernan & Ratcliffe, 2005), financial planning challenges (Hacker et al., 2014; Morduch & Schneider, 2017), increased parent and child stress (Hardy, 2014; Sandstrom & Huerta, 2013), and adverse downstream effects on child development (Gennetian et al., 2015, 2018; Hardy, 2014; Hardy et al., 2019). In

the longer term, employment instability may also be associated with permanent changes in the trajectory of parents' future earnings, particularly for mothers (Altonji et al., 2013; Lundberg & Rose, 2000). Evidence shows that working mothers reduce employment around the time of a birth (Byker, 2016; Hotchkiss et al., 2008; Lu et al., 2017), while fathers' employment tends to remain steady or increase slightly (Glauber, 2018).

Perinatal employment instability does not affect all families equally and can have distributional consequences (Gault et al., 2014; Hotchkiss et al., 2008; Pilkauskas et al., 2016). For example, working parents of color and parents working in lower-wage jobs are less likely to report having access to paid parental leave compared to White working parents and working parents earning higher wages (Gault et al., 2014; Goodman et al., 2021). Research also demonstrates differences in perinatal income volatility across household structure; single-mother households are more likely to experience large income declines around a birth compared to two-parent households (Stanczyk, 2020).

Public assistance programs could help families smooth income when faced with earnings changes (Blundell et al., 2008; Blundell & Pistaferri, 2003; East & Kuka, 2015). Multiple programs that provide cash or near-cash assistance are either specifically targeted at families with young children or encourage eligibility among this population by, for example, waiving work requirements for families with newborns. Studies have shown that use of means-tested programs increases around a birth. However, these programs do not fully attenuate changes in earnings (Stanczyk, 2020).

Despite the prevalence and potential consequences of perinatal economic disruptions, research on household earnings and income volatility has not fully engaged with the time around a birth. In fact, much of the literature on individual-level earnings volatility has focused solely on

male earners to avoid perceived analytic complications from the expected volatility of women's earnings, referred to in one paper as the "complexities of the female nonparticipation decision" (Guvonen et al., 2015, p. 1). Furthermore, while structural inequalities in the labor market and inadequacies in parental leave policies are well-documented, evidence on heterogeneity in economic instability around a child's birth is limited (Stanczyk, 2020). Data limitations often restrict researchers to focusing on fairly blunt measures of household wellbeing, such as overall yearly income or whether or not parents were employed, or prevent researchers from breaking out these analyses by subgroup. Much of the current research on perinatal economic circumstances has used survey data, which is limited in several ways discussed in more detail below. In addition, work on the extent to which the social safety net smooths earnings volatility (Hardy, 2017) has typically focused on year-to-year income changes, which obscures instability that families experience on a shorter time scale.

This paper contributes new evidence to this literature, leveraging administrative microdata from Washington State to examine volatility in parental employment and household income around the time of a birth with new levels of detail. Bridging research on earnings and income volatility with research on perinatal economic circumstances, this study demonstrates that the time around a birth is essential to understanding economic volatility. First, a descriptive analysis of employment around a birth illustrates perinatal trends in employment and heterogeneity in these outcomes across demographic and employment characteristics of parents. I explore trends in parental employment instability for all Washington State parents, and across racial groups, educational attainment, and wage rate quintile. Multiple measures of economic vulnerability depict a variety of employment and earnings volatility experiences that workers may encounter. Trends in employment rate, earnings and hours levels, likelihood of returning to

the same employer, and earnings volatility are reported. Next, the linking of parents on birth certificates is leveraged to examine *household-level* measures of economic wellbeing and volatility in the perinatal period. The analysis describes household earnings levels and volatility around a birth. As far as I am aware, this is the first paper that directly connects earnings volatility to the perinatal period by analyzing how measures commonly used to study earnings volatility vary around a birth. Next, I explore the role of means-tested safety net programs in supporting families' earnings during this time. Analyses depict trends in use of three programs in the perinatal period and explore how they affect families' income levels and volatility: Supplemental Nutrition Assistance Program (SNAP), also called Basic Food in Washington; Working Connections Child Care (WCCC), the state's child care subsidy; and Temporary Assistance for Needy Families (TANF).

Research on employment and income around a birth

A substantial body of literature has studied parental employment and earnings and, to a lesser extent, household-level measures of income and earnings around the time of a birth. In this section, I review what is known about households' economic conditions in the perinatal period and the effects of perinatal economic trends on longer-run outcomes..

Parental employment¹

Research demonstrates that mothers significantly reduce employment around the time of a birth, particularly at the end of pregnancy and in the first few months after a child is born (Florian, 2018; Han et al., 2011; Hotchkiss et al., 2008; Lu et al., 2017). In one study, for example, the transition to parenthood in a given year was found to be associated with a 26% reduction in earnings for married mothers and an 11% reduction for single mothers (Harkness,

¹ Studies of parental employment around a birth often focus on mothers. I note when studies focus on mothers and when they address outcomes among parents more broadly.

2022). Researchers have found that mothers weigh costs and benefits of these employment decisions based on factors that affect the marginal utility of working compared to not working, such as health concerns of the child, marital status and spouse earnings, and characteristics of their jobs pre-birth (Desai & Waite, 1991; Hotchkiss et al., 2008; Ramos-Olazagasti et al., 2014). The dynamic between mothers' own earnings and overall family income appears to affect mothers' employment decisions, for example. While mothers with higher wages are more likely to return to work earlier (all else being equal), higher income of the entire family unit was associated with mothers delaying employment following a birth (Leibowitz et al., 1992).

Some research has documented heterogeneity in employment around a birth across demographic and socioeconomic characteristics of parents. Findings on the economic conditions of parents around the time of a birth by race and ethnicity are somewhat mixed. Lu et al (2017) find that Black, Hispanic, and Asian women have stronger labor force attachment in the year following a birth compared to White women. Mothers who have recently immigrated to the U.S. are less attached to the labor force than U.S.-born women (Lu et al., 2017). More highly-educated mothers work later into pregnancy and return to work more quickly after a birth (Laughlin, 2011).

Employment disruptions around a birth may be associated with permanent changes in the trajectory of parents' future earnings (Hotchkiss et al., 2017). Wages in jobs taken following spells of unemployment tend to be lower than previous jobs, both because jobs following unemployment tend to be lower-wage and because the disruption from unemployment results in shorter tenure at the new employer (Altonji et al., 2013). While either parent may experience a spell of not working around the time of a birth, having children disproportionately affects the earnings of mothers more than fathers. A large body of work has studied the "motherhood wage

penalty,” finding that women with children tend to earn less than women without children, while the opposite is true for fathers (Budig & England, 2001; Glauber, 2018; Lundberg & Rose, 2000; Yu & Kuo, 2017). Work on the causes of the motherhood wage penalty has found that differences in wages between women with and without children can be accounted for by accumulated months not in the labor force and not in school (Staff & Mortimer, 2012). Since fathers do not experience this wage penalty and may in fact experience a premium, disparities emerging from employment disruptions around the time of a birth are a likely contributor to the overall gender wage gap (Waldfogel, 1998).

Household income and poverty

At the household level, as well as for individual parents, the time around a birth is associated with reductions in income and increased risk of poverty (Hamilton et al., 2023; Stanczyk, 2020; Stevens, 2012). The association between the birth of a child and entering poverty is partly because increasing family size raises the poverty threshold for families, but also partly due to reductions in income that occur around a birth. One study on poverty rates around a birth between 2013 and 2019 found that between the month before a birth and the month after, families’ poverty rate rose 8 percentage points (from 17.5 to 25.2%) (Hamilton et al., 2023). In a study of causes of poverty entrances, McKernan and Ratcliffe (2005) find that the likelihood of entering poverty in a given month increases by 2.7 percentage points when a child under the age of six enters the household. Of all the poverty triggers the authors studied, having a young child enter the household had the second strongest association with poverty entrance – after losing a job (job loss of the head of household was associated with an 11 percentage point increase in likelihood of poverty entry). Stanczyk (2020) conducts an in-depth analysis of household economic circumstances around a birth with a framework of income adequacy, tracking trends in household income relative to the Federal Poverty Level (FPL) in the months preceding and

following a birth. Income adequacy declines significantly around the time of a birth, and these declines are largely driven by declines in mothers' earnings. Some studies have also connected household income changes to experiences of material hardship, which capture families' ability to afford essential resources. In a sample of low-income single mothers of infants (with pre-birth family income at or below 200% of FPL), Ybarra et al. (2019) found material hardship to be prevalent around the time of a birth. Forty-one percent of their sample did not meet essential expenses (as defined by respondents) in the year after birth, 20% did not pay their rent or mortgage, and 33% did not pay a gas, oil, or electricity bill. Some research has also assessed disparities in poverty around a birth across demographic characteristics, though evidence on this is more limited. Ybarra et al. (2019) find some evidence that Black, low-income single mothers experience more material hardship than other low-income single mothers. Hamilton et al. (2023) find that poverty rates around a birth are significantly higher for Black and Latina mothers than for White mothers.

A deep research literature has studied the effects of economic disadvantage in childhood on child outcomes, reinforcing the importance of parents' income and earnings in the time around and after a birth. Research has documented that poverty in early life can have detrimental effects on children's health, development, educational achievement, and even economic wellbeing in adulthood (Duncan et al., 2014; National Academies of Sciences, Engineering, and Medicine, 2019). Poverty affects cognitive developmental and educational outcomes through multiple mechanisms, including material hardship, parent stress, and households' capacity to invest in child development (including through high-quality early care and education) (Chaudry & Wimer, 2016). Furthermore, findings that these effects may be especially pronounced for

children experiencing poverty early in childhood (Chaudry & Wimer, 2016; Wagmiller et al., 2006) underscore the importance of economic wellbeing in a child's earliest years of life.

Earnings and income volatility

Few studies explicitly examine the link between employment around childbirth and earnings and income volatility, but research on gender differences in earnings volatility provides suggestive insights. Ziliak et al. (2011) find that earnings volatility is higher for women than for men. However, volatility fell for women between 1973 and 2009, while it rose for men, suggesting that these trends are on track to converge. The sex gap in earnings volatility therefore appears to be closing over time, indicating that variability in men's and women's earnings have become more similar in recent decades. This has happened alongside a rise in female labor force participation and, specifically, a rise in employment among mothers with children (Laughlin, 2011). Also, the decomposition of earnings variance accounted for by continuous employment variation (i.e., within-job or between-job changes) compared to transitions into and out of the labor force is becoming more similar for men and women over time. However, key differences in earnings dynamics remain. Interestingly, Ziliak et al. (2011) find that for men, earnings volatility is countercyclical; that is, an increase in the unemployment rate is associated with an increase in volatility. In contrast, for women, earnings volatility is procyclical, such that earnings volatility declines for women with an increase in the unemployment rate. The authors do not offer an in-depth interpretation of these findings, suggesting that more work is needed to understand earnings dynamics differences by sex.

While studies of earnings and income volatility have not directly addressed heterogeneity in volatility around the time of a birth, researchers studying economic volatility more broadly have estimated how volatility varies across race and ethnicity, socioeconomic status, and household structure. Black and Hispanic individuals experience overall higher economic

insecurity compared to White individuals (Hacker et al., 2014), and Black families experience uniformly higher variability in earnings, regardless of the macroeconomic context (Hardy, 2017). Family income volatility is higher among the bottom 10% of the income distribution compared to the top 10% (Hardy & Ziliak, 2014), and households in the lowest income quintile are significantly more likely to experience an income change of 50% or more over the previous year (Dahl et al., 2011). Single-earner households experience more earnings volatility and economic instability than multiple-earner households (Dahl et al., 2011; Hacker et al., 2014; Hardy, 2017).

Researchers have examined the effects of earnings and employment volatility, including some work that has looked specifically at families around the birth of a child. In the short term, parents commonly experience health insurance coverage changes and gaps around birth, due at least in part to changes in employment (Daw et al., 2017). Research on earnings volatility more broadly has identified a number of adverse effects that emerge from a lack of stability in earnings. Changes to household earnings can make financial planning difficult (Hacker et al., 2014; Morduch & Schneider, 2017), increase parent and child stress (Hardy, 2014; Sandstrom & Huerta, 2013), and can have adverse downstream effects on child development (Gennetian et al., 2015, 2018; Hardy, 2014; Hardy et al., 2019; Hill et al., 2013).

The role of means-tested programs

In the absence of or in addition to paid leave, households may be eligible for means-tested public assistance programs that could support household income around the time of a birth (Hill, 2012; Stanczyk, 2020; Ybarra et al., 2019). Circumstances around a birth could influence eligibility for public programs in potentially contradictory ways. First, if parents reduce work around a birth, they may no longer qualify for programs that require earned income. However, several programs are targeted at parents with young children, having eligibility requirements or benefit schedules that are determined based on the number of children in the home. Therefore,

having an additional child could increase eligibility for programs or increase the benefit amounts received. Furthermore, in the case of Temporary Assistance for Needy Families (TANF), various states have at times elected to waive work requirements for single mothers with infants (Hill, 2012).

Researchers have documented the overall prevalence of program use among different samples of parents with young children. For example, Slack et al. (2014) study benefit use among a sample of mothers who had income less than 200% FPL when their child was one year old. A significant majority of these mothers participated in Medicaid (73%). However, receipt of other types of government assistance was less common, likely due to Medicaid's relatively higher income eligibility thresholds in contrast to other means-tested programs. Less than half of these mothers received SNAP benefits (41%), and even fewer received TANF benefits (28%) and the Earned Income Tax Credit (EITC) (28%). Seventeen percent of mothers received child support, 16% received housing subsidies, 7% received child care subsidies; 7% received SSI; and 4% received Unemployment Insurance. Studying a broader sample of all households with births during data collection in the 1996-2008 panels of the Survey of Income and Program Participation, Stanczyk (2020) builds on this knowledge of what share of low-income mothers use means-tested programs around a birth by tracking changes in benefit receipt over time during the perinatal period among a broader, nationally representative sample of households. Stanczyk finds that the share of income coming from public programs (relative to all other sources of income) increased significantly around the time of a birth, starting to increase (relative to pre-birth levels) in the later months of pregnancy and peaking in the second month after the birth. Absolute income amounts coming from SNAP, WIC, TANF, the EITC, and the CTC increased around the time of a birth. Public programs were especially important among single-mother

households with no other adults present, for whom more than half of overall income came from public programs in the birth month. On average, across all families, there was a sharp decline in mothers' earnings as a share of household income and a sharp increase in public programs as a share of income for single-parent families. While the presence of means-tested programs did attenuate income declines resulting from reduced earnings, they did not fully compensate for earnings reductions; household income adequacy still declined following a birth after accounting for these sources of income. Gross household income, including public programs but not accounting for the increase in needs resulting from increased household size, is significantly lower than pre-birth levels from the month before a birth to three months after. Stanczyk also uses an income-to-needs measure that takes into account public program income as well as the increase in household needs generated by the addition of the new baby. Using this measure, household income adequacy remains 18% lower one year after a birth than one year before a birth. Stanczyk's findings are mirrored in a study of poverty around a birth (Hamilton et al., 2023), and qualitative research has found similar themes in interviews with low-income mothers of infants, who expressed that safety net programs were inadequate to meet family needs in the first year of their children's lives (Marti-Castaner et al., 2022).

The current study

This study addresses the following research questions. First, what is the prevalence of employment instability around a birth among parents of newborns in Washington, including employment intensity, employer continuity, and earnings volatility? How does perinatal employment instability vary by demographic and employment characteristics? How does household earnings change around a birth, and how does this vary by family structure? Finally, what is the contribution of means-tested programs to household income around a birth? Do these

programs mitigate the household economic instability that results from perinatal employment changes?

I use linked longitudinal microdata from birth records, Unemployment Insurance wage records, and public assistance program records to analyze patterns of parental employment and household earnings and income around a birth. This study leverages the unique advantages of a novel administrative data resource in Washington State, the Washington Merged Longitudinal Administrative Data (WMLAD) (Romich et al., 2018). WMLAD is a compilation of merged longitudinal datasets from six Washington State agencies linked with a single unique identifier. Dr. Jennie Romich (Principal Investigator, WMLAD) worked with staff at the Washington State Department of Social and Health Services, Research and Data Analysis (RDA) to create WMLAD through data-sharing agreements with multiple state agencies and approval from the Washington State IRB (Romich et al., 2018). The resulting dataset is held on a secure server through the University of Washington Data Collaborative. These data are well-positioned to describe earnings and income in the perinatal period; I am able to examine quarterly income dynamics and disaggregate results by subgroup with precise detail.

This project builds on the current literature by addressing several limitations of prior research. First, most past studies of parental employment around birth rely on survey data, which is subject to concerns about recall bias, social desirability bias, and non-response bias. There is evidence that these problems have been increasing in recent years (Meyer et al., 2015). The administrative data used in this project are not subject to the same biases that arise from survey research.

Second, the existing literature has been limited in the types of employment outcomes that can be examined. Detailed longitudinal information on employment history, with a high degree

of temporal granularity, and linked to data on birth timing, often cannot be ascertained. The rich nature of the WMLAD administrative data allows for more nuanced measures of employment instability. The data links detailed quarterly employment histories, including information on hours worked, wages earned, employer size, and industry code, to birth records. This allows the construction of new measures of employment instability around birth, beyond the typical focus on static earnings and income. Washington is one of few states that reports hours worked in UI records, allowing analyses of employment intensity that would not be possible in other states. I can estimate the prevalence of different forms of employment instability across the complete population of biological parents listed on Washington birth certificates between 2010 and 2016.

Third, there is a need for more evidence on heterogeneity in experiences of employment instability; that is, which demographic, socioeconomic, and employment characteristics are associated with these outcomes. Heterogeneity in parent experiences of employment disruption around birth has been less studied in the prior literature compared to overall trends, potentially due to data limitations (Stanczyk, 2020). Also, because of survey sample sizes, the studies that do look at heterogeneity in parental economic conditions have often been limited to studying larger groups. In contrast, the administrative data used in this project allow for granular analyses due to the large sample size and also capture a number of salient characteristics. I use the detailed demographic data in the Washington birth records to provide new evidence about which parents are most at risk of different forms of employment disruptions. The birth records contain rich data on parent demographic and socioeconomic characteristics, including parent-reported indicators of racial and ethnic identity, sex, and educational attainment.

Finally, this study bridges the literature on earnings volatility with research on economic conditions of parents the time around a birth. Studies of earnings volatility often focus on male

earners and have not fully engaged with female workers' experiences of employment and earnings instability. This study begins to fill this gap by directly addressing the employment experiences of mothers around the time of a birth.

It is important to note that economic changes around a birth may be intentional and/or planned for. Some families may be able to better weather these changes by, for example, using savings to retain adequate resources while earnings are reduced (Jappelli & Pistaferri, 2010). However, not all households can smooth consumption in the face of an income shock; households with lower wealth or higher levels of debt reduce consumption more when faced with a reduction in income (Baker, 2018; Blundell & Pistaferri, 2003; Ganong et al., 2020). Variation in families' ability to plan for or weather changes to earnings and income is outside the scope of this paper, which focuses instead on describing earnings and income around a birth with the acknowledgment that not all households will experience these changes equally.

Policy context: Births in Washington State, 2010-2016

I focus on births occurring between 2010 and 2016. This study period was prior to the passage of the state's Paid Family and Medical Leave (PFML) policy, which would later expand access to paid family and medical leave for a large portion of the state's parents starting in 2020. During the study period, prior to PFML implementation, wide variation existed in access to parental leave in Washington, with paid leave largely provided by employers. This pre-PFML policy environment in Washington is quite similar to that faced by parents in the majority of states who have not implemented paid leave policies at the state level.

The analysis also examines three public assistance programs² that were available to some parents in the sample during this time. All three programs are means-tested assistance programs

² Families may also receive support from other programs, notably tax credits such as the Earned Income Tax Credit and the Child Tax Credit. However, information on these benefits is not contained in Washington State administrative records.

that provide cash or near-cash resources to families, and all have eligibility rules that demonstrate an intention to specifically benefit families with young children. SNAP, also known as Basic Food in Washington, is a means-tested program that provides cash-like vouchers that can be used to purchase for households with income less than 200% of the Federal Poverty Level (FPL). Benefit amounts vary by household size; for example, in 2015, the maximum benefit amount was \$357 per month for a family of 2, \$511 for a family of 3, and \$649 for a family of 4 (U.S. Department of Agriculture, 2024).

The Temporary Assistance for Needy Families program provides cash assistance for pregnant women or families with children with very low assets. TANF benefit amounts are based on family size and income, with families with lower income receiving higher benefit amounts. For example, the maximum benefit amount that would be received by a family with no income was \$385 for a family of two, \$478 for a family of one, and \$562 for a family of four (Washington State Senate Committee Services, 2015). Eligible applicants must also participate in Washington's WorkFirst program, a program in which individuals participate in job search and work preparation activities; however, these requirements are waived for parents with children under the age of two.

Finally, Working Connections Child Care subsidizes the cost of childcare for families with income at or below 200% of FPL. Households are eligible for WCCC if parents engage in approved activities, including employment, education (if coupled with partial employment), or WorkFirst activities associated with the receipt of TANF. Families pay a co-pay for childcare dependent on their income, with the lowest-income families exempted from paying. Unlike SNAP and TANF, WCCC recipients are required to work or participate in other approved employment- or training-related activities even if they are pregnant or have young children.

Data and measures

This analysis uses administrative data from the state of Washington to examine employment histories for the population of parents who were listed on a birth certificate in the state between 2010 and 2016. I use data from three primary sources within WMLAD. First, Washington State Department of Health (DOH) records identify births occurring during this period linked to information on parents. Unemployment Insurance records from the Washington State Employment Security Department (ESD) report quarterly employment hours and earnings for all workers in the state. Finally, public assistance program records from the state's Department of Social and Health Services (DSHS) report on use and benefits from means-tested public assistance programs in the state.

DOH birth records

Birth certificate records contain rich information about biological parents listed on a child's birth certificate, including race/ethnicity, nativity, age, and education. Birth certificates initially request information on the biological mother and father, regardless of whether those individuals will be the child's guardians. Parents who wish to change information on the birth certificate to reflect more accurately the guardianship can do so after the birth certificate is filed. The data do not reflect these later changes. This means that in the case of same-sex parents or other cases of surrogacy, adoption, or sperm donation, there may be some biological parents included in the analysis who do not have financial or instrumental parenting responsibilities. However, this is likely a small share of the overall birth records.

Due to HIPAA regulations, the birth records available in WMLAD do not include the date of birth. To identify the timing of the birth relative to quarters of employment, therefore, I impute the missing birth quarter using birth certificate number. Birth certificate numbers are assigned when records are received by WA DOH, which corresponds closely to the temporal

ordering of births throughout the year. Since births do not occur evenly throughout the year, I use reports published by DOH to identify the monthly distribution of births each year in Washington (i.e., what percentage of that year's births occurred in January, February, etc.). I then apply this monthly distribution to the records sorted by certificate number for each year in the birth data. For example, if 8.1% of 2014 births occurred in January, I assume that the first 8.1% of records (sorted by certificate number) were births that occurred in January. I then assign birth quarters based on the estimated birth month.

ESD Unemployment Insurance wage reports

Second, Unemployment Insurance (UI) records from ESD provide data at the worker-job-quarter level on hours worked, wages earned, and employer characteristics for all work in UI-eligible jobs in the state of Washington. The records include employer characteristics, such as industry classification and firm location, and also contain an employer identifier that can be used to identify continuity of a worker's employment with the same firm. The UI data do not include work for employers located outside the state, self-employment as an independent contractor (i.e., 1099 employment), or "under-the-table" employment. A significant group of workers that is likely to be underrepresented in these data is undocumented immigrants. Also, employers are not required to report hours that an employee takes leave while employed except in the case of vacation leave (PTO). If an employee was offered paid parental leave or paid sick leave by the employer and used that leave, those hours were not recorded in the UI data and thus appeared to be *non-working hours* in the analysis. For this reason, when I show shares of mothers and fathers with no or reduced hours of work around a birth, I cannot interpret whether this is due to unemployment, leaving the labor force, or being employed and on leave.

DSHS program records

Finally, records from DSHS reports on receipt and benefit amounts for three key means-tested safety net programs: SNAP, WCCC, and TANF. I aggregate program benefit amounts to the assistance unit level, a grouping of individuals who apply for benefits as a single administrative unit. For each birth, I calculate all benefits received by an assistance unit of which the mother was a member. Summed up, that is the benefit amount received by each household in a given quarter. I report on whether or not households received benefits from each program in a given quarter, as well as average benefit amounts received.

Study population

This analysis studies employment patterns among biological mothers and fathers listed on a birth certificate filed in Washington between 2010 and 2016. The analysis focuses on adult (18 years or older) working parents, defined as working 100 or more hours in the year prior to the birth. The sample is referred to as “working parents” throughout the paper. Table 1.1 reports annual sample sizes for the working parent sample as a share of all parents included in the DOH birth records.

[Table 1.1 about here]

Household-level analyses

While the first set of analyses focuses on working parents as the unit of analysis and describes individual-level employment trajectories, I then present analyses that estimate how *household-level* measures of earnings and income evolve around the time of a birth. I use two approximations of household membership that rely on different assumptions about household membership based on birth certificate data. Household Specification 1 constructs membership in a household associated with a birth according to the question in the birth certificate data asking whether or not the mother is married. If the birth certificate indicates the mother is married, Household Specification 1 includes both the mother and father listed on the birth certificate to

calculate household earnings. If the birth certificate indicates the mother is not married, Household Specification 1 only includes the mother's earnings to calculate household earnings and income measures. This specification could underestimate household earnings if the mother and father are not married but belong to the same household. Assuming that mother marital status as reported on the birth certificates determines household composition could also inaccurately report household earnings if the mother is married but not to the biological father linked through birth certificate records. Household Specification 2, in contrast, assumes that both parents listed on a birth certificate comprise the household associated with that birth. If no father is listed, only the mother's earnings are used to calculate household earnings. Otherwise, both parents' earnings are aggregated to construct household-level earnings. This assumption could overestimate household earnings if the biological parents listed on the birth certificate do not belong to the same household. Furthermore, neither specification incorporates other earners who may be a part of the household. Nevertheless, these two specifications provide useful information on combined wage income of adult earners in a household around a birth.

These specifications are also used to disaggregate analyses by household composition, distinguishing between single-mother and two-parent households. In Household Specification 1, this distinction is made based on the "mother married" variable. If the mother is listed as married, the household is considered "two-parent." In Household Specification 2, this distinction is made based on whether one or two parents are listed on the birth certificate. If only a mother is listed, the household is considered a single-mother household; if two parents are listed, the household is considered a two-parent household. Results from both specifications are reported throughout the analysis.

Parent demographic and socioeconomic characteristics

This analysis examines heterogeneity in outcomes across demographic, socioeconomic, and employment characteristics based on DOH and UI data. *Biological sex* is identified based on whether the record is for the biological mother or father; data on mothers and fathers are collected separately as part of the birth certificate records process. *Race/ethnicity* is self-reported by parents in DOH records and disaggregated into seven mutually exclusive categories: White, not Hispanic/Spanish/Latino/a; Black, not Hispanic/Spanish/Latino/a; Asian, not Hispanic/Spanish/Latino/a; Native Hawaiian/Pacific Islander, not Hispanic/Spanish/Latino/a; Native American/Alaska Native, not Hispanic/Spanish/Latino/a; Multi-racial, not Hispanic/Spanish/Latino/a; and Hispanic/Spanish/Latino/a, any race.³ *Educational attainment* is reported in DOH records and is disaggregated into four categories: High school diploma or less; Some college/Associate's degree; Bachelor's degree; and more than Bachelor's degree (i.e., graduate/professional degree). *Wage rate quintile* in the main job prior to birth is calculated by dividing wages earned by hours worked in the "main job" (the job with the most hours) in the most recent quarter in which the parent was employed prior to the quarter of birth. Results that disaggregate by *industry of employment*, which is derived from the NAICS code associated with the parent's "main" pre-birth job, are also reported in the Technical Appendix.

Employment and income measures

Multiple measures capture parents' and households' employment and income trajectories around the time of a birth. I focus on nine quarters, reported relative to the quarter of birth: four prior to the birth, the quarter of the birth certificate, and four quarters afterwards. With the

³ Throughout this paper, I refer to mothers who indicated that they were of "Hispanic origin," which the birth certificate form defines as "Spanish/Hispanic/Latina," as "Latina."

exception of employer continuity, which is a birth-level outcome, all other outcomes are reported quarterly for the time period around a birth event. I use the following measures.

Employment status is a binary measure capturing the share of workers who are employed—that is, they worked one or more hours in a UI-covered job in Washington State. *Employment intensity* is a categorical measure that divides workers into three groups based on hours worked in all jobs during a quarter: no hours, 1-389 hours, and 390 or more hours. Working 390 hours in a quarter can be thought of as an approximation of “full time” status, corresponding to working an average of 30 or more hours per week throughout the quarter. Working 1-389 hours is less than full-time work, which could reflect part-time hours throughout the quarter, full-time hours for part of the quarter, or a combination of work and leave. *Mean quarterly hours* is the average hours worked among all parents in a given quarter. *Mean quarterly earnings* is the average inflation-adjusted wages earned across parents in a given quarter.

Employer continuity is defined relative to a worker’s main job (i.e., the job with the highest number of hours) in the quarter before a birth. A worker was defined as working for the same employer following birth if, in the first quarter they worked following a birth, they worked some number of hours for the employer of their main job pre-birth.

The standard deviation of arc percent change is used to characterize quarterly earnings volatility. I first calculate the quarter-over-quarter arc percent change in earnings, a measure of variability in earnings from one quarter to the next. Given earnings in two consecutive quarters

E_{q-1} and E_q , the arc percentage change is: $\frac{E_q - E_{q-1}}{\left(\frac{E_q + E_{q-1}}{2}\right)} * 100$.⁴ To summarize overall volatility in

⁴ The arc percentage change is commonly used to measure income volatility (see for example Dahl et al 2011). It has the following useful features: (1) it is bounded by -200 and 200, reducing the influence of outliers; (2) it is equal for

earnings across a population of parents, I use the standard deviation of the arc percent change as the main summary statistic (Dahl et al., 2011). This measure captures the spread of quarter-to-quarter arc percent changes among a group of parents, summarizing the overall volatility of earnings from one quarter to the next. The *share of parents experiencing large reductions in earnings* is another measure commonly used to capture economic volatility. Following prior literature on earnings and income volatility (Hacker et al., 2014; Maag et al., 2017), I identify the share of parents experiencing reductions of 25% or more, according to the quarter-over-quarter arc percentage change.

Means-tested benefit use is characterized using two measures. The *share of households receiving benefits* is based on the share of mothers who were in an assistance unit receiving any benefits from SNAP, TANF, or WCCC. *Benefit amounts* are calculated as the mean (inflation-adjusted) quarterly benefit amount received by all households, as well as the mean benefit amount among recipient households (conditional on receiving benefits).

Mean household earnings is reported as the average of the sum of the earnings of the one or two parents in the household, as defined by either Household Specification 1 or 2. *Mean household income* is calculated by adding household earnings and program benefits. Measures that include each individual program, as well as all programs, are reported.

Household earnings volatility is measured as the standard deviation of the arc percent change and the share of households experiencing large drops in earnings measures (see above for details). *Household income volatility* is measured as the standard deviation of the arc percent change and the share of households experiencing large drops for income measures (see above for details).

the same magnitude of increase or decrease from a given base value; and (3) it is defined when expenditures are zero in either y or $y-1$.

Analytic approach

I descriptively examine employment outcomes for all parents and across subgroups for the four quarters before the birth quarter, the birth quarter, and the four quarters after the birth quarter. I report on means-tested benefit use in these same quarters. Finally, I describe household earnings and income levels and volatility for household-level measures – for all households and disaggregated by household type (single-mother versus two-parent).

Results

Employment around a birth: all mothers and fathers

Figure 1.1 depicts quarterly measures of employment status and intensity among mothers and fathers in the quarters around a birth, for all parents in the sample (i.e., parents working at least 100 hours in the year prior to birth). Results are disaggregated to compare mothers' and fathers' employment trajectories. Panel A depicts the share of parents who were employed in each quarter. Panel B shows the share of parents belonging to one of three categories of employment intensity: full time, defined as working 390 or more hours in quarter, averaging to 30 or more hours a week; part time, or working 1-390 hours in a quarter; and not employed, or working 0 hours in a quarter.

[Figure 1.1 about here]

Each of these graphs suggests that mothers experienced substantially more disruptions in employment around a birth when compared to fathers. Working mothers' rate of working any hours fell substantially during the time around a birth, from a peak of 92% three quarters before a birth to a low of 68% in the quarter immediately following a birth. The share of mothers working part-time jumped up around the quarter of birth and the quarter after, then returned to pre-birth levels. Notably, though, the share of mothers who were not working at all increased steadily starting in the quarter before birth and remained at roughly 30% a year out – three times the pre-birth rate. Fathers' employment remained steady compared to mothers', although the share of

fathers who were not employed dipped slightly in the quarter before birth and then rose approximately 5 percentage points from pre-birth levels after a year. Mothers' and fathers' rates of working any amount were similar at the beginning of the study period (a year before a birth); the share of mothers and fathers working no hours was similar a quarter before a birth. These trends diverged sharply in the quarter before birth and remained different from that point forward.

Figure 1.2 indicates that disruptions in maternal employment were also evident when examining average hours worked per quarter and average wages earned per quarter. Working mothers worked significantly fewer hours and earned less per quarter, on average, than working fathers. Mothers' hours and earnings were at their lowest in the quarter after birth and increased in subsequent quarters but did not reach pre-birth levels by the end of the study period. Fathers' average work hours trended slightly down in the perinatal period, but average earnings increased gradually but steadily in the two years around a birth.

[Figure 1.2 about here]

Figure 1.3 below indicates the share of parents who returned to the same employer following birth. This is calculated as a share of all parents who worked in any of the four quarters after a birth, assessing what share returned to their primary employer from the quarter before a birth. The analysis is restricted to parents who were working both in the quarter before birth and at some point in the year following. Figure 1.3 illustrates that among parents who worked following a birth, roughly the same share of mothers and fathers returned to the same employer. Among parents who worked in the four quarters after a child was born, 87% of both mothers and fathers returned to the same employer at some point. It is important to remember that this rate is calculated as a share of all parents *employed* both in the quarter before birth and

the year following. Therefore, this analysis does not capture parents who did not work during various parts of the perinatal period.

[Figure 1.3 about here]

Figure 1.4 examines two measures of earnings volatility that capture instability in earnings over the period around a birth. First, quarter-over-quarter volatility is captured by calculating the standard deviation of the arc percent change in quarterly earnings from one quarter to the next. This graph shows the standard deviation of quarter-over-quarter arc percent changes across all mothers and all fathers in a given quarter. A larger standard deviation represents greater overall volatility in the sample, while a smaller standard deviation represents less volatility – that is, smaller fluctuations in earnings in that quarter across the parents included in the sample. Figure 1.4 Panel A depicts this metric for mothers and fathers. An alternative measure of volatility calculates the share of parents experiencing a large decline in earnings in any given quarter – here defined as parents whose earnings fell by greater than 25% in any given quarter, relative to the previous quarter, according to the arc percent change. Panel B shows the share of mothers and fathers experiencing these large reductions in earnings in each quarter around a birth.

Both volatility metrics indicate that earnings volatility spiked dramatically for mothers around the time of a birth, particularly in the quarter of birth and the quarter after. The standard deviation of the arc percent change in earnings peaks dramatically in the quarter after a birth. Similarly, in the quarter before birth, the quarter of birth, and the quarter after, 23%, 49%, and 40% of mothers experienced an earnings reduction of 25% or more when compared to the previous quarter. In contrast, fathers' volatility metrics remain relatively consistent throughout

the period. Between 15% and 20% of fathers experienced a large earnings drop in any given quarter in this study period.

[Figure 1.4 about here]

Heterogeneity by mother characteristics

Since mothers' employment trajectories are more dynamic, the following analyses focus on heterogeneity in mothers' perinatal earnings dynamics by mother characteristics. The share of mothers working any hours, rate of continuity with the same employer, and the share of mothers experiencing earnings reductions of 25% or more are reported in the main figures, while three other metrics are reported in the Appendix: mean hours worked, mean earnings, and the standard deviation of the arc percent change in quarterly earnings.

Figure 1.5 presents key metrics of employment instability among mothers disaggregated by race and ethnicity: employment rate (Panel A), employer continuity (Panel B), and earnings volatility as measured by the share of mothers experiencing a 25% or larger drop in earnings (Panel C). Overall, mothers who were not White or Asian reduced employment more intensely in the quarters leading up to a birth and were less likely to work throughout most of the period compared to White and Asian mothers. Native American/Alaska Native mothers, Native Hawaiian/Pacific Islander mothers, and Latina mothers had the lowest employment rates on average throughout the period, particularly in the quarters leading up to a birth. Gaps between White mothers and non-Asian mothers of color narrowed in the quarters after birth, although Asian mothers remained significantly more likely to work through the post-birth year. White, and Asian mothers were most likely to return to the same employer following birth when compared to other mothers. While all mothers saw earnings volatility spike in the period immediately after a birth, White and Asian mothers were less likely to experience volatility, on average, than other groups. Native American/Alaska Native mothers, Native Hawaiian/Pacific

Islander mothers, Black mothers, and Latina mothers experienced comparatively higher volatility in earnings throughout the perinatal period, except in the quarter after a birth, when White and Asian mothers were most likely to experience a large reduction in earnings.

[Figure 1.5 about here]

Disaggregating mothers' employment trajectories by educational attainment also illustrates heterogeneity in experiences of employment instability, as shown in Figure 1.5. Panel A illustrates that more highly-educated mothers are more likely to work over the period around a birth, while less-educated mothers stop work earlier. Mothers without a four-year degree are less likely to work at baseline, and also reduce work more intensely during pregnancy and in the quarters right around birth. Disaggregating employer continuity (Panel B) by education replicates these differences. Mothers with a bachelor's degree and mothers with graduate or professional degrees are significantly more likely to return to the same employer following birth when compared to mothers without a four-year degree. Finally, as shown in Panel C, earnings volatility spikes for all mothers around the time of a birth, but is much higher at in the prenatal period for mothers with less educational attainment. In the quarter after a birth, this pattern reverses, and mothers with a four-year postsecondary degree are more likely to experience large earnings reductions in the quarter after a birth. However, because more highly-educated mothers have higher income levels to begin with, on average, these reductions may not have the same impacts for families (see Appendix Figure 1.5, which reports average earnings by educational attainment).

[Figure 1.6 about here]

Figure 1.7 demonstrates that results disaggregated by wage quintile display a similar pattern as those disaggregated by educational attainment. Mothers working in higher-wage jobs

prior to birth were consistently more likely to work throughout the period around a birth when compared to mothers working in lower-wage jobs. Mothers working in lower-wage jobs reduced employment earlier and more intensely during pregnancy. Mothers working in lower-wage jobs were significantly less likely to return to the same employer following birth, and this disparity was especially stark. Among mothers who worked after birth, 72% returned to the same employer, compared to 96% of mothers in the highest fifth. Earnings volatility spiked for all groups of mothers regardless of wage rate, but was higher in the prenatal period and the birth quarter for mothers in lower-wage jobs – then, higher for mothers in higher-wage jobs in the quarter after a birth. Taken together, these findings suggest that mothers experienced significant employment instability around regardless of wage rate, but employment instability was more intense for mothers working in lower-wage jobs.

[Figure 1.7 about here]

Household earnings levels and volatility

Figure 1.8 shows results after adding mother and father earnings together to estimate household earnings around a birth. While results above demonstrated that fathers' earnings exhibit significantly less volatility than mothers' earnings, adding together earnings of both parents still illustrates significant perinatal changes. Under the assumptions of Specifications 1 and 2, households saw a 19% and 17% average reduction in earnings income between the quarter before birth and the quarter after, respectively. These findings are confirmed by estimates of household-level earnings volatility in Figure 1.9. The standard deviation of the arc percent change in household earnings spikes significantly around a birth. Depending on the specification, between 35% and 40% of households experienced an earnings drop of 25% or more in the birth quarter.

[Figures 8 and 9 about here]

Figures 10 and 11 disaggregate this analysis by household composition, reporting estimates of household earnings levels and volatility separately for single-mother and two-parent households. Analysis of mean household earnings in Figure 1.10 illustrates some similarities in household experiences by composition, but other differences. Both types of households experience significant reductions in household earnings in the perinatal period. However, in part because household earnings (under either household specification) in two-parent households is much higher at baseline, volatility measures (depicted in Figure 1.11) reveal higher earnings instability among single-mother households. Single-mother households have a higher standard deviation of the arc percent change in quarter-over-quarter earnings, and have higher likelihoods of experiencing large reductions in earnings in each quarter through the quarter of birth. Over half of single-mother households experienced a quarter-over-quarter earnings reduction of 25% or more between the quarter before birth and the quarter of birth. Interestingly, the rate of large earnings reductions evens out between the two household types in the postnatal period. This is consistent with findings in the literature that single-earner households experience more earnings volatility when compared to multiple-earner households (Dahl et al., 2011; Hardy, 2017).

[Figures 1.10 and 1.11 about here]

Use of means-tested programs around a birth

Next, I examine another key source of income for families: benefits from means-tested safety net programs. I first report results for all households. Figure 1.12 demonstrates that use of each program increases through the perinatal period, although they follow different patterns. The share of households participating in SNAP increases steadily in the perinatal period, peaking at just under 30% in the quarter after a birth then falling slightly. SNAP is used by a significant share of families throughout the perinatal period, ranging from 16.6% a year before a birth to 28.8% in the quarter after a birth. The share of households participating in TANF is quite a bit

lower – less than 8% throughout the perinatal period – but does increase in the quarters preceding a birth, peaking around the time of a birth and the quarter after. This pattern aligns with research showing that TANF can function like maternity leave for low-income single mothers (Hill, 2012). Use of WCCC exhibits the opposite pattern. Fewer households use this program in the quarters right around a birth, possibly because parents are more likely to stay home to care for children during this time. Use of the program increases steadily after the quarter of birth. Still, a small share of households use this program; 6.5% of households in the sample received WCCC benefits a year after a birth. It is important to keep in mind that these rates are calculated as a share of all households and do not take into account eligibility for the program; therefore, they should not be interpreted as take-up rates. The overall rates of receipt of these programs around a birth are roughly aligned with other estimates using administrative data, such as Heflin et al.’s analysis using Virginia administrative data, which finds that about 4 times as many infants’ households receive SNAP at birth as receive TANF (Heflin et al., 2022).

[Figure 1.12 about here]

Next, Figure 1.13 depicts the inflation-adjusted average dollar value of benefit amounts received among all households (Panel A) and among recipient households conditional on receiving benefits (Panel B). Panel A depicts a similar temporal pattern to Figure 1.12. Panel B provides information about quarterly household benefits for each program among recipient families. WCCC had the highest quarterly benefit value and was the highest (slightly over \$1000 per quarter) in the year following a birth. Average SNAP quarterly benefits among recipients ranged from approximately \$450 to \$550, peaking in the quarter after a birth. Average TANF benefits were in a similar range and were highest in the quarter of a birth.

[Figure 1.13 about here]

Figure 1.14 replicates these analyses disaggregated by household type, depicting significantly different patterns of benefit use between single-mother and two-parent households. Temporal patterns around a birth are similar between both household types, but the rate of taking up each program is significantly higher for single mothers than for two parent households. SNAP is by far the most-used program regardless of household type. Depending on the household specification used, between 55 and 65% of single-mother households used SNAP in the quarter after a birth, compared to between 15 and 25% of two-parent households. Single mothers are also more likely to use TANF; between 15 and 20% of single-mother households use TANF in the quarter of birth and the quarter after compared to less than 5% of two-parent households. More single mothers use WCCC, as well; use of this program increases steadily to roughly 15-20% of single-mother households by a year after a birth, compared to less than 5% of two-parent households. Changes in the share of households using benefits in these quarters around a birth reflects substantial movement of households into and out of benefit use.

[Figure 1.14 about here]

Figures 15 and 16 depict similar results for benefit amounts disaggregated by household type. The average benefit dollar value received across all households, including those that did not receive benefits, was significantly higher among single-mother households than two-parent households, as depicted in Figure 1.15. This is to be expected based on the fact that a larger share of single-mother households use these programs, as demonstrated in Figure 1.14. Figure 1.15 demonstrates the impact of these programs on incomes among the population of single-mother households. For example, SNAP increases single mothers' income by approximately \$300-\$330, on average (including non-participating households), in the quarter after a birth. This represents a significant addition to income among an economically vulnerable population. Figure 1.16

demonstrates that after conditioning on benefit receipt, the amount of benefits received by households was more similar across household types.

[Figures 1.15 and 1.16 about here]

Household income levels and volatility

Figure 1.17 plots household-level income measures during the perinatal period, including just earnings and earnings plus means-tested benefit program income. Under both household specifications, with or without means-tested benefit income added, households still experience significant economic volatility on average in income during the perinatal period. Figure 1.18, Panel A demonstrates that the addition of means-tested benefits, particularly SNAP, to household income does somewhat mitigate volatility as compared to earnings alone -- as measured by the standard deviation of the arc percent change. Under both household specifications, perinatal spikes in income volatility are lower after adding in benefit programs, especially SNAP. However, income plus benefits does not exhibit significantly fewer large decreases (25% or more) than earnings alone, as demonstrated in Panel B.

[Figures 1.17 and 1.18 about here]

Figures 1.19 through 1.22 present these same analyses with results disaggregated by household type. Results shown in Figure 1.19 demonstrate that means-tested benefits are larger relative to overall income for single-mother households relative to two-parent households in the perinatal period. Figure 1.20 demonstrates that benefits' mitigation of earnings volatility is much more significant for single-mother households compared to two-parent ones. Figure 1.21 illustrates that adding in benefit income results in relatively little change in the share of households experiencing large reductions in income, for both single-mother and two-parent families.

[Figures 1.19, 1.20, and 1.21 about here]

Discussion and conclusion

Leveraging a novel administrative data resource, this paper demonstrates that households in Washington State experience a high prevalence of employment instability around the time of a birth. Examining employment and household income confirms findings from prior literature (e.g., Stanczyk, 2020) that households experience significant reductions in resources around the time a child is born, primarily driven by reductions in mothers' earnings.

Mothers experience significant employment instability resulting in durable changes to employment status that persist a year following a birth. In contrast, fathers' employment trajectories are quite steady throughout the perinatal period. I find that across two different measures, earnings volatility spikes for mothers around the time of a birth. Nearly half of mothers experience a quarter-over-quarter earnings reduction of 25% or more in the quarter of a birth, and four in ten experience this size of reduction in the quarter after a birth. These results suggest that the overall study of earnings volatility must directly address the time around a birth if researchers are to capture the full scope of volatility experienced by U.S. workers.

Results also demonstrate significant inequalities in experiences of perinatal economic instability. Mothers' employment trajectories differed substantially by race/ethnicity, educational attainment, and pre-birth wage rates. Mothers who were not White or Asian tended to have lower employment and earnings throughout the perinatal period. Patterns of volatility also differed across racial groups. Black, Native American/Alaska Native, Native Hawaiian/Pacific Islander, and Latina mothers experienced more earnings volatility throughout the perinatal period than White and Asian mothers, with one exception. Between the quarter of a birth and the quarter after, White and Asian mothers saw the largest reductions in earnings. This could reflect White and Asian mothers being more likely to use employer-provided paid leave. While research

consistently finds that Latina mothers are less likely than White, Black, and Asian mothers to have access to paid leave through work, it is less consistent on whether Black mothers have less leave access (Bartel et al., 2018; Gault et al., 2014). It is also important to keep in mind that the same amount of volatility may have different consequences for families depending on what earnings were prior to the perinatal period (which I find are highest for White and Asian mothers) and wealth (which is unobservable in these data).

I also find that employment patterns differ by educational attainment and wage quintile. Mothers without a college degree reduce employment more intensely during pregnancy and up to the time of a birth, while more highly-educated mothers are more likely to experience reductions in earnings in the quarter after a birth. Similarly, mothers with lower wage rates experience significantly more earnings volatility prior to a birth, but this pattern briefly reverses in the quarter after a birth when mothers working in higher-wage jobs are more likely to see large earnings reductions. More intense post-birth earnings changes among more highly-educated mothers and mothers in higher-wage jobs may be related to increased access to paid parental leave through employers. More highly-educated mothers and mothers working in higher-wage jobs were more likely to return to the same employer following a birth, reflecting more employment stability among those who remained employed.

The economic volatility resulting from parental employment instability was reduced but not eliminated when examining perinatal earnings trajectories at the household level. When examining combined parental earnings at the household level, volatility is reduced relative to individual parents' earnings. However, households still experience substantial economic volatility in the perinatal period. Furthermore, these analyses reveal substantial inequalities

between single- and two-parent households. Single-mother households have lower earnings, on average, and significantly more earnings volatility when compared to two-parent households.

Among all households, a relatively small share use means-tested benefits in the perinatal period. However, rates of use of these programs are much higher among single-mother households. Means-tested benefit use increases throughout the perinatal period, with SNAP and TANF most likely to be used in the quarters around a birth and WCCC more likely to be used in the year following a birth. Means-tested benefits do buffer the volatility of perinatal earnings to some extent, but primarily for single-mother families who are significantly more likely to use the benefits. Household income volatility among both household types remains prevalent in the perinatal period after taking into account these benefits. Taken together, these findings confirm prior work indicating that the perinatal period is an economically volatile time for households (Stanczyk, 2020).

Limitations

Several limitations of this work are important to note. This analysis does not capture the full range of supports available to working parents around the time of a birth. For example, I am not able to observe use of employer-provided leave, as well as other government programs such as the Earned Income Tax Credit that can support incomes of families with young children. Examining earnings and income as outcomes are valuable, but they miss important information about families' economic wellbeing. I am not able to observe the number of other children families have or other members of the household other than the biological parents of a recent newborn; this prevents me from calculating poverty rates or income-to-needs ratios as done in other work on economic conditions around a birth (Stanczyk, 2020). Self-reported measures of economic security, such as questions that assess families' level of material hardship, could provide additional context on economic wellbeing but are not available through these data. The

fact that the birth certificates only identify biological parents also presents a significant limitation. I do not have self-reported relevant information on household composition and therefore am not always able to correctly identify the adults who are responsible for the care of the newborn. These limitations point to areas for improvement in future data collection efforts, as well as future research.

Implications for policy

These findings offer important implications for policy and practice. First, the research suggests that policymakers aiming to promote equitable economic security must attend to the time around a birth. Income from earnings significantly declines in the perinatal period, with potentially harmful consequences especially for families that are already economically vulnerable. Means-tested programs are reaching some families around the time of a birth, but this research suggests that expanded access to assistance could further smooth income disruptions. Expanding access to paid leave could also help attenuate the economic volatility shown above; I explore this policy response in Chapters 2 and 3.

Tables and figures

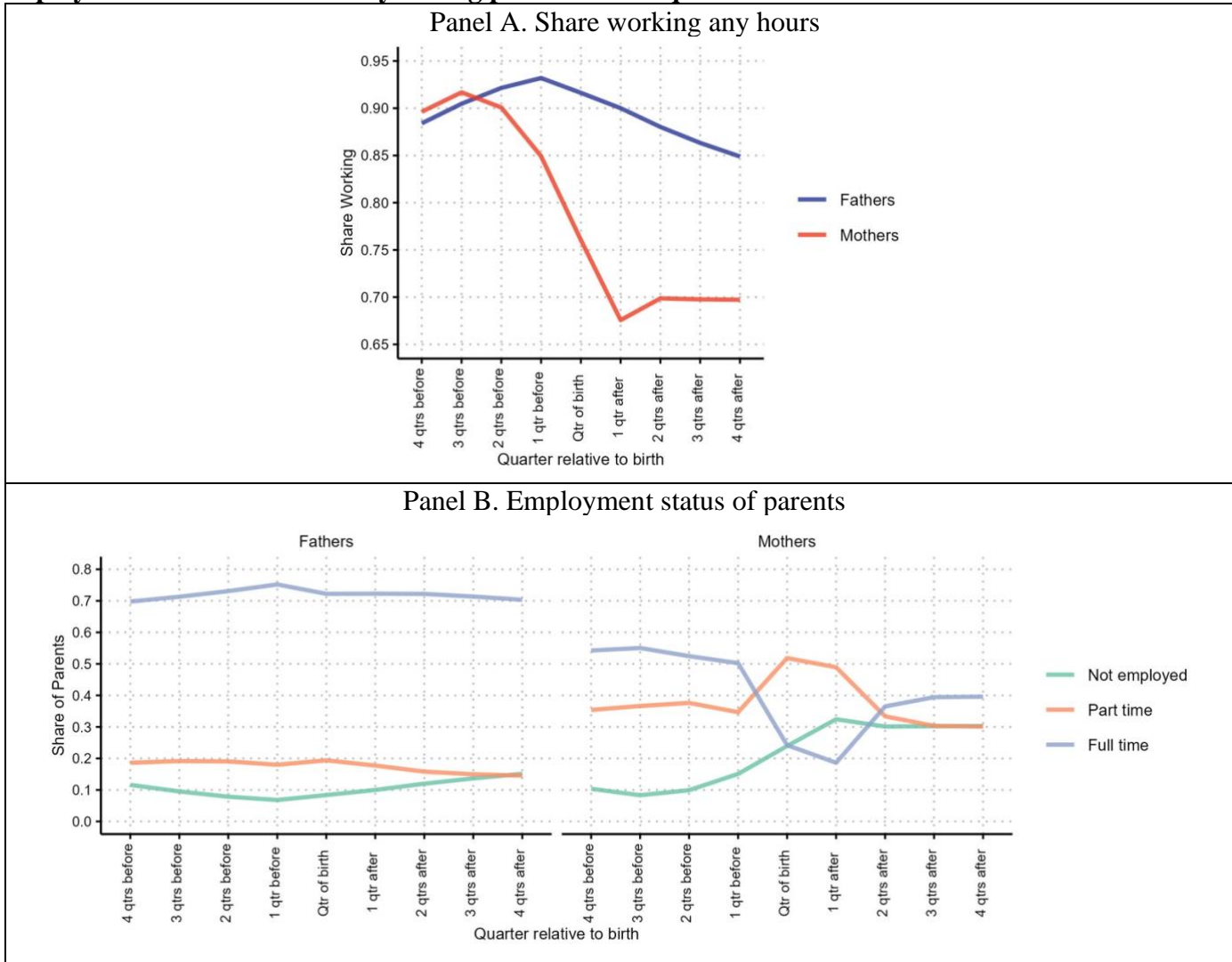
Table 1.1. Sample size and share of parents included in sample

Year	Mothers			Fathers		
	All mothers on birth certificates	Mothers working 100+ hrs	Share of mothers on birth certificates included in study	All fathers on birth certificates	Fathers working 100+ hrs	Share of fathers on birth certificates included in study
2010	82897	40227	0.485	78356	49163	0.627
2011	83551	40350	0.483	78866	49131	0.623
2012	84043	41520	0.494	78550	50055	0.637
2013	83380	42280	0.507	77079	50542	0.656
2014	85664	44472	0.519	77755	51468	0.662
2015	86099	46051	0.535	76930	51745	0.673
2016	87579	48267	0.551	79162	53499	0.676

Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Parents were included in the analysis if they worked 100 or more hours in UI-eligible employment in the four quarters prior to the quarter in which they were listed on a birth certificate.

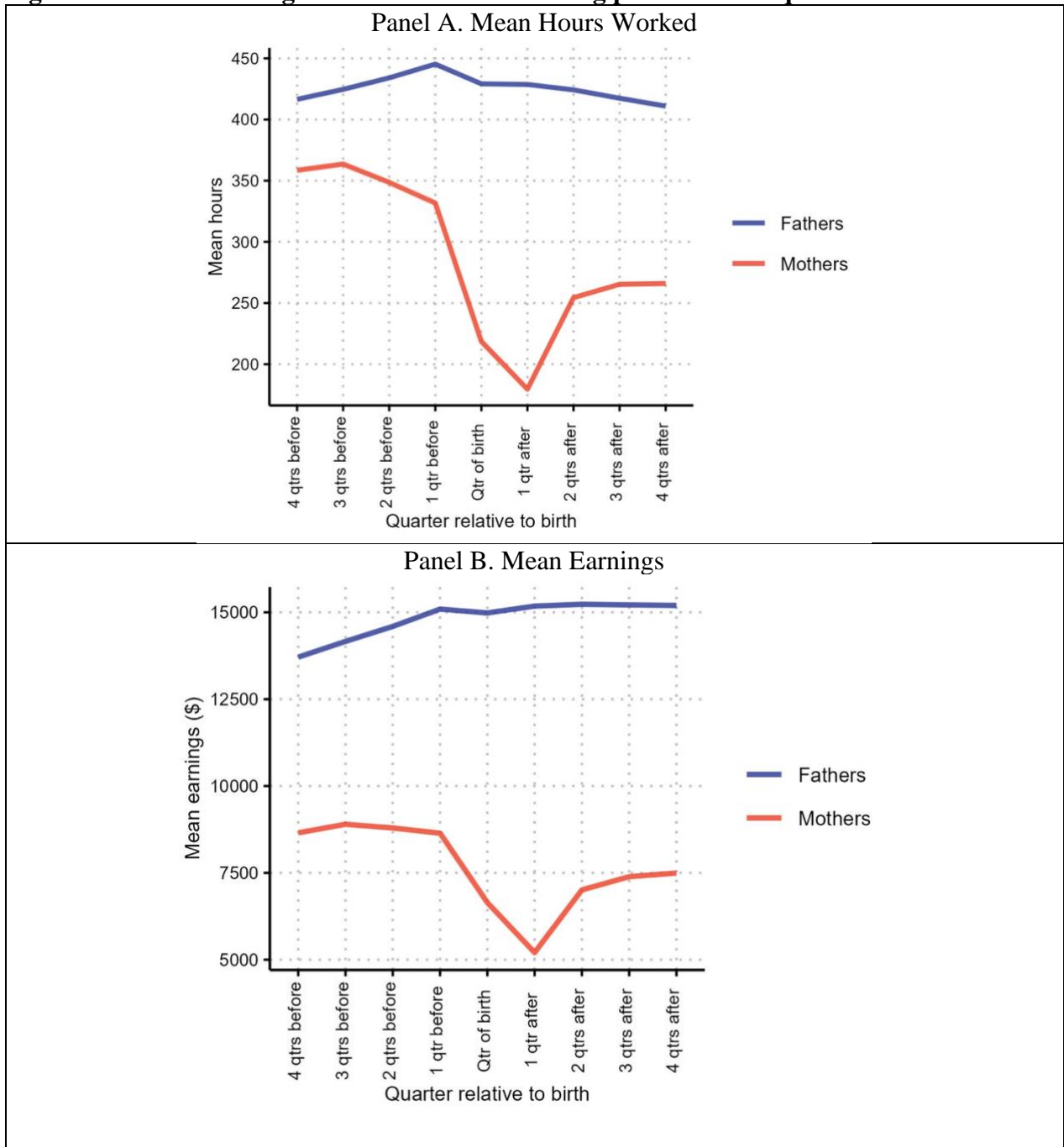
Figure 1.1. Employment status and intensity among parents in the quarters around a birth



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. “Full time” is defined as working 390 or more hours in quarter; “part time” is defined as working 1-390 hours in a quarter.

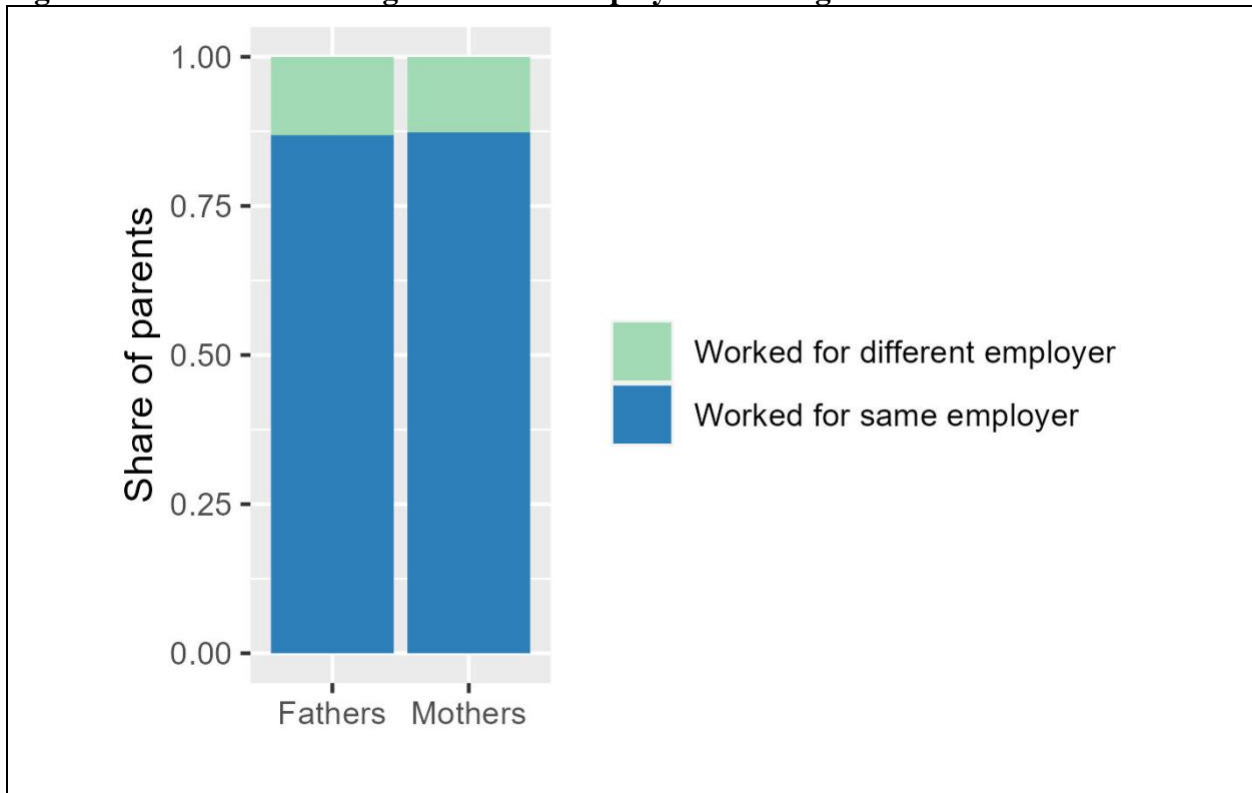
Figure 1.2. Mean earnings and hours worked among parents in the quarters around a birth



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015.

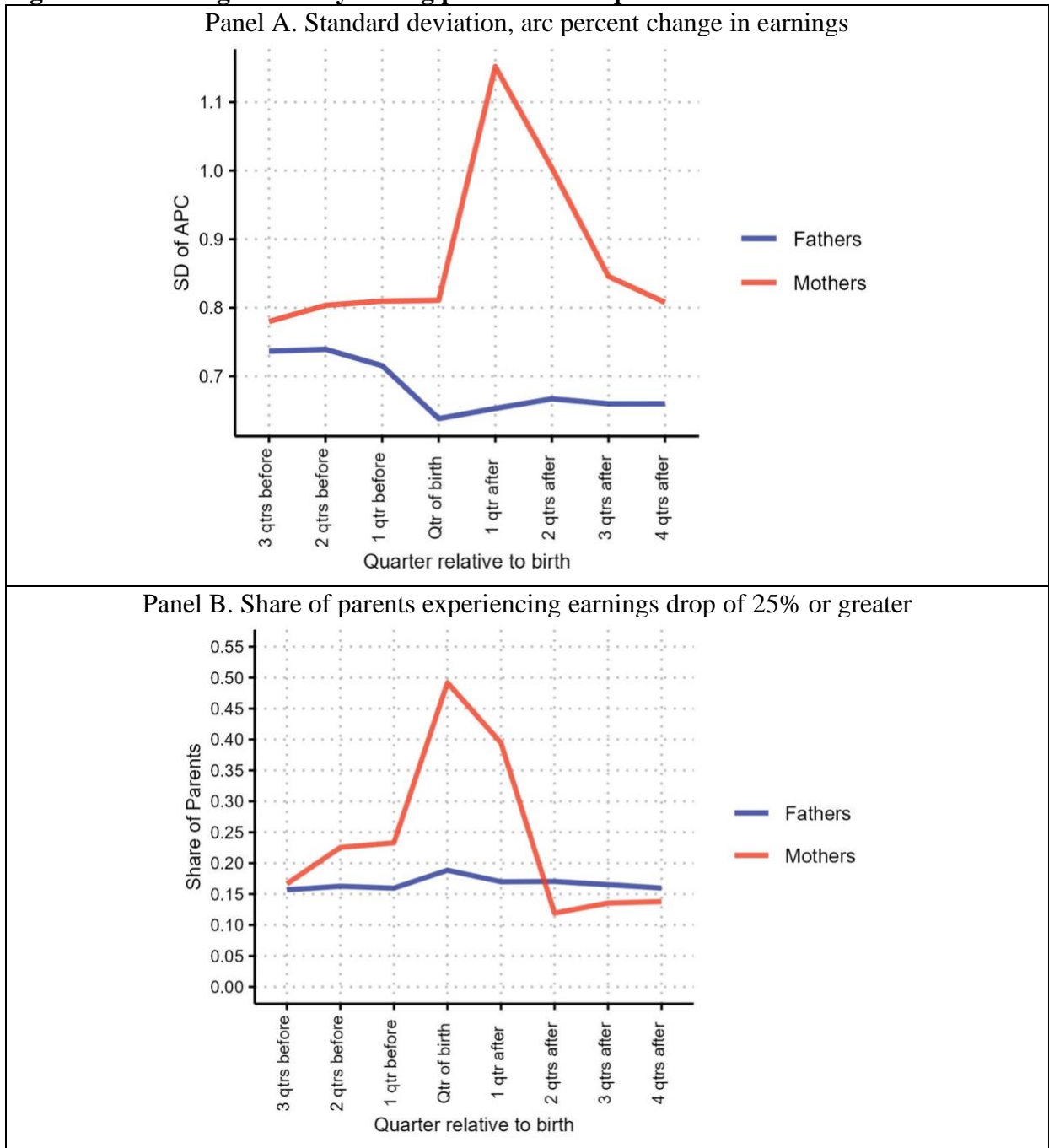
Figure 1.3. Rate of returning to the same employer following a birth



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Parents were considered to have worked for the same employer following birth if they worked for the same employer in their first quarter employed following birth as in their primary job prior to birth. Only parents who worked following birth are included in this analysis.

Figure 1.4. Earnings volatility among parents in the quarters around a birth



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015. Statistics for each quarter represent the change between that quarter and the quarter before.

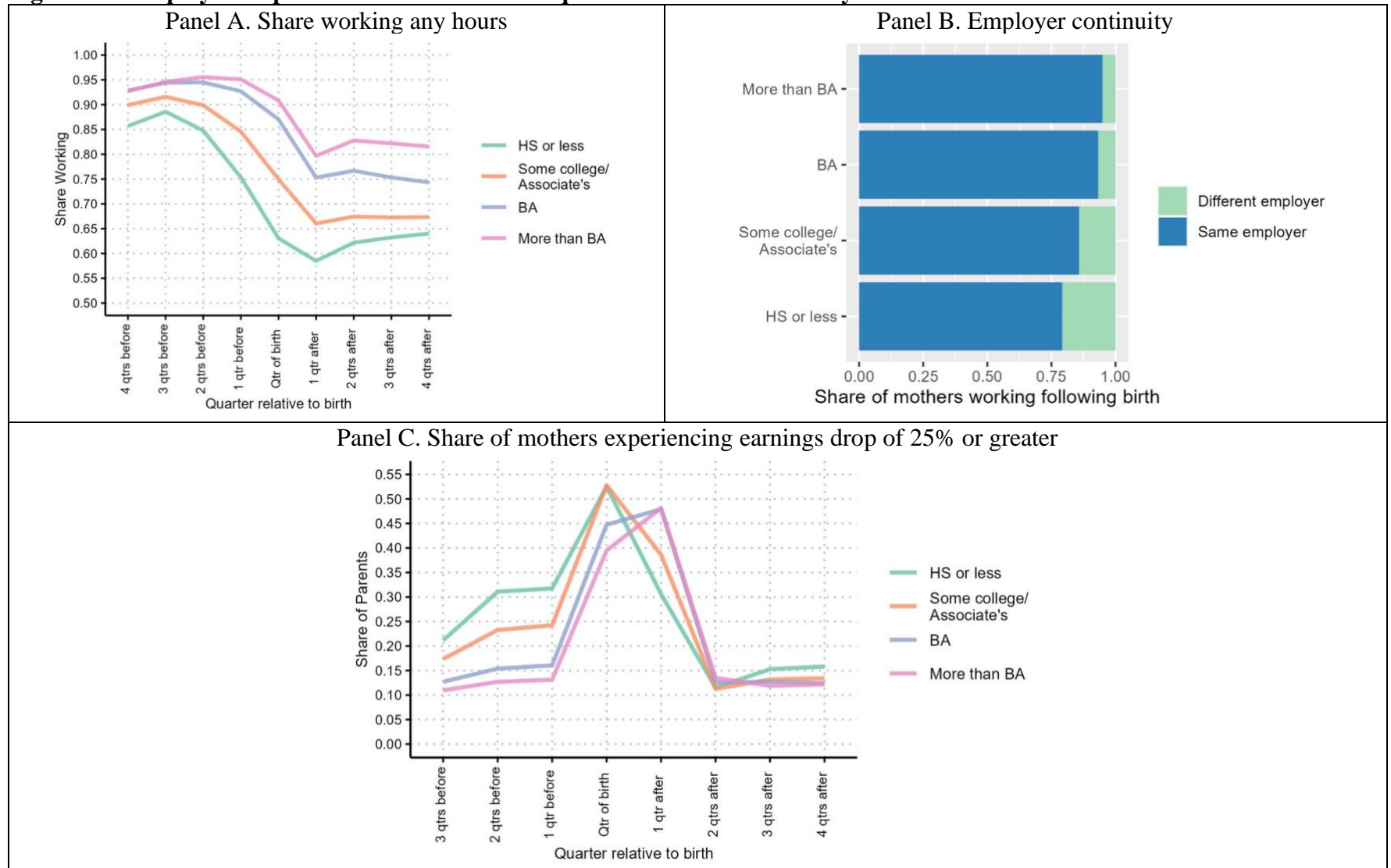
Figure 1.5. Employment patterns of mothers in the quarters around a birth: By race/ethnicity



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before.

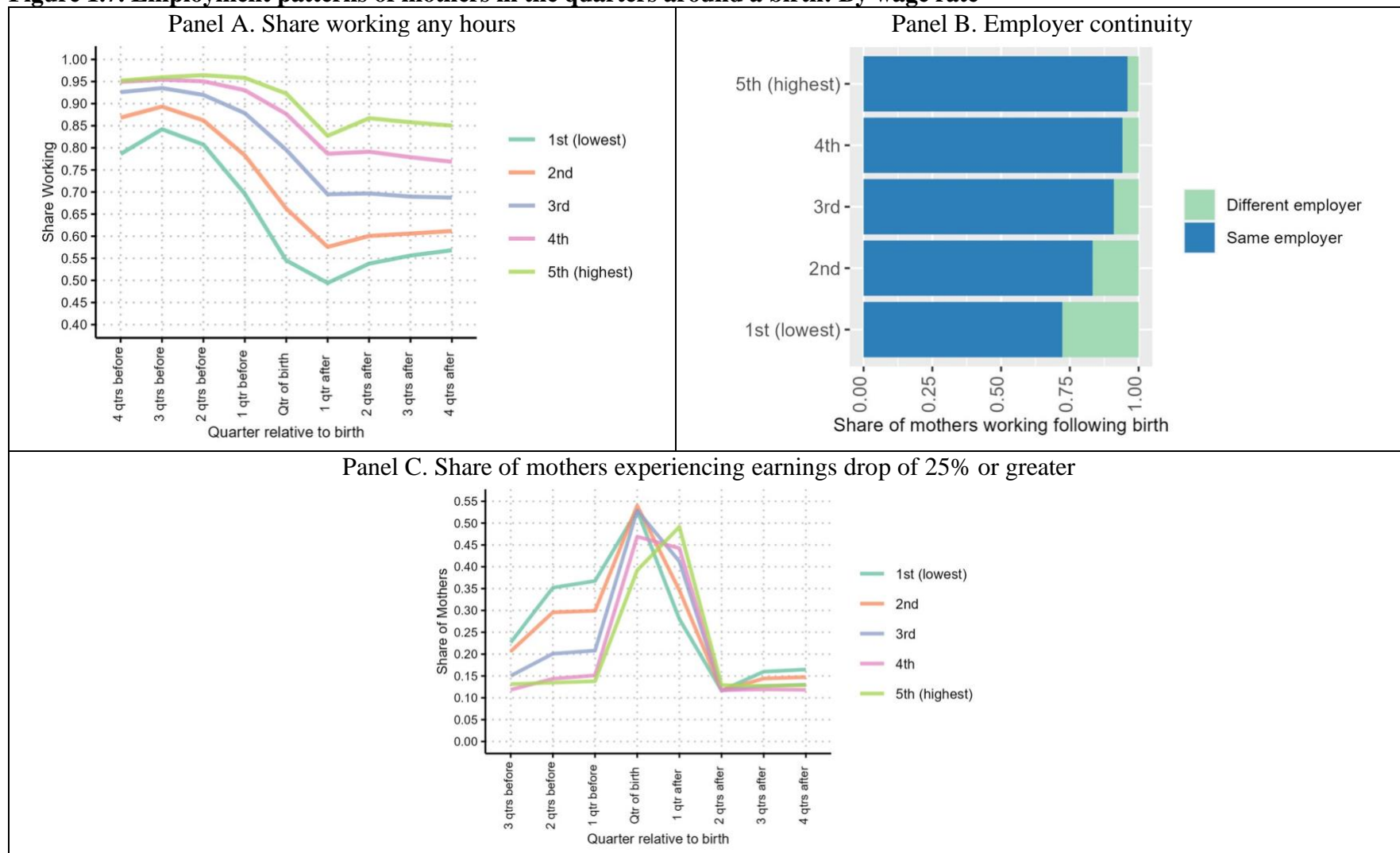
Figure 1.6. Employment patterns of mothers in the quarters around a birth: By educational attainment



Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before.

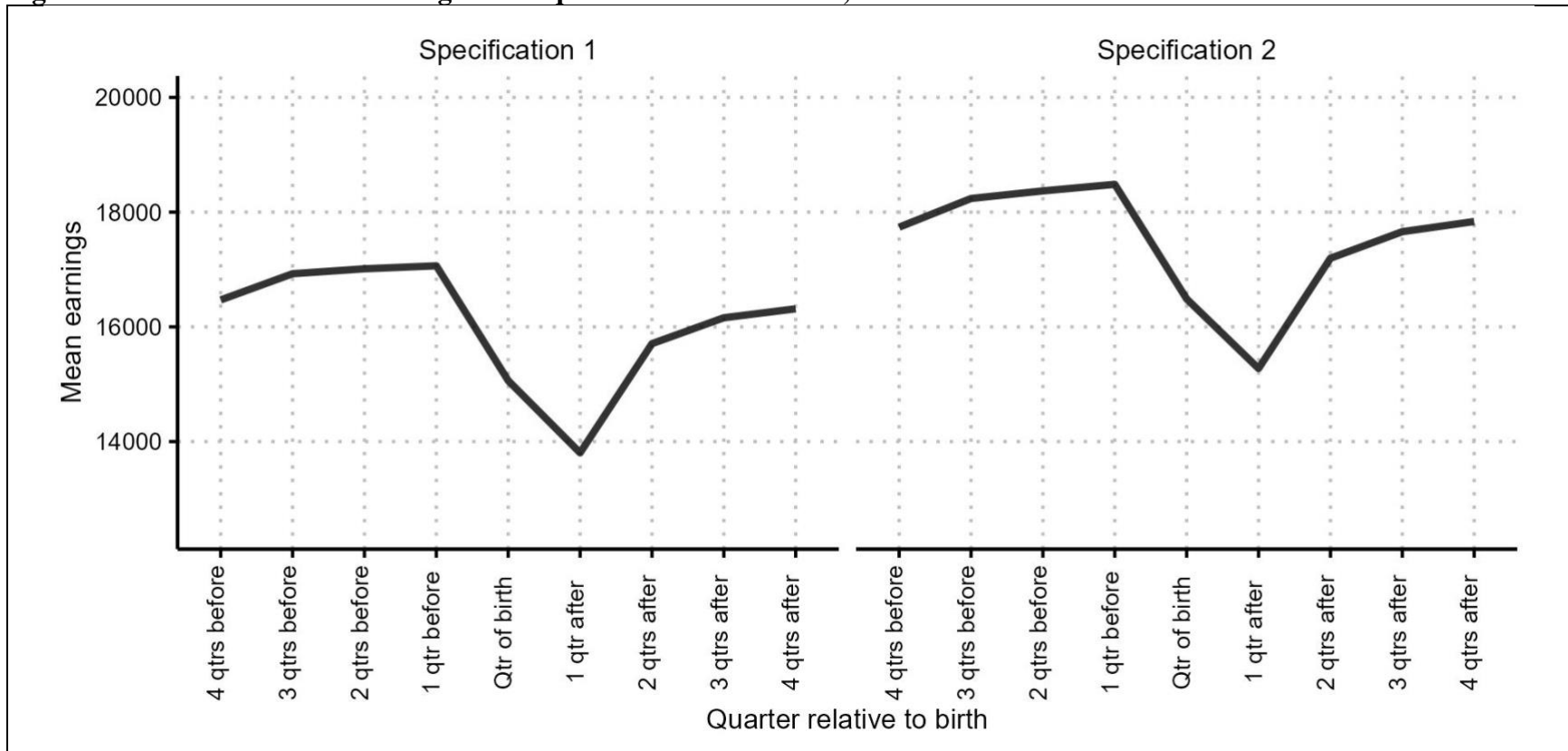
Figure 1.7. Employment patterns of mothers in the quarters around a birth: By wage rate



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before. Wage rate quintile is measured based on the main job (job with the most hours) in the most recent pre-birth quarter in which the mother worked.

Figure 1.8. Mean household earnings in the quarters around a birth, all households

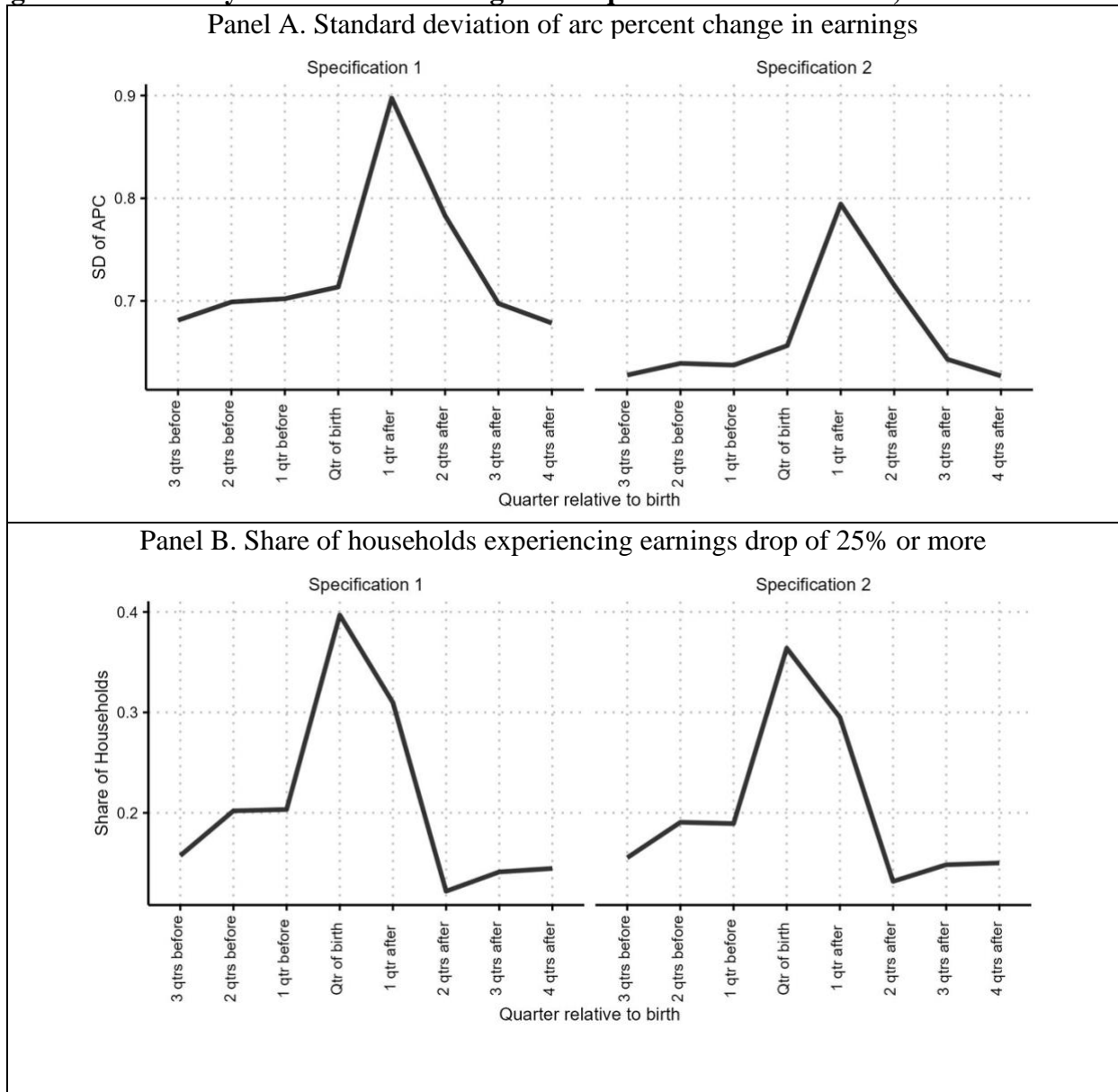


Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015.

Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

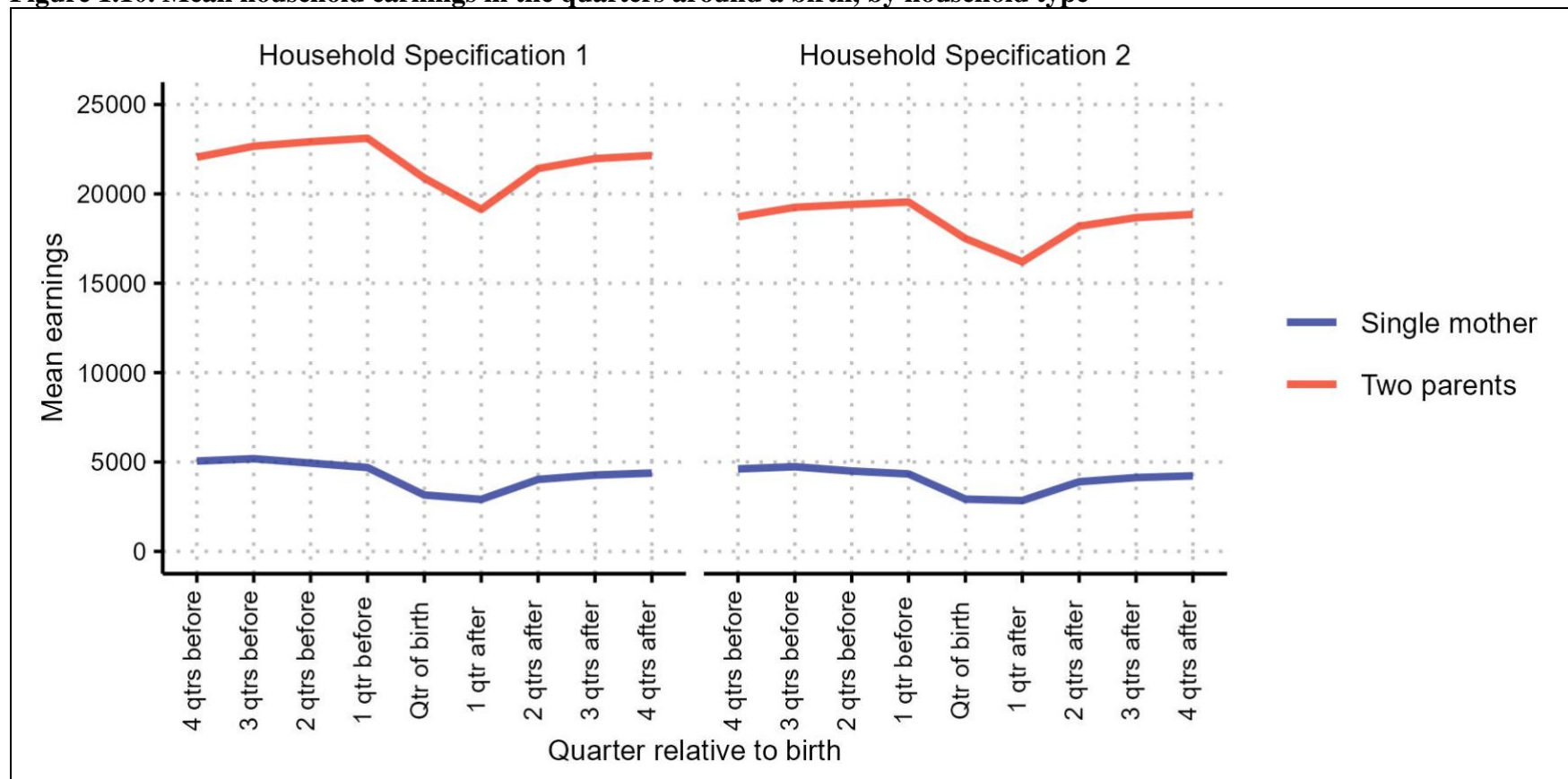
Figure 1.9. Volatility of household earnings in the quarters around a birth, all households



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

Figure 1.10. Mean household earnings in the quarters around a birth, by household type

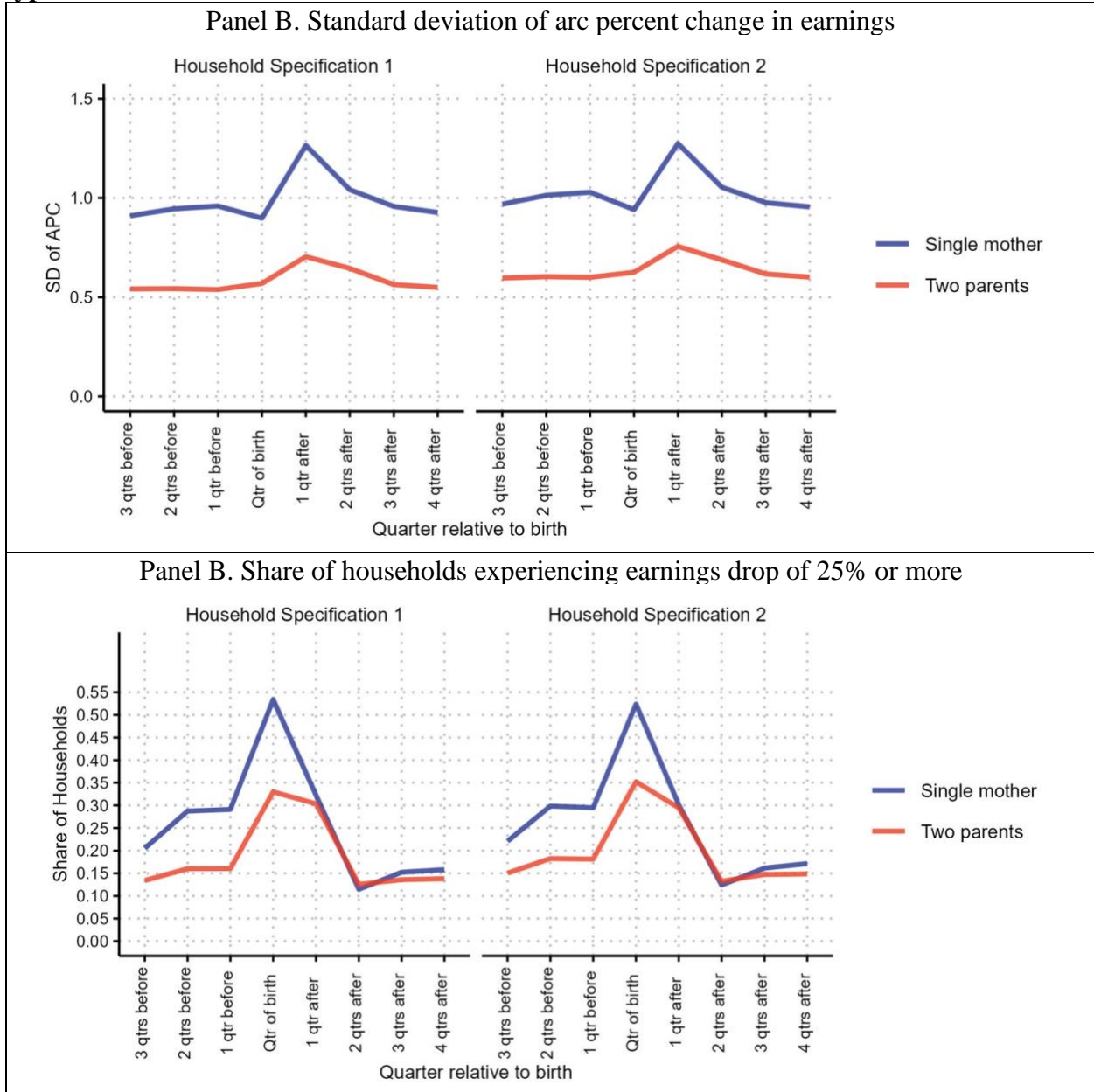


Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015.

Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

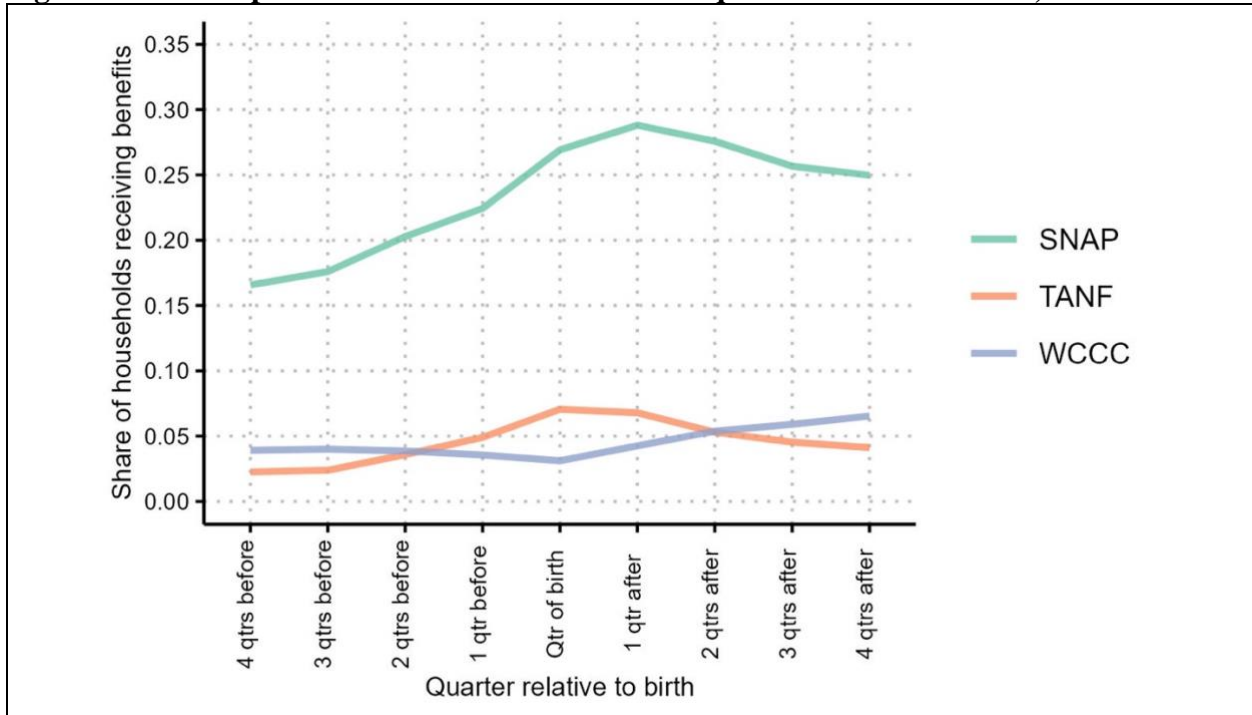
Figure 1.11. Volatility of household earnings in the quarters around a birth, by household type



Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

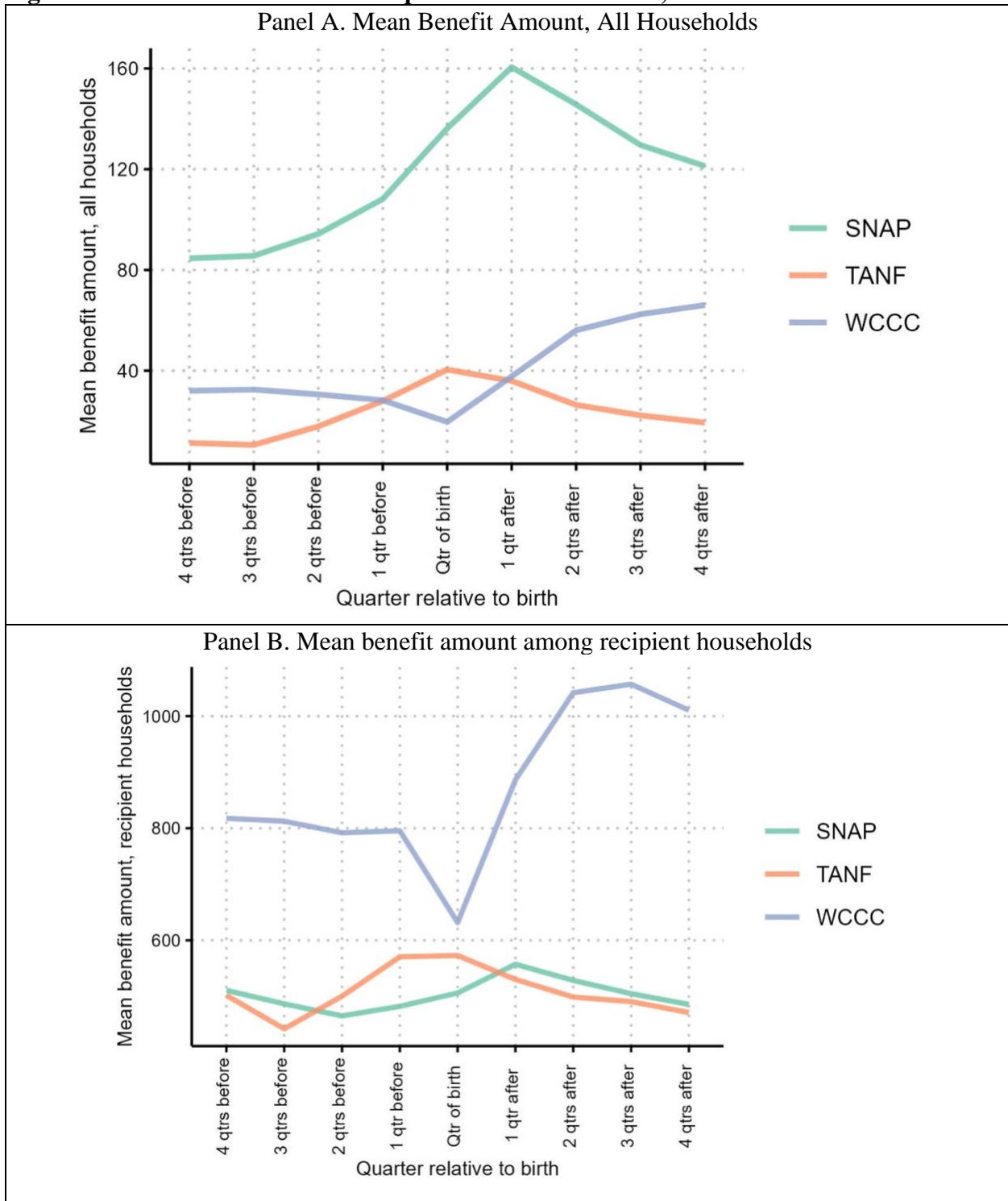
Figure 1.12. Receipt of means-tested benefits in the quarters around a birth, all households



Sources: Author's analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth.

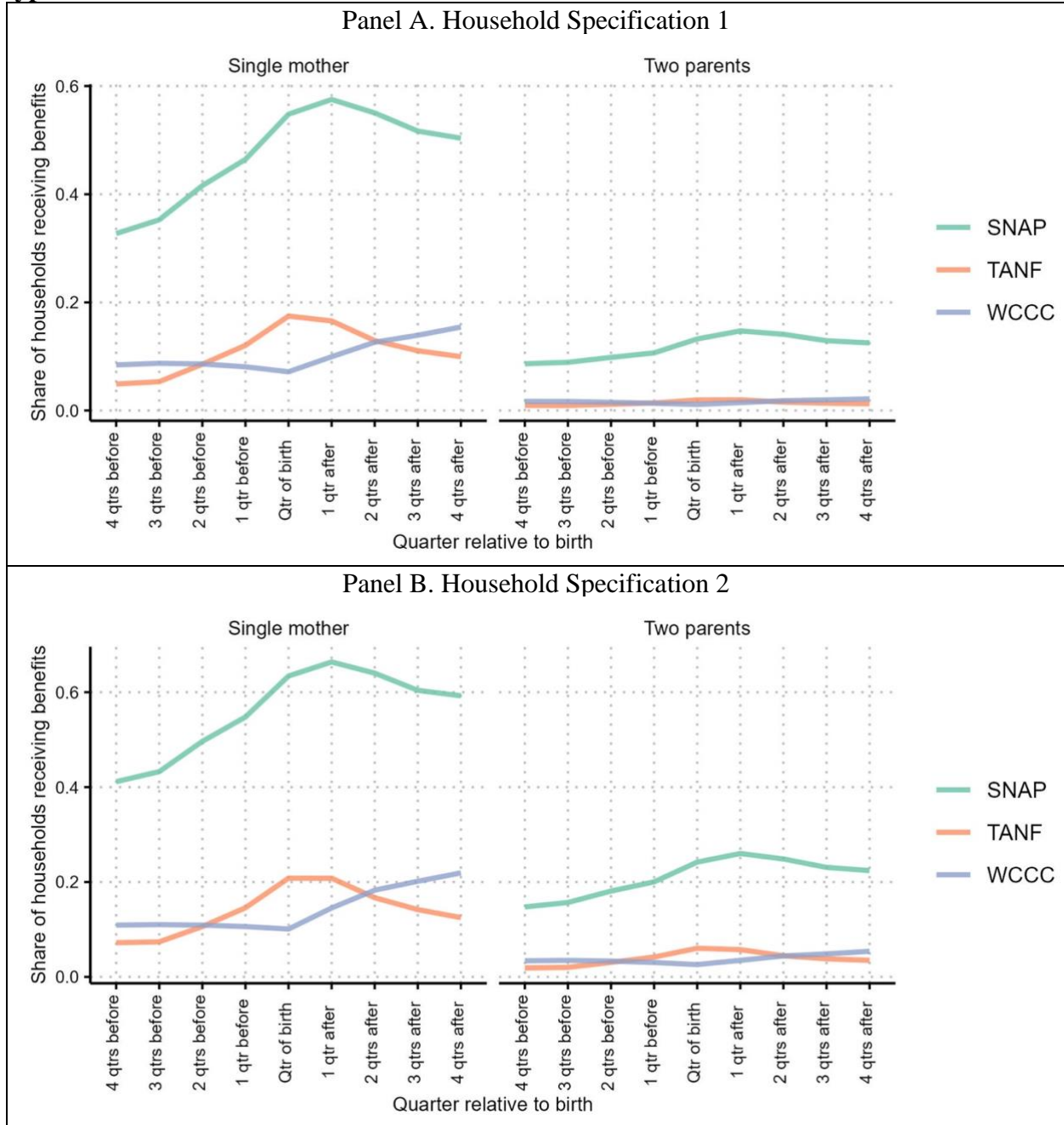
Figure 1.13. Benefit amounts in the quarters around a birth, all households



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Benefit amounts reflect the total dollars received by the household linked to the mother on the birth certificate. Benefit amounts are adjusted for inflation and reported in \$2015.

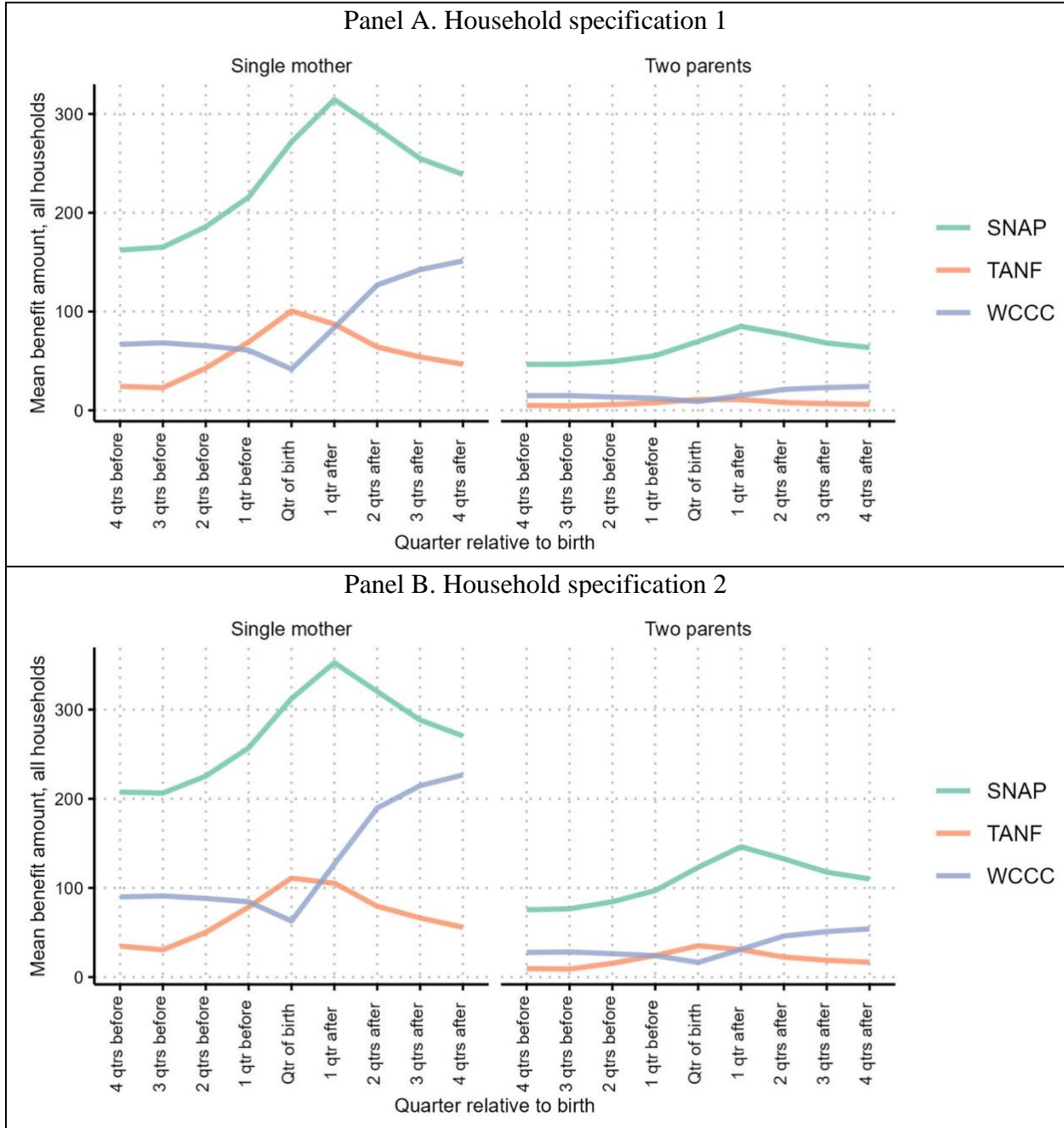
Figure 1.14. Receipt of means-tested benefits in the quarters around a birth, by household type



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

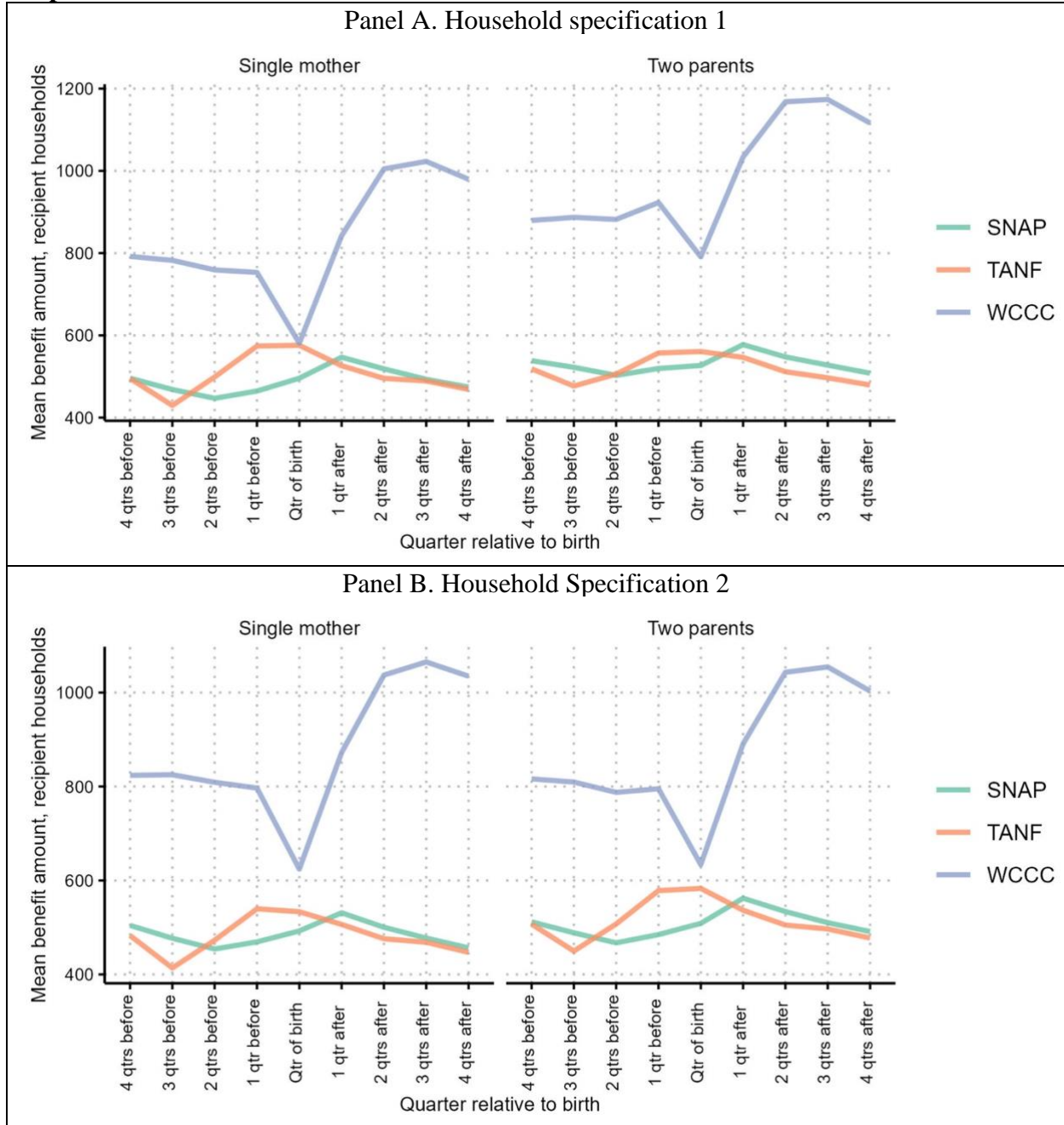
Figure 1.15. Benefit amounts in the quarters around a birth, by household type: all households



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Benefit amounts are adjusted for inflation and reported in \$2015. Benefit amounts reflect the total dollars received by the household linked to the mother on the birth certificate. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

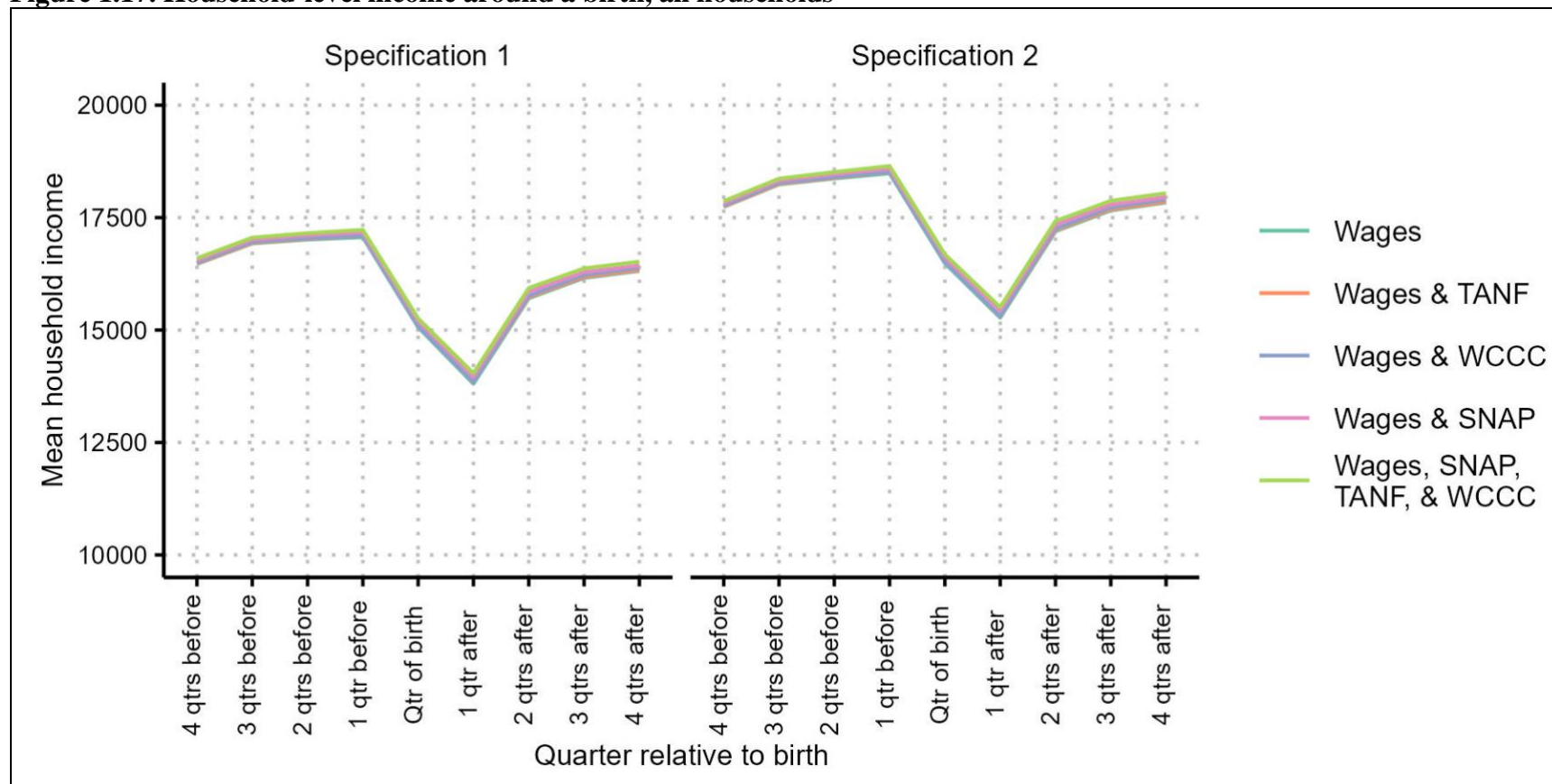
Figure 1.16. Benefit amounts in the quarters around a birth, by household type: among recipient households



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Benefit amounts are adjusted for inflation and reported in \$2015. Benefit amounts reflect the total dollars received by the household linked to the mother on the birth certificate. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

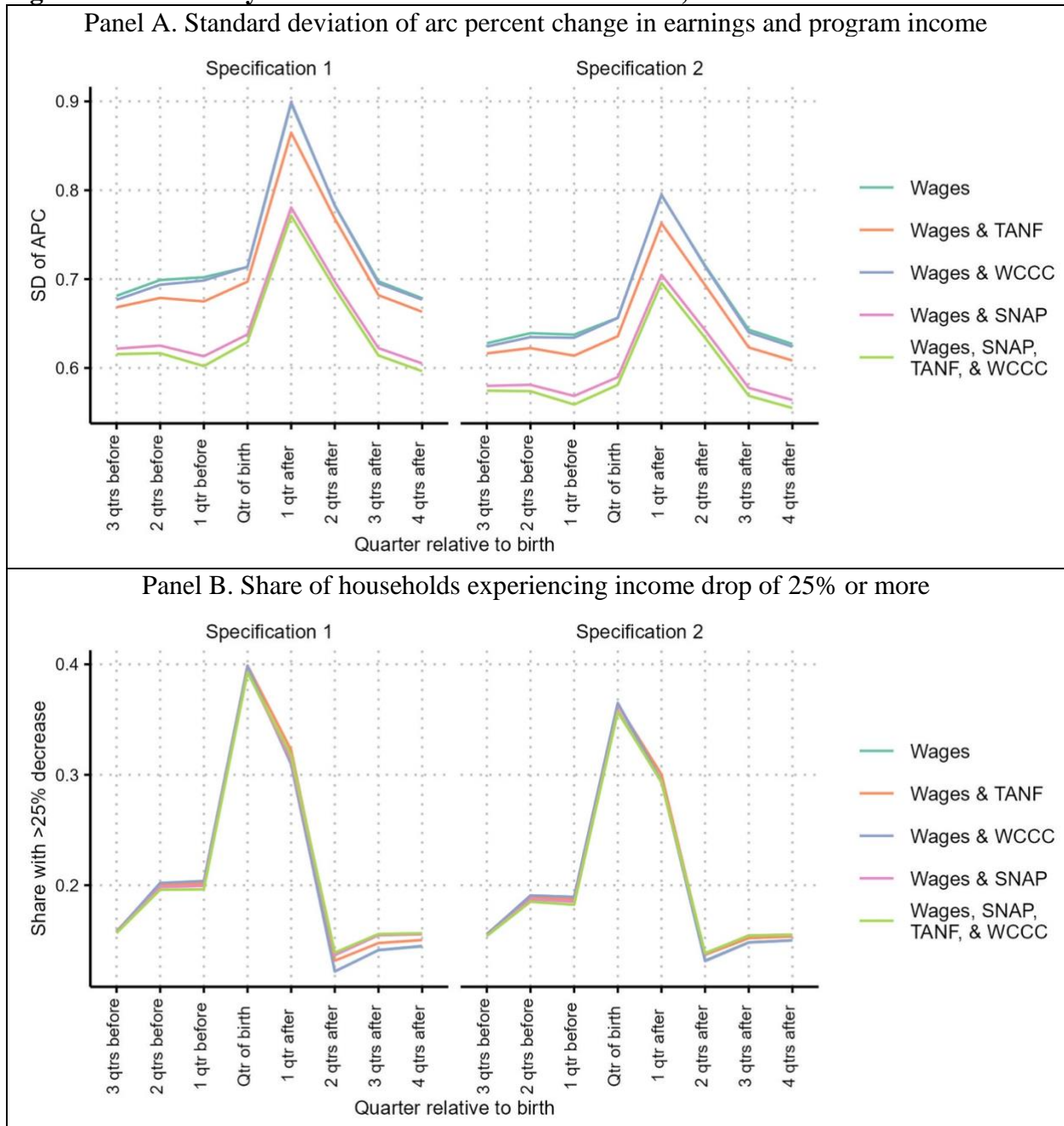
Figure 1.17. Household-level income around a birth, all households



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings and benefit amounts are adjusted for inflation and reported in \$2015. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

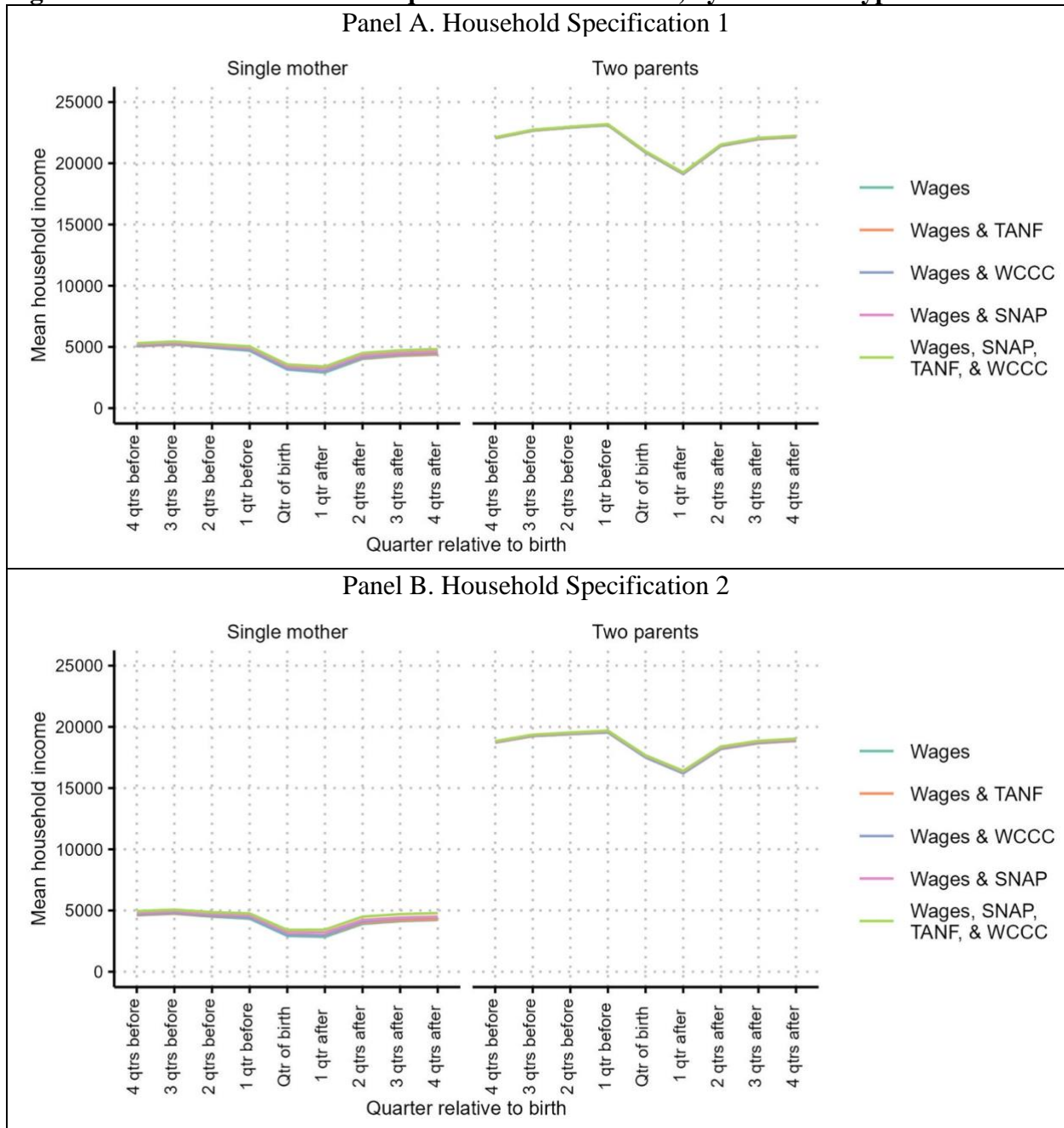
Figure 1.18. Volatility of household income around a birth, all households



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings and benefit amounts are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before. Benefit amounts reflect the total dollars received by the household linked to the mother on the birth certificate. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

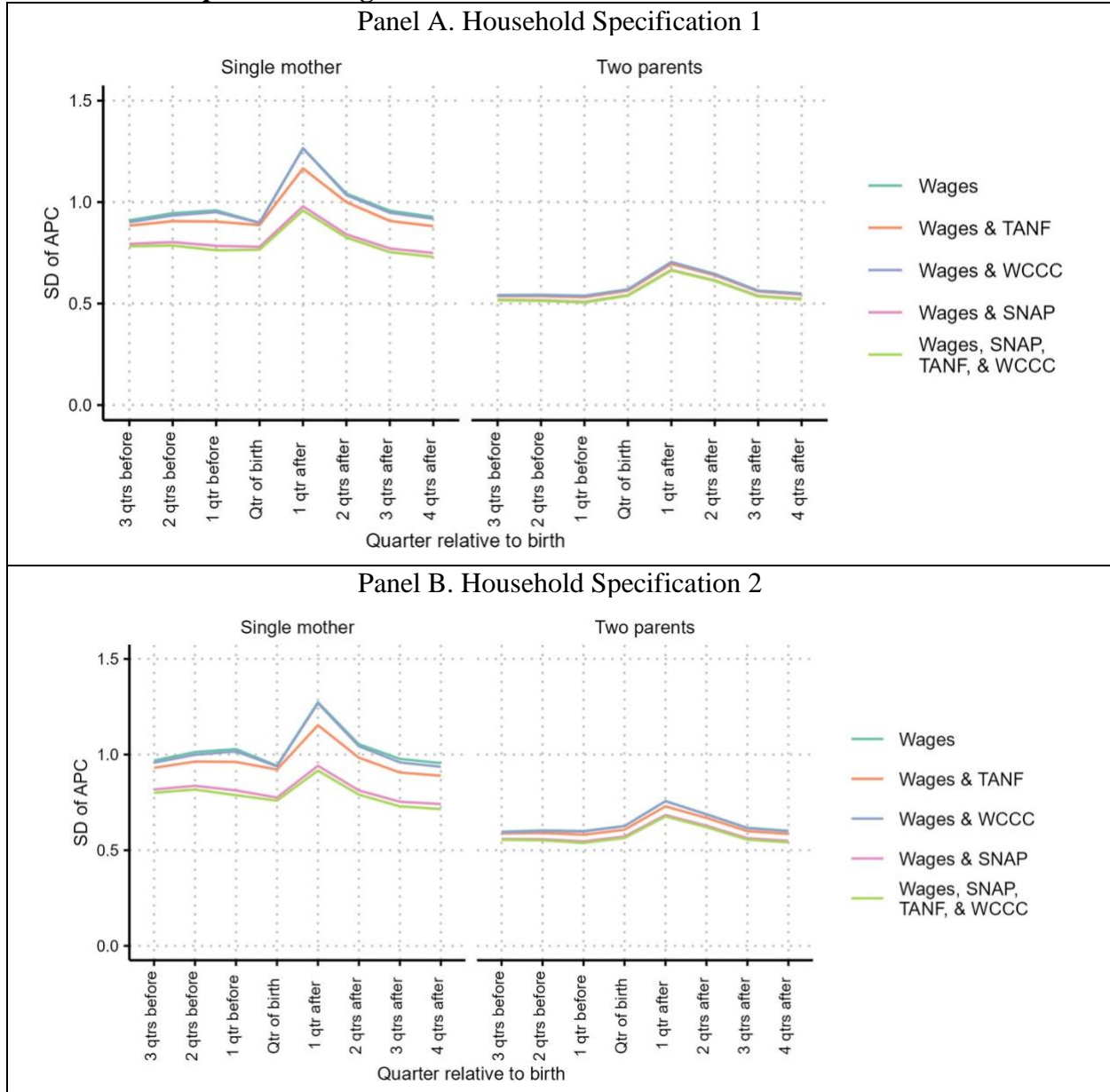
Figure 1.19. Household income in quarters around a birth, by household type



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings and benefit amounts are adjusted for inflation and reported in \$2015. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

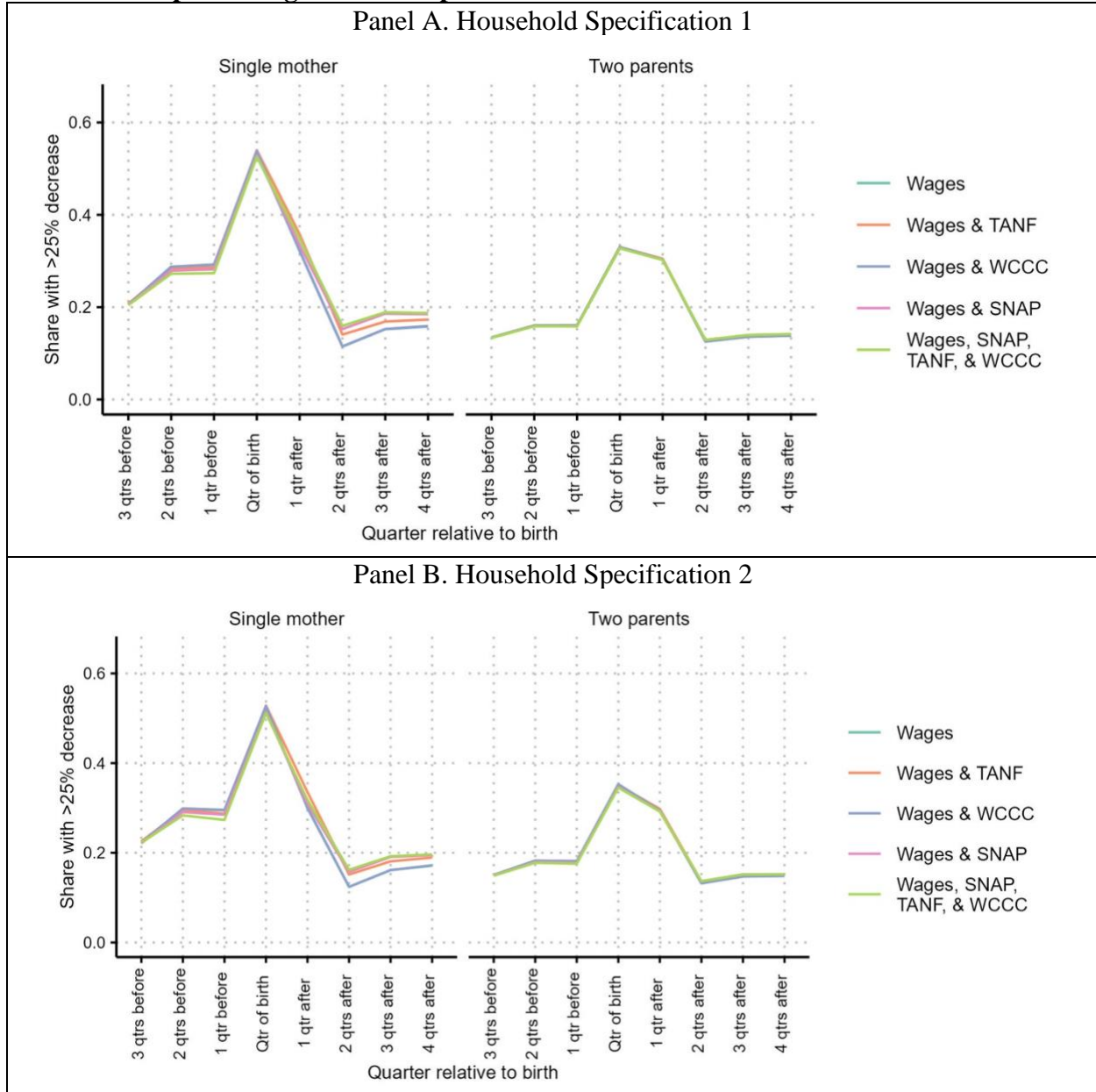
Figure 1.20. Volatility in household income around a birth, by household type: Standard deviation of arc percent change in income



Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings and benefit amounts are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before. Benefit amounts reflect the total dollars received by the household linked to the mother on the birth certificate. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

Figure 1.21. Volatility in household income around a birth, by household type: Share of households experiencing income drop of 25% or more

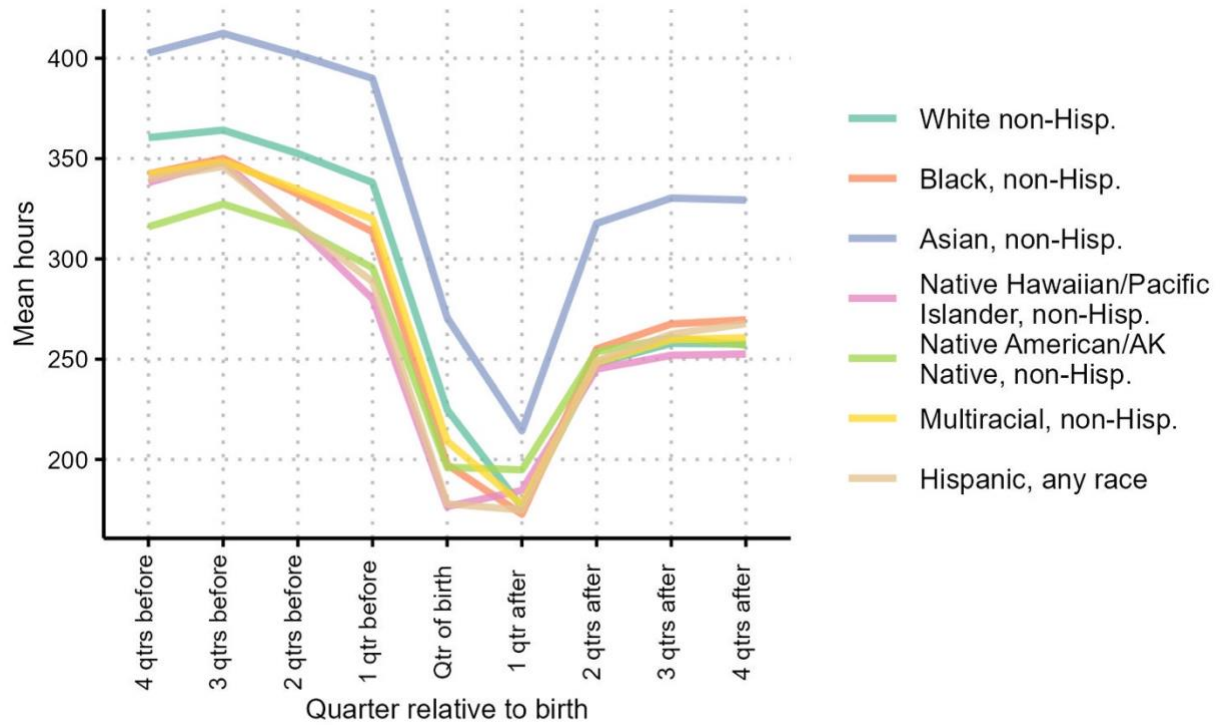


Sources: Author’s analysis of records from Washington State Employment Security Department, Washington State Department of Health, and Washington State Department of Social and Health Services.

Notes: Study population is parents who worked 100 or more hours in the year before a birth. Earnings and benefit amounts are adjusted for inflation and reported in \$2015. Volatility statistics for each quarter represent the change between that quarter and the quarter before. Benefit amounts reflect the total dollars received by the household linked to the mother on the birth certificate. Household Specification 1 assumes that for all mothers listed as “married” on birth certificates, household earnings is the sum of earnings of the mother and father listed on the birth certificates; for all mothers listed as not married, household earnings is just the mother’s earnings. Births where the “mother married” variable was not reported are excluded from this analysis. Household Specification 2 assumes that household earnings is the sum of earnings for all parents listed on the birth certificate. See text for a more detailed description of the implications of these assumptions.

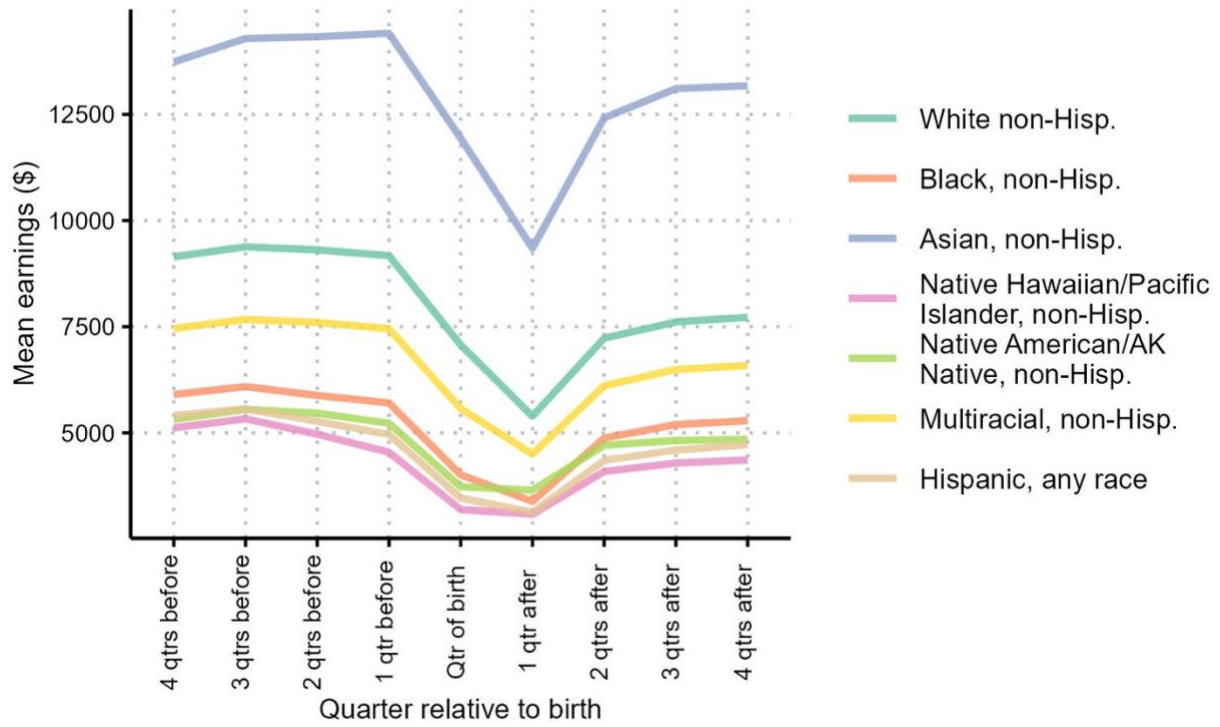
Appendix: Supplemental analyses

Appendix Figure 1.1. Hours worked by mothers, by race and ethnicity



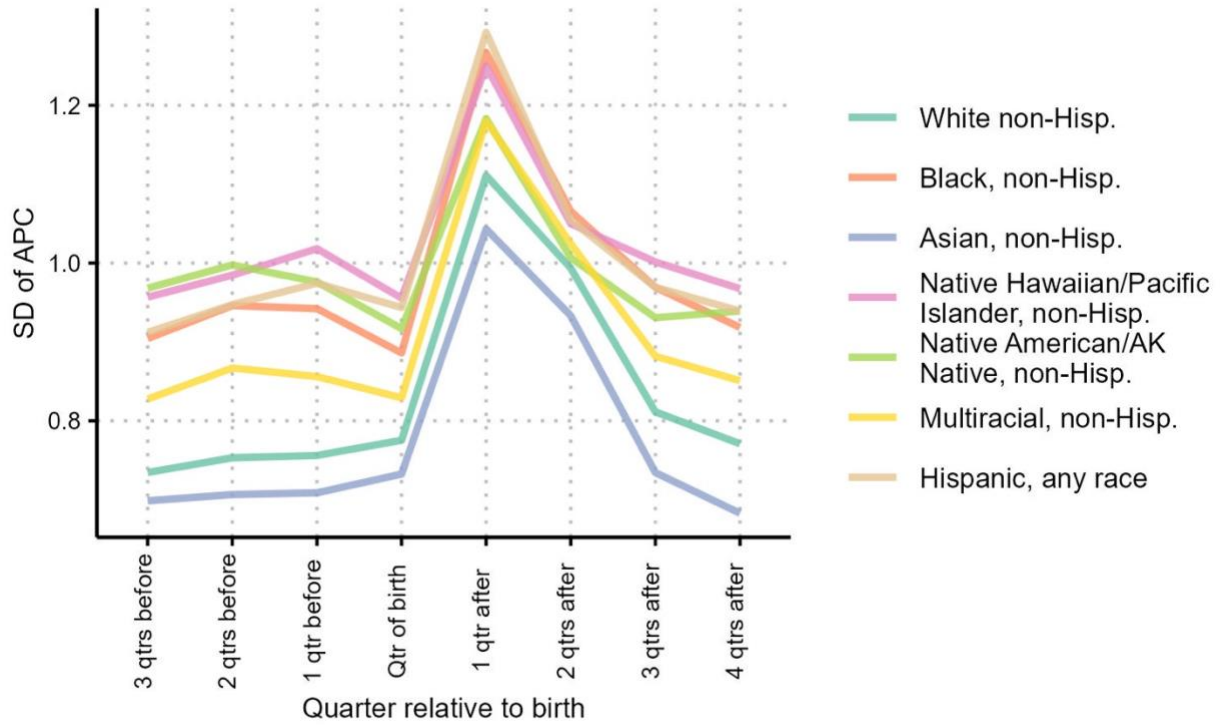
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.2. Mothers' earnings, by race and ethnicity



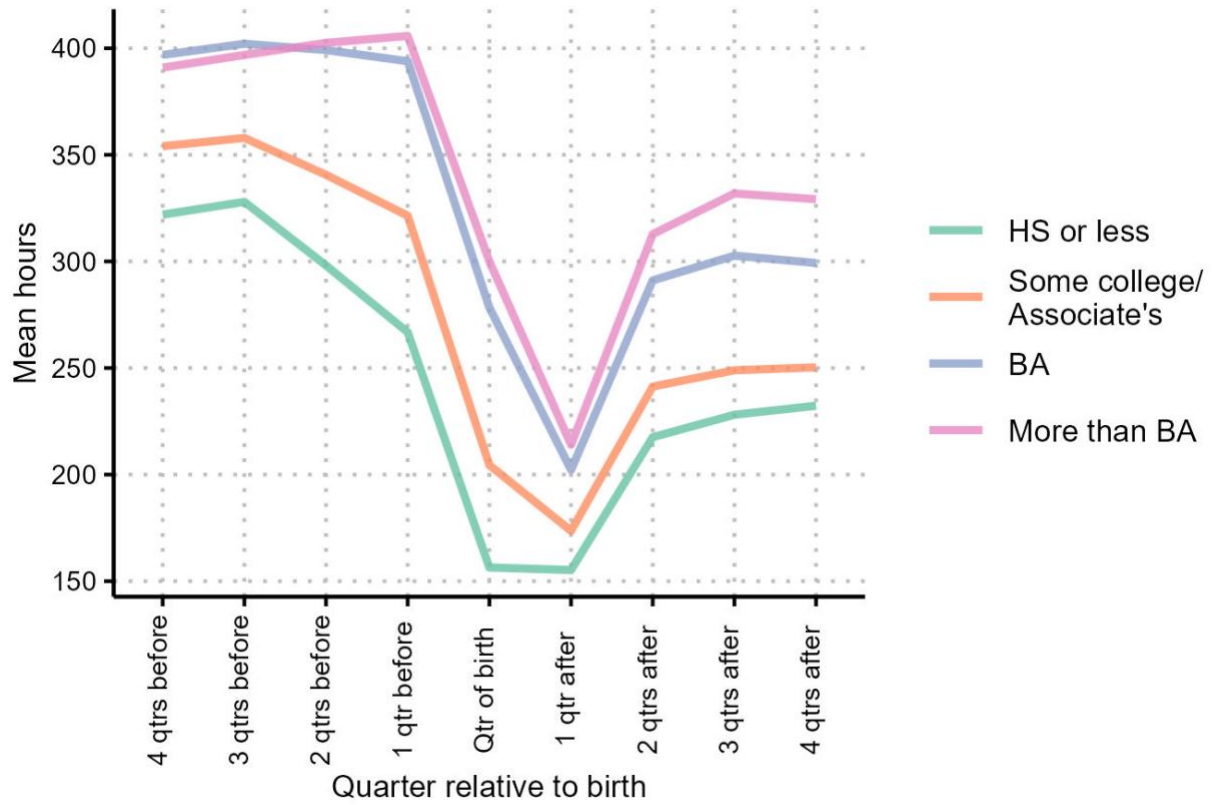
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.3. Standard deviation of arc percent change in mothers' earnings, by race and ethnicity



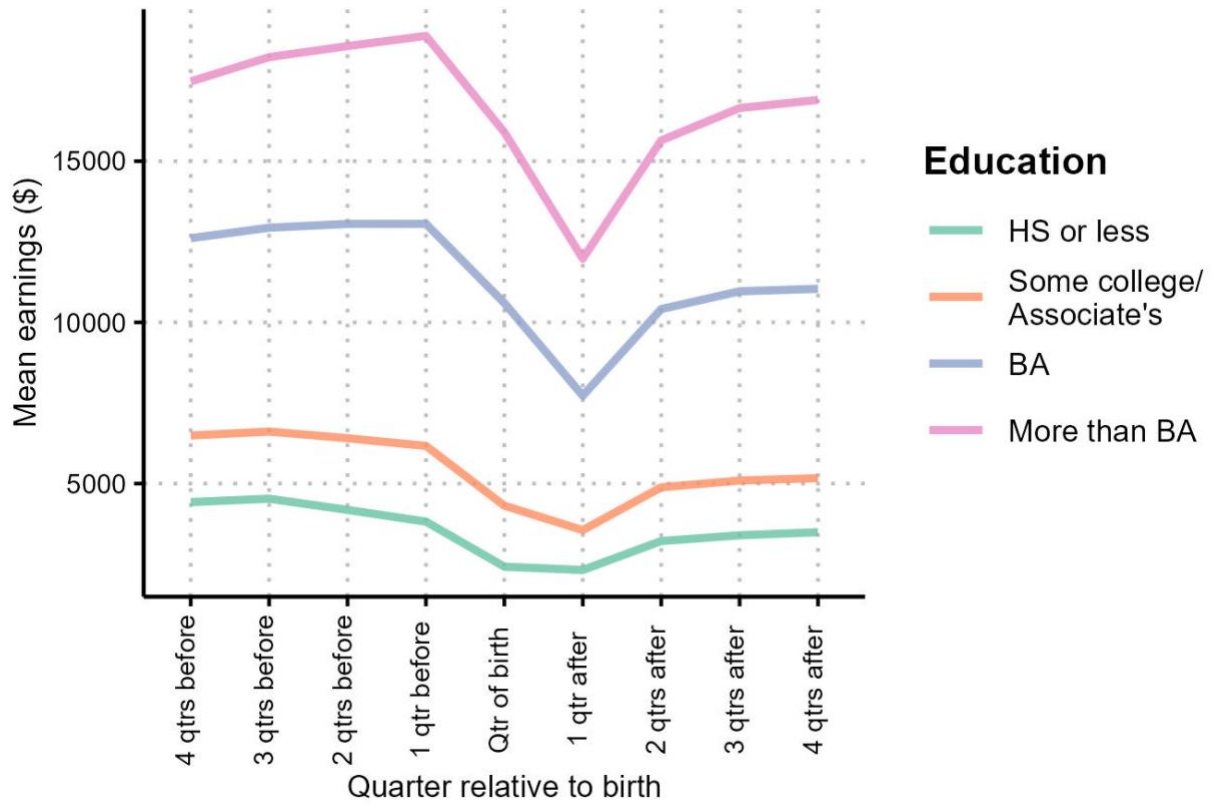
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.4. Hours worked by mothers, by educational attainment



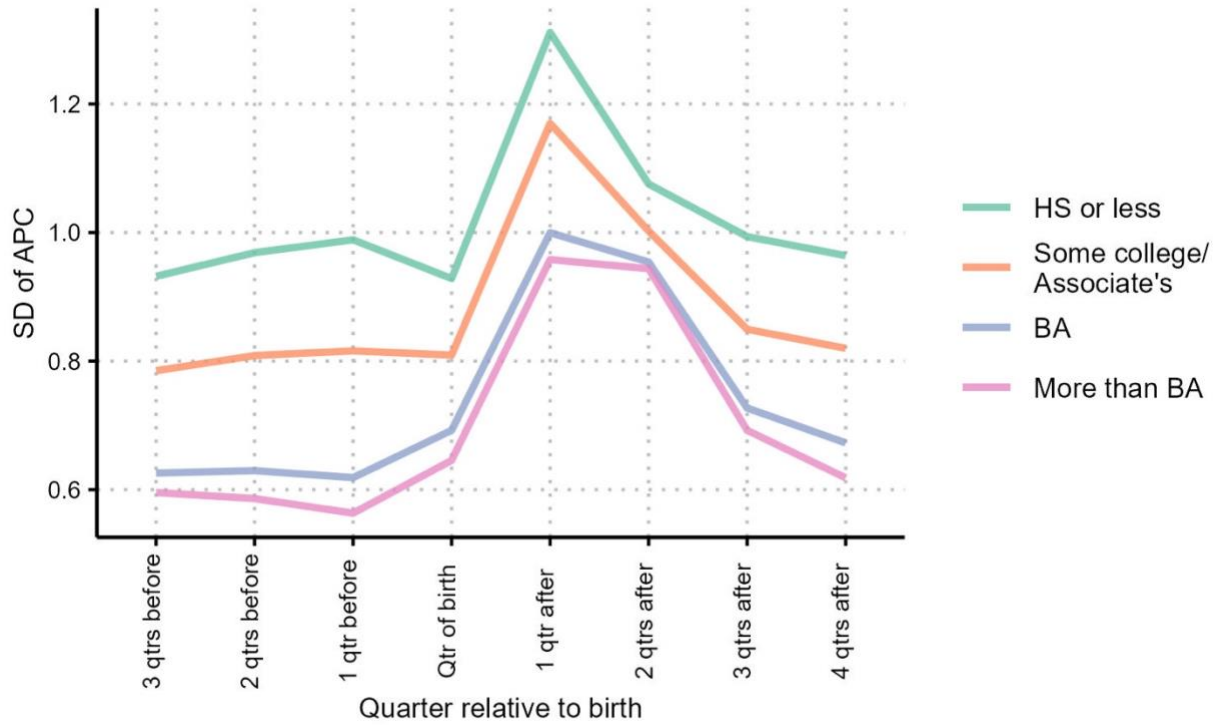
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.5. Mothers' earnings, by educational attainment



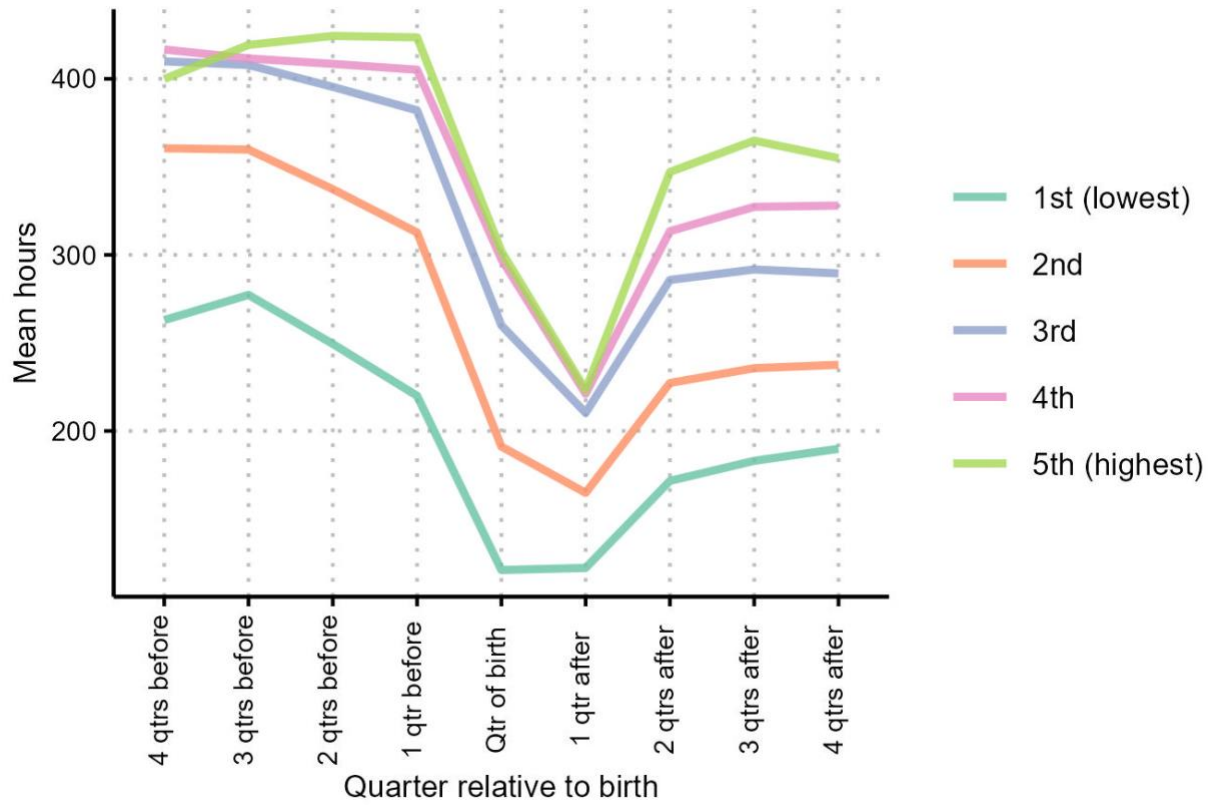
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.6. Standard deviation of arc percent change in mothers' earnings, by educational attainment



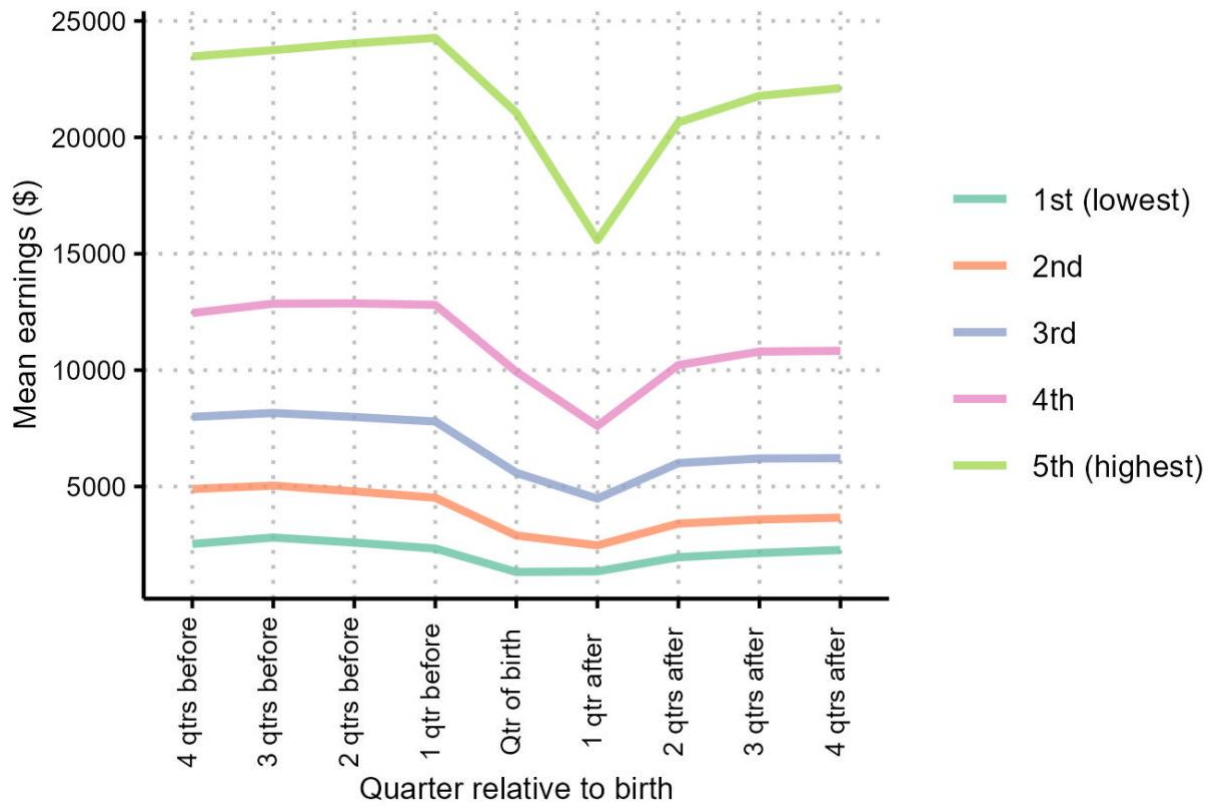
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.7. Hours worked by mothers, by wage quintile



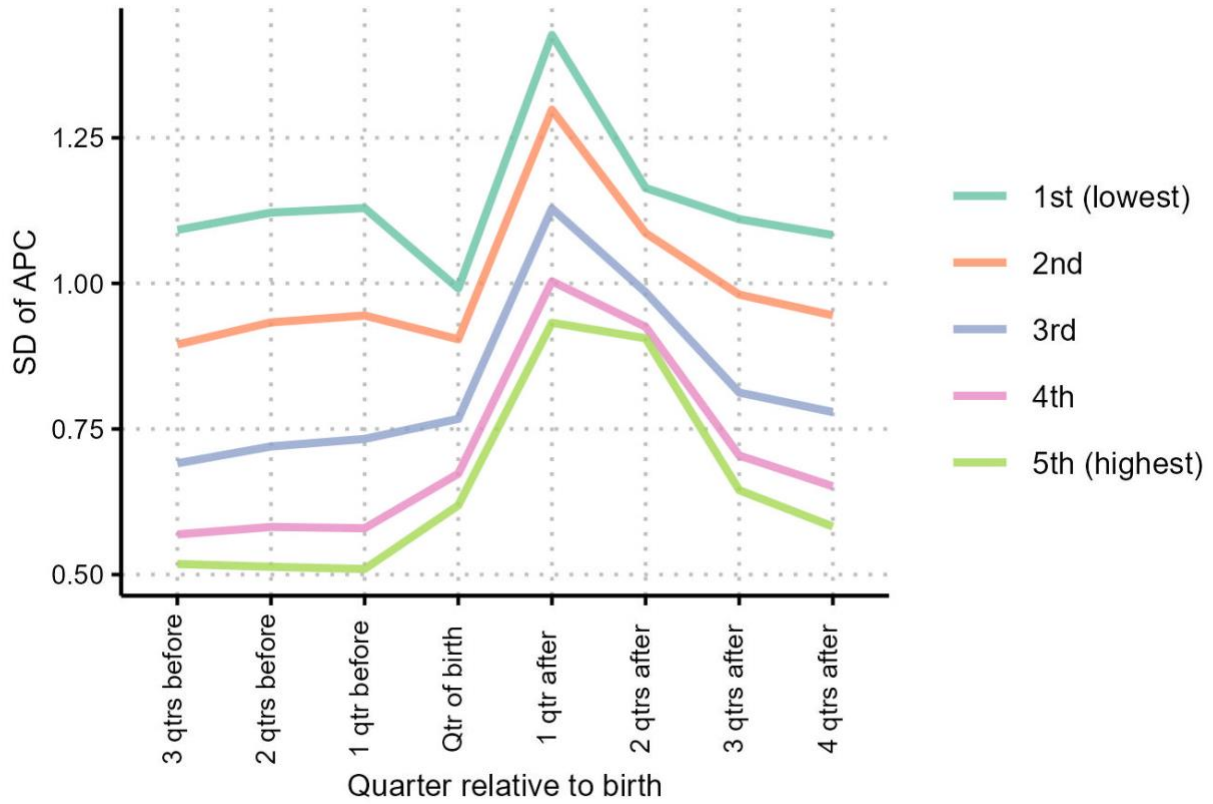
Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.8. Mothers' earnings, by wage quintile



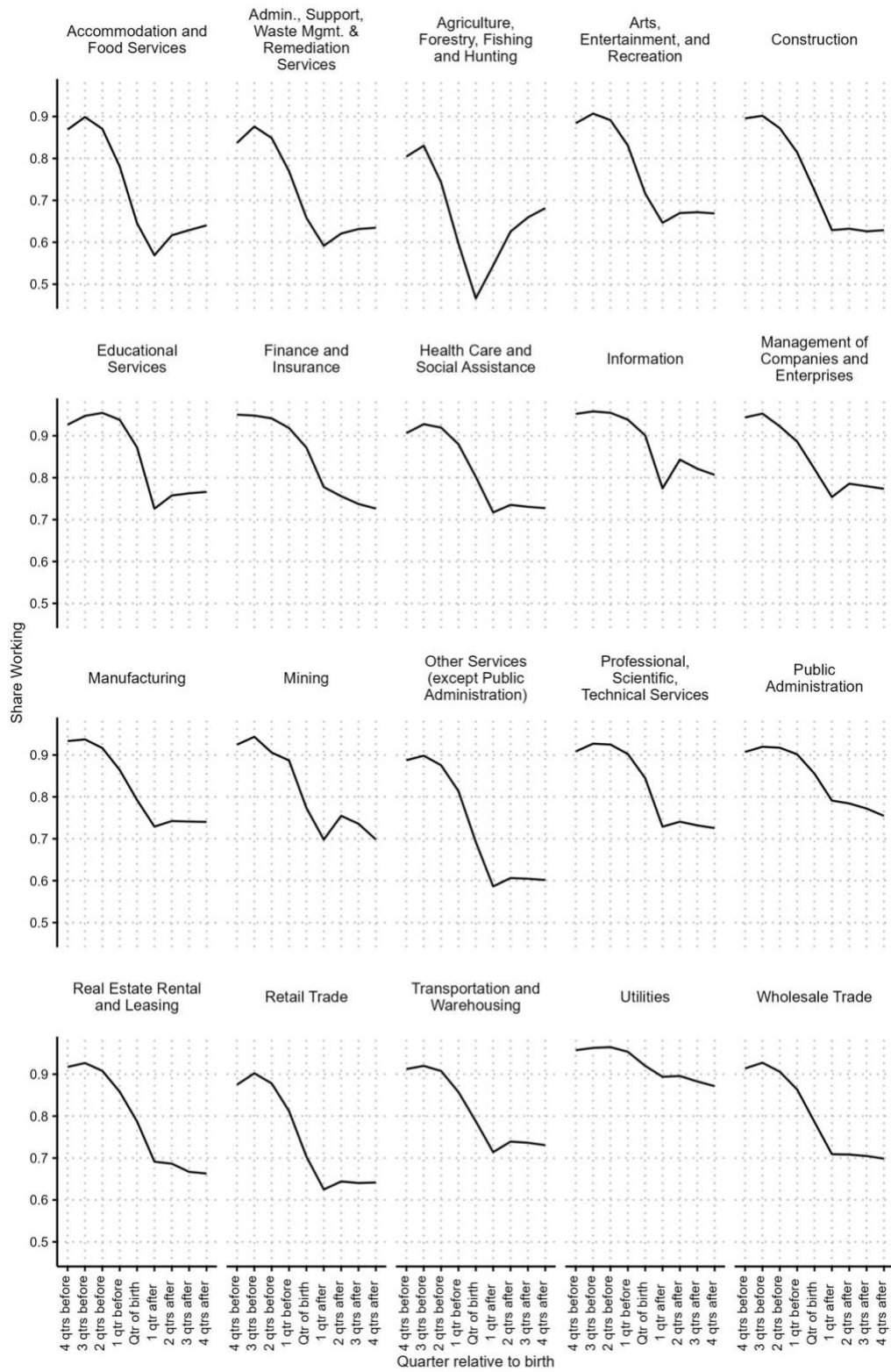
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.9. Standard deviation of arc percent change in mothers' earnings, by wage quintile



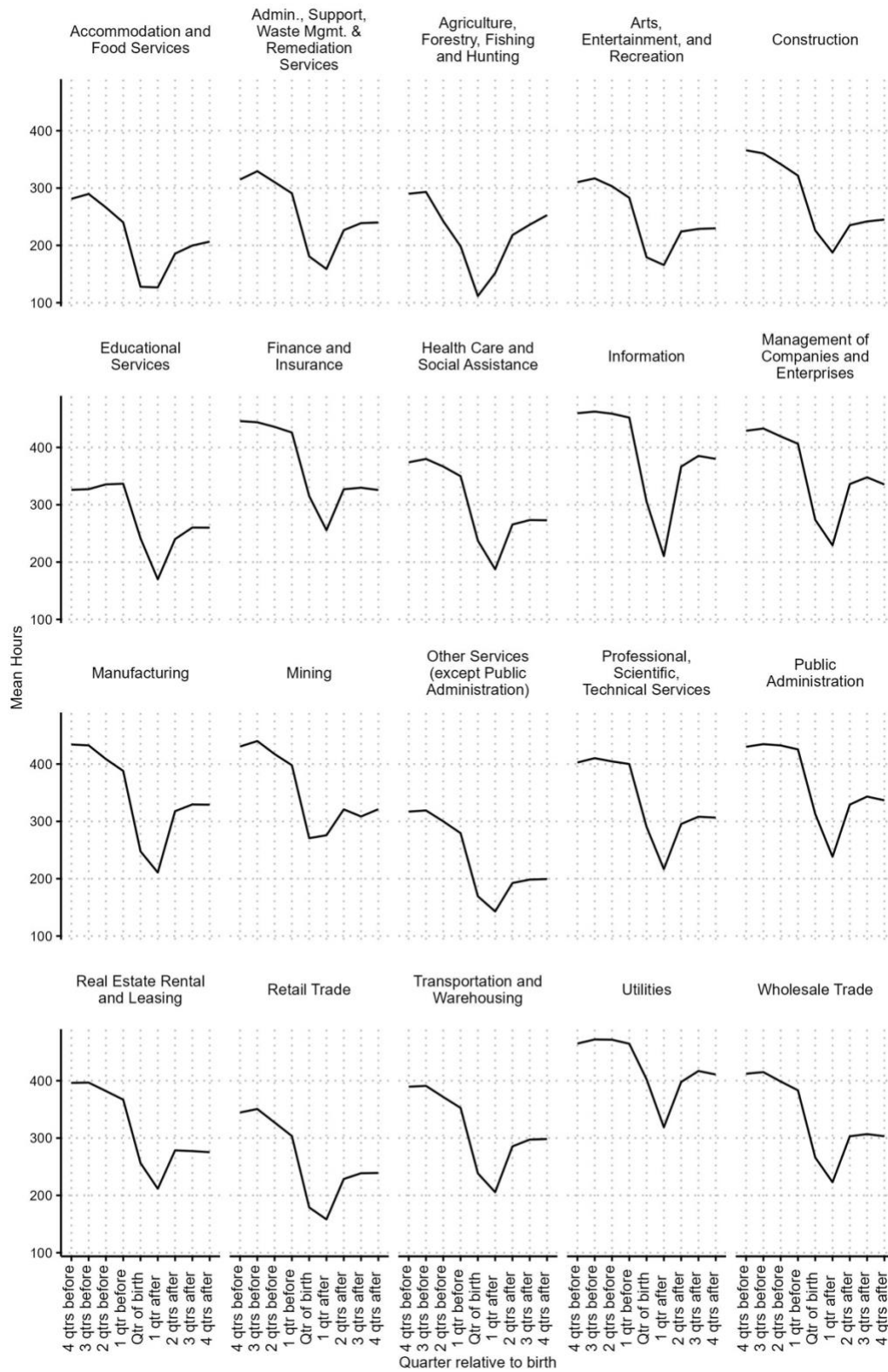
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.10. Employment rates of mothers, by industry of employment



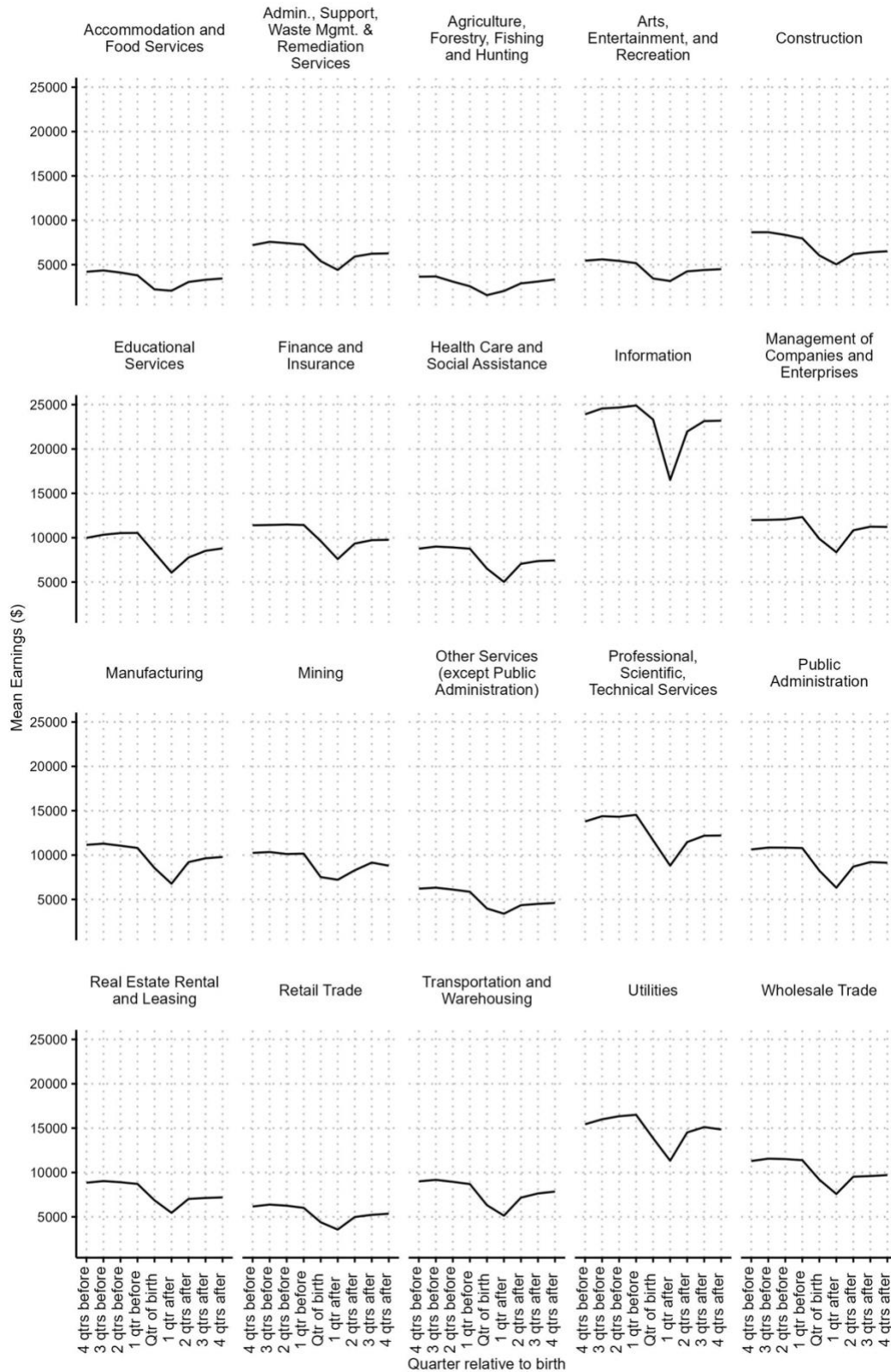
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.11. Hours worked by mothers, by industry of employment



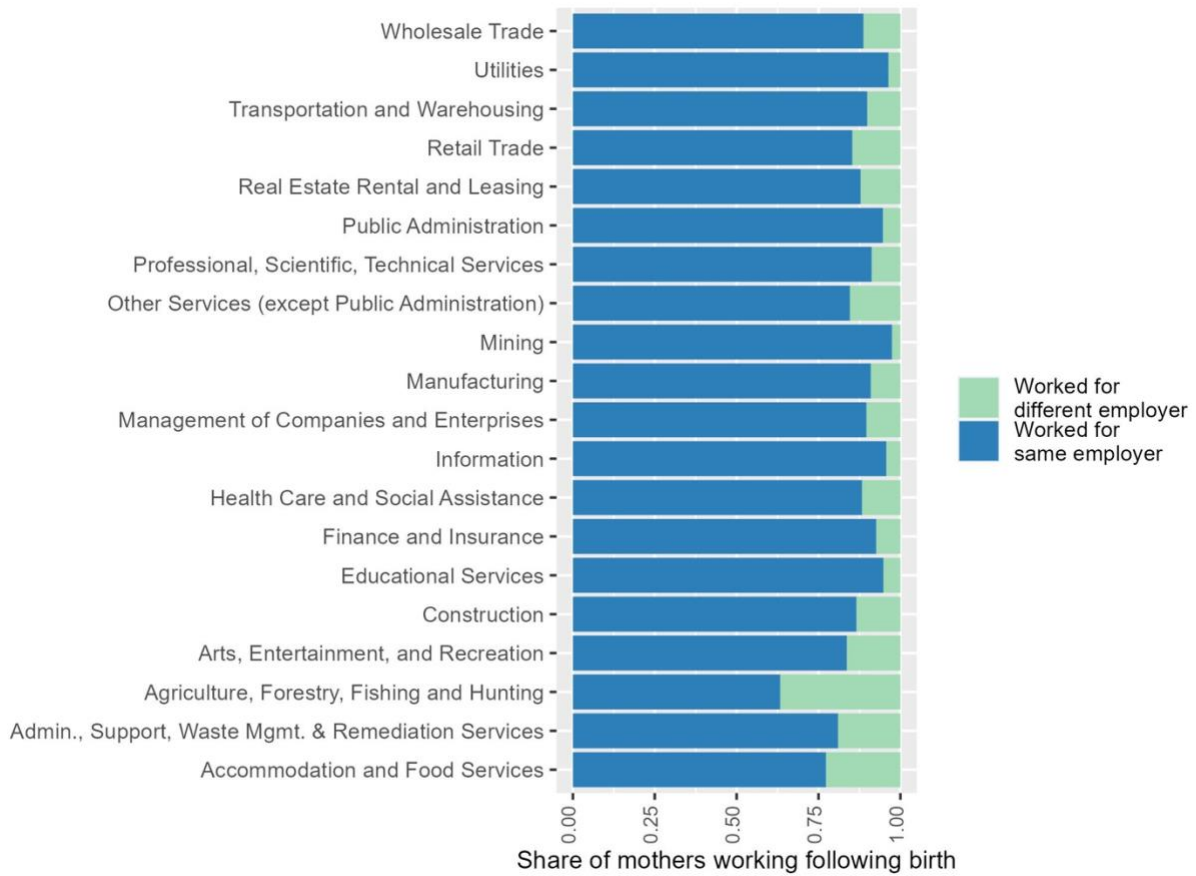
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.12. Mothers' earnings, by industry of employment



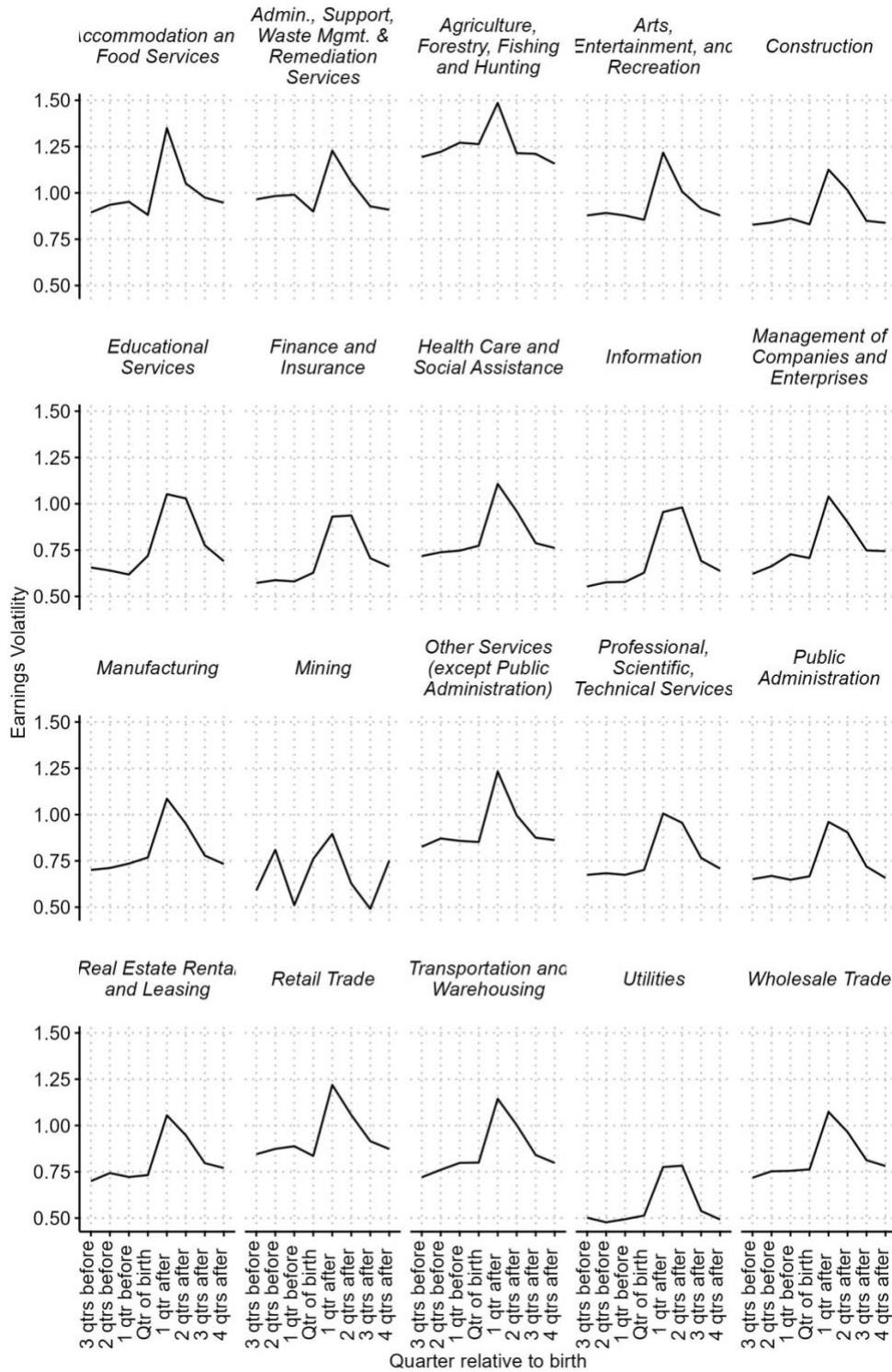
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.13. Share of mothers returning to pre-birth employer, among those working in year following birth, by industry of employment



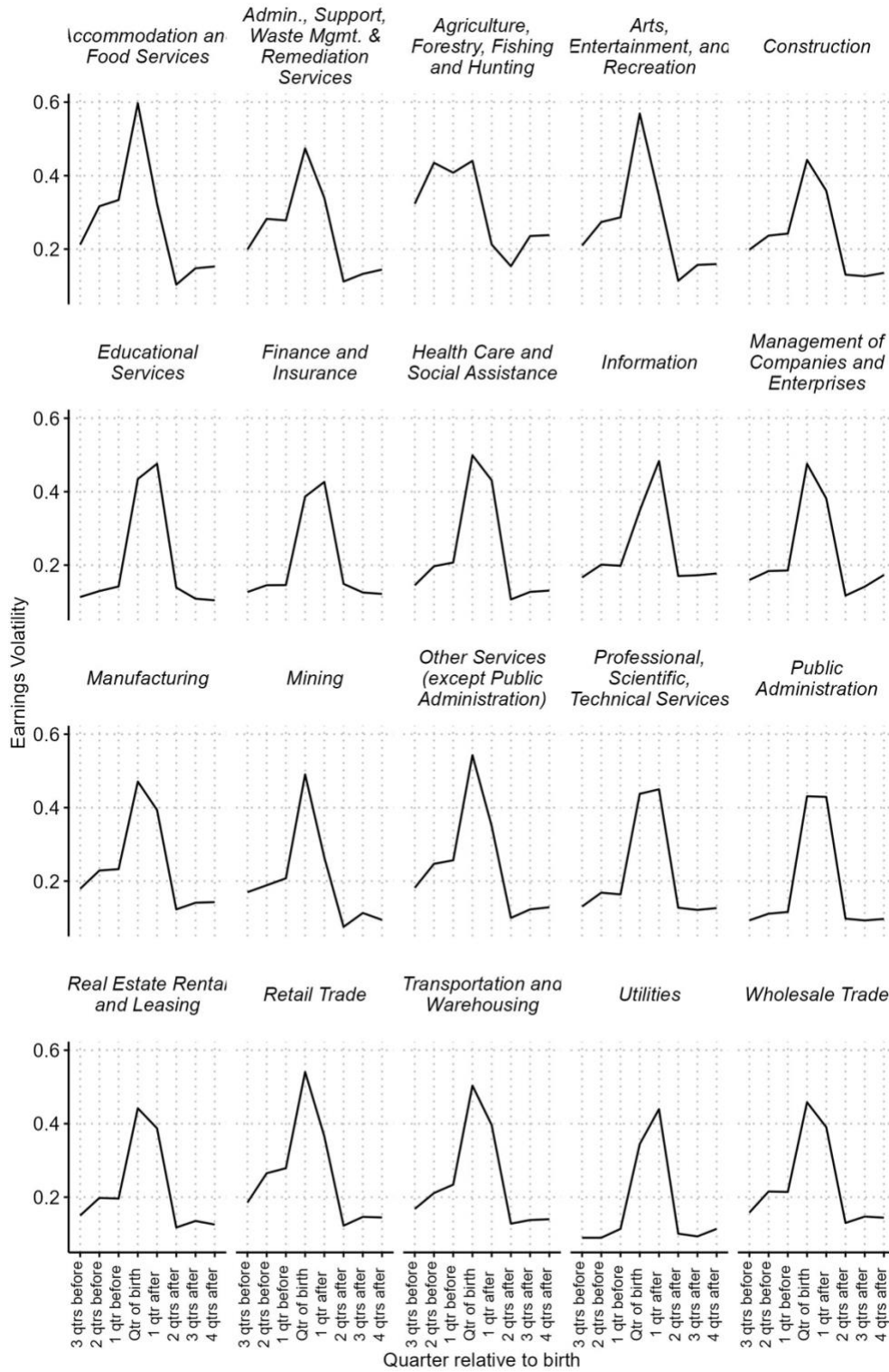
Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.14. Standard deviation of arc percent change in mothers' earnings, by industry of employment



Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Appendix Figure 1.15. Share of mothers experiencing earnings drop of 25% or more, by industry of employment



Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Chapter 2 : How state policy design shapes eligibility for paid family leave: Evidence from a simulation with administrative data

Introduction

Unlike almost all other high-income nations, the United States does not guarantee parents paid time off work when a child is born. Instead, U.S. workers who welcome a new child face a patchwork array of parental leave policies provided by employers, states, and localities. This is despite a large body of research that shows that paid family leave (PFL) supports maternal and child health and families' economic stability. Providing mothers with paid time off around the time of a birth has been shown to improve health outcomes for both mothers and newborns (Bullinger, 2019; Bütikofer et al., 2021; Rossin-Slater & Uniat, 2019; Van Niel et al., 2020). Access to paid leave is also related to increased parental earnings and employment, reduced household poverty, and job continuity around and after a birth (Baum & Ruhm, 2016; Bedard & Rossin-Slater, 2016; Byker, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019).

In contrast to unpaid leave policies, whose benefits largely accrue to more highly educated and married mothers (Han et al., 2009), paid leave increases employment and earnings most significantly for less-educated, lower-income, and unmarried mothers (Baum & Ruhm, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019). This mirrors findings that parents of color, particularly Latinx parents, and parents working in lower-wage jobs are less likely to report having access to paid parental leave through their employers compared to White working parents and working parents earning higher wages (Gault et al., 2014). Policies that expand access to paid family leave, therefore, have the potential to both improve overall maternal and child well-being as well as reducing economic and health disparities between more and less advantaged families.

In the absence of a federally mandated paid leave policy in the United States, several states have recently passed their own policies to provide eligible parents with between four and twelve weeks of paid time off to care for and bond with a new child. As of May 2024, thirteen states and Washington, D.C. have all passed and/or implemented laws that mandate access to PFL. Expanding access to paid parental leave has the potential to reduce disparities in perinatal economic instability and maternal and child health (Montez et al., 2020). However, the success of these policies in doing so is contingent on policy design decisions, which shape equity implications of the policies (Chang & Cassidy, 2021; National Partnership for Women & Families, 2018; Setty et al., 2016). These policies vary dramatically across states with potentially significant implications for policy effectiveness and equity.

This paper focuses on paid leave program eligibility requirements, key features of state PFL policy designs that have important implications for equity and access to paid leave. Currently, all states with paid leave policies determine who may qualify for PFL based on employment histories in the months preceding a qualifying event. Because of this, disparities in labor market experiences prior to a qualifying event may also be replicated in eligibility for PFL, such that parents with lower wages or more tenuous labor market connections are less likely to qualify for the policy. Therefore, eligibility requirements mediate the extent to which the policy resolves or exacerbates existing health and economic inequalities. However, research to date has not examined the implications of specific state policy designs for paid leave access and equity.

This study fills this gap in the literature by assessing how differences in state eligibility requirements might affect the overall share of parents who are eligible for paid leave, as well as disparities across parent subgroups. The analysis leverages unique granular employment microdata from Washington State that can be used to explore the implications of different PFL

eligibility requirements. Eligibility requirements from ten different states' paid leave programs are applied to a population of working parents who were listed on birth certificates in Washington State between 2010 and 2016, before paid family and medical leave was instituted in that state. Based on parents' employment histories as reported in Washington administrative microdata, I simulate which parents *would have been eligible* for PFL under the policy regimes of California, New Jersey, Rhode Island, Washington, Oregon, Connecticut, Massachusetts, Maryland, Colorado, and Delaware.

This approach allows me to isolate the effect of PFL eligibility requirements by manipulating just these rules and applying them to a constant population of potential policy users. Importantly, the administrative data allows the estimation of PFL eligibility with a high degree of accuracy and facilitates analysis across relevant subgroups. Simulations compare eligibility rates between mothers and fathers, then compare mothers' eligibility across racial and ethnic identity, educational attainment, wage quintile in pre-birth employment, and industry of employment. Finally, simulations examine the impact of specific policy design decisions under hypothetical state policies. I discuss what these results show about the implications of state policy decisions for policy accessibility and equity.

These simulations reveal policy-relevant insights about the design of paid leave policies. While all state policies result in disparities in eligibility across demographic and socioeconomic characteristics, overall eligibility rates and disparities in eligibility vary significantly across state policy designs. State policies with more stringent employment requirements disproportionately exclude mothers (versus fathers); mothers working in low-wage jobs; mothers with lower educational attainment; and Black, Indigenous, and Latina mothers from qualifying for paid leave. In general, policies that are less restrictive overall and allow more parents to access paid

leave also significantly narrow disparities in who is eligible. These results have relevance to states considering passing paid leave policies, states with existing policies considering amendments or rule changes, and any federal discussion of paid leave that may occur in the future.

Policy context: Paid family leave in the United States

U.S. workers who welcome a new child encounter a complex array of leave policies provided by employers, states, localities, and the federal government. Since 1993, eligible workers have been guaranteed up to twelve weeks of job-protected but unpaid leave through the federal Family and Medical Leave Act (FMLA). FMLA eligibility criteria are quite restrictive; employees must have worked for a covered employer for at least twelve months, worked at least 1,250 hours for that employer, and must be employed at a worksite where at least 50 employees work for the same firm within 75 miles. Estimates based on the FMLA Employee Survey suggest that roughly 44% of workers are ineligible due to either the worksite size requirement, tenure and hours requirement, or both (Brown et al., 2020). Furthermore, FMLA only provides unpaid leave, which many families cannot afford to take (Joshi et al., 2020). Research demonstrates that while expanding access to unpaid leave (such as FMLA) does increase leave-taking among mothers and fathers, these changes are much larger for college-educated and married mothers who are more likely to be able to afford to take unpaid leave (Han & Waldfogel, 2003). Therefore, the benefits of FMLA are limited and likely accrue to a narrow subset of families (Heymann et al., 2021).

In addition to unpaid leave provided through FMLA, some workers have access to paid leave as an employer-provided benefit. Furthermore, in 2020, employees of the federal government were guaranteed up to 12 weeks of paid leave through the Federal Employee Paid Leave Act. As with FMLA, however, leave policies that are contingent on employer provision

create disparities in which parents are eligible for these programs. Of particular concern is evidence that working parents of color, particularly Latinx parents, and parents working in lower-wage jobs are less likely to report having access to paid parental leave compared to White working parents and working parents earning higher wages (Gault et al., 2014). The Bureau of Labor Statistics estimates that 23% of workers had access to employer-provided paid family leave in 2021 (U.S. Bureau of Labor Statistics, 2021).

Finally, thirteen states and Washington D.C. have passed and/or implemented laws guaranteeing eligible workers paid parental leave that can be used when welcoming a new child. California's paid family leave policy was the first of its kind, enacted in 2004. Most recently, in July 2023, Maine enacted paid family and medical leave legislation that will take effect starting in 2026. While this suite of state policies is often discussed as a group, the policies differ significantly. For workers experiencing the qualifying event of welcoming a new child, these policies have provided between four and twelve weeks of leave for new parents. In recent years, several states providing fewer weeks of leave such as California, New Jersey and Rhode Island have increased their policies' generosity, but cross-state variation persists. For each week a worker claims PFL, the programs pay workers some share of their pre-qualifying event earnings. However, states vary in how pre-birth earnings are determined and how wage replacement rates are calculated. All states have a cap on weekly benefits, but the maximum benefit amounts parents can receive varies. Finally, and the focus of this paper, states all base eligibility on work history prior to a qualifying event but varying requirements mean that different populations of parents qualify for PFL in each state.

Recently, these state innovations, combined with a growing awareness about the importance of care work in light of the Covid-19 pandemic, have inspired conversations about

mandating paid family leave at the federal level. While momentum on federal reform had largely stalled as of June 2024, paid leave policies continue to diffuse across states, and the majority of policy action remains at the state level. Therefore, building evidence on existing state policies offers potentially useful lessons for federal policymaking as well as future state efforts.

Policy design and inequality

Policy designs, and specifically those that use employment-based eligibility requirements, have historically been a mechanism through which policy can exacerbate existing socioeconomic and labor market inequalities (Dobrotić & Blum, 2020; McKay et al., 2018; Nichols & Simms, 2012; Trattner, 1999). Paid leave, like Unemployment Insurance or Social Security, can be thought of as a social insurance policy; it is conceptualized as a system that all workers pay into for the right to receive benefits given a qualifying event. Social insurance programs are often considered to be more universal when compared to more targeted or means-tested public assistance programs. However, despite this relatively universal framework, eligibility requirements can vary substantially, with important implications for which workers can access benefits. Eligibility requirements interact with labor market histories of potential beneficiaries to determine who is eligible to claim leave (Dobrotić & Blum, 2020).

Historically, workers' employment histories and labor market experiences have interacted with eligibility requirements to produce disparities in access to other social insurance programs. In the U.S., for example, the history of Unemployment Insurance illustrates how eligibility requirements led workers to be excluded in ways that generated racial and socioeconomic disparities. Farm workers and domestic laborers, who were disproportionately Black, were initially excluded, and benefits were conditioned on long-term stable labor force participation (Trattner, 1999). Eligibility has since been expanded to cover more types of employment, although concerns remain about the exclusion of workers with part-time or unstable

employment, and disparities in receipt of Unemployment Insurance across race and education persist (Desilver, 2020; Gould-Werth & Shaefer, 2012; McKay et al., 2018; Nichols & Simms, 2012).

Though there is less research on the equity implications of paid leave policy design, researchers have made similar connections between eligibility requirements and disparities in benefit access. Specifically, a study of the FMLA's eligibility requirements found that that policy's employer size, employment tenure, and minimum hours requirements disproportionately exclude women and Black, Indigenous, multiracial, and Latinx workers (Heymann et al., 2021). Employment dynamics specific to the perinatal period are also important here, and have been explored in prior literature. Research on employment trajectories of parents around the time of a birth finds demographic and socioeconomic heterogeneity in employment with potential implications for paid leave eligibility. For example, studies of work during pregnancy has found that Black and Latina mothers and mothers with lower educational attainment were less likely to work during pregnancy when compared to White, Asian, and more highly-educated mothers (Hill et al., 2021; Laughlin, 2011). Given that pregnancy likely aligns with many states' base periods to qualify for paid leave following a birth, it follows that these labor force disparities may be replicated in paid leave eligibility. However, no studies to date have explicitly compared across the eligibility requirements of state-level PFL programs.

The current study

This study uses administrative data from the state of Washington to simulate paid leave eligibility and benefits under different policy regimes. I focus on the following research questions. First, what share of Washington mothers and fathers of newborns would be eligible for paid family leave under each state's eligibility rules? Second, how would these eligibility rates differ among mothers by wage quintile, industry of employment, educational attainment,

and racial or ethnic identity? Finally, how would rates of eligibility for paid leave change for mothers and fathers and across subgroups under hypothetical policy rules as eligibility parameters vary continuously?

Data and measures

To study simulated eligibility for PFL under different state policy regimes, I link administrative data from two sources to identify a population of parents of newborns in Washington State and analyze their employment histories prior to a birth. I link individuals in the Washington State Department of Health (DOH) records, which identify births in the state between 2010 and 2016, and Unemployment Insurance records from the Washington State Employment Security Department (ESD), which report quarterly hours worked and wage earnings for all workers in the state. These data are accessed through the Washington Merged Longitudinal Administrative Data (WMLAD), a compilation of merged longitudinal data from six Washington State agencies linked with a single unique identifier (Romich et al., 2018).

Department of Health birth certificate records

Birth certificate records report rich information about parents, including race/ethnicity, nativity, age, and education. Due to HIPAA regulations, the birth records available in WMLAD do not include the date of the birth, so I use birth certificate numbers to estimate quarter of birth based on the general temporal ordering of births throughout the year.⁵ Birth certificates collect information, whenever available, on a child's biological mother and father, regardless of whether those individuals will be the child's guardians, so there are some individuals included in the data

⁵ Birth certificate numbers are assigned when records are received by WA DOH, which corresponds closely to the temporal ordering of births throughout the year. Since births do not occur evenly throughout the year, I use reports published by DOH to identify the monthly distribution of births each year in Washington (i.e., what percentage of that year's births occurred in January, February, etc.). I apply this monthly distribution to the records sorted by certificate number for each year in our birth data. For example, if 8.1% of 2014 births occurred in January, I assume that the first 8.1% of records (sorted by certificate number) were births that occurred in January. I then assign birth quarters based on the estimated birth month.

who are not caretakers of a newborn; however, this is likely to represent a small share of all records.⁶

Employment Security Department Unemployment Insurance wage records

Unemployment Insurance (UI) wage records from ESD report data at the worker-job-quarter level on hours worked, wages earned, and employer characteristics for all work in UI-eligible jobs in the state of Washington. I adjust earnings amounts for inflation, converting to 2023 dollars to match the era of the policy requirements examined. The records include employer characteristics, such as industry classification and firm location, and contain an employer identifier that links workers to employers over time so that employer continuity can be identified. Multiple limitations to these data are important to note. First, employers are not required to report hours that an employee takes leave except in the case of vacation leave (PTO). If an employee was offered paid parental leave or paid sick leave by the employer and used that leave, those hours were not recorded in the UI data and thus appeared to be *non-working hours* in my analysis. Second, UI data do not include work for employers located outside the state, self-employment as an independent contractor (i.e., 1099 employment), or “under-the-table” work.

Study population

This analysis restricts the population of parents on birth certificates to working parents, defined as parents who worked some amount (i.e., nonzero hours) in either the quarter before birth and/or the quarter of birth. The study population, then, consists of all working parents who were listed on a birth certificate in the state between 2010 and 2016 (n=625,838). This represents

⁶ Parents who wish to change information on the birth certificate to reflect more accurately guardianship can do so after the birth certificate is filed. The data do not reflect these later changes, so some parents included in our analysis may not have financial or instrumental parenting responsibilities. I estimate that this is likely a small share of the overall birth records.

a likely population of policy users⁷ who are connected to the labor market to some extent around the time of a qualifying event—in this case, a birth. State paid leave policies allow workers to take leave for reasons other than bonding with a newborn baby, but I focus on working parents listed on birth certificates for two primary reasons. First, parental bonding is a common reason to take paid leave; for example, in Washington, roughly 33% of paid leave claims were for bonding leave as of January 2023 (Washington State Employment Security Department, 2023b). Second, it is more feasible to identify potential users of bonding leave using administrative records compared to other types of leave. While administrative birth records can easily identify parents of newborns, it would be comparatively harder to identify other populations of potential users of the policy, such as workers who care for ailing relatives or workers with serious health issues.

The use of state administrative data means that findings about this study population are not nationally representative and do not necessarily generalize beyond the Washington State context. To explore the generalizability of this analytic sample to a national context, Table 2.1 compares characteristics of parents listed on Washington birth certificates between 2010 and 2016 to a comparable nationally representative population from the American Community Survey (ACS) (Ruggles et al., 2023; U.S. Census Bureau, 2023). The American Community Survey one-year samples from 2010 through 2016 are filtered to all parents who had own children in the household under the age of 1, approximating the population of parents who welcomed a child in a given year. I report the composition of these samples by race/ethnicity and educational attainment, then calculate mean and median age and yearly earnings. Compared to

⁷ Some states allow parents who are not currently working at the time of a qualifying event to qualify for paid family leave. For example, Washington allows all state residents who met the employment requirement in the base period to qualify for paid leave regardless of current employment status – although Unemployment Insurance and workers' compensation cannot be claimed at the same time as paid leave. Massachusetts allows workers who have been unemployed for 26 weeks or less to qualify for leave. These policy differences highlight an important dimension of access to paid leave. However, this paper focuses on a population of parents who are working around the time of a qualifying event.

the national sample, a larger share of Washington parents identify as White, Asian or Pacific Islander, Native American/Alaska Native, or multiracial. Washington parents are less likely to identify as Black or Latinx compared to ACS estimates. Educational attainment among Washington parents is relatively similar to the ACS estimates, with the exception that Washington fathers are more likely to have some sort of post-high school degree compared to fathers nationwide. Washington parents tend to be slightly younger than parents nationwide, mostly driven by differences among fathers. Washington parents also tend to have higher earnings than parents nationwide; this is particularly true for mothers.

Despite some differences between the population of Washington parents and nationwide estimates from the ACS, I believe that this is a compelling analytic approach due to the nature of the data and the sample. Washington is the thirteenth-most populous U.S. state, with a diverse population that includes both rural and urban areas. Further, using state administrative records offers advantages over nationally representative survey data, specifically the ability to estimate detailed employment histories without relying on self-report and the ability to produce estimates across small but important subgroups. These results have clear policy relevance in Washington, where decisionmakers could use them to directly understand how different policy rules would affect Washington parents' eligibility for paid leave. Some features of local inequalities and labor markets would likely generalize to a nationwide context. Furthermore, the analysis presents proof of concept of an analytic method that could be replicated in other states and with other data sources.

[Table 2.1 about here]

Parent demographic and socioeconomic characteristics

In addition to overall eligibility rates, this analysis also examines heterogeneity in outcomes across demographic, socioeconomic, and employment characteristics based on DOH

and UI data. First, *sex* is identified by comparing mother and father records. *Racial and ethnic identity* is reported in DOH records. For the purposes of this analysis, I report results disaggregated across seven mutually exclusive categories, which are constructed from self-reported fields on the birth certificate: White, not Hispanic/Spanish/Latino/a; Black, not Hispanic/Spanish/Latino/a; Asian, not Hispanic/Spanish/Latino/a; Native Hawaiian/Pacific Islander, not Hispanic/Spanish/Latino/a; Native American/Alaska Native, not Hispanic/Spanish/Latino/a; Multi-racial, not Hispanic/Spanish/Latino/a; and Hispanic/Spanish/Latino/a,⁸ any race. *Educational attainment* is also self-reported in DOH records and is broken down into four categories: high school diploma or less; some college/associate's degree; bachelor's degree; and more than bachelor's degree (i.e., graduate/professional degree). Wage rate and industry are calculated using ESD UI records. *Wage rate quintile* in main job prior to birth is calculated by dividing wages earned by hours worked in the "primary job" (the job with the most hours) in the most recent quarter in which the parent was employed prior to the quarter of birth. *Industry of employment* is reported using the broad NAICS category associated with the "main job" (job with the most hours) in the most recent quarter in which the parent was employed prior to the quarter of birth.

Estimating paid leave eligibility

I selected ten states with varying policy designs for which I could reasonably estimate parents' eligibility using the Washington State administrative data. Table 2.2 summarizes key features of each state's paid leave program and explains how eligibility is operationalized using the Washington employment data.

[Table 2.2 about here]

⁸ Throughout this paper, I refer to mothers who indicated that they were of "Hispanic origin," which the birth certificate form defines as "Spanish/Hispanic/Latina," as "Latina."

Some state eligibility requirements could not be accurately estimated using the ESD data. For example, New York’s eligibility requirements for part time workers are dependent on working a certain number of days and hours per week, which cannot be approximated using the quarterly Washington administrative records. Washington, D.C.’s requirements are based largely on time spent working in the city of D.C. rather than other jurisdictions, a specific context due to D.C.’s proximity to Maryland and Virginia which does not apply in Washington State. New Jersey’s eligibility requirements also rely on weekly earnings, but an upper and lower bound eligibility estimate can be approximated by making different assumptions about how weekly earnings are distributed throughout the quarter; both upper and lower bounds are reported for New Jersey in each figure.

Results

Table 2.3 illustrates how the population of parents on birth certificates is narrowed to the study sample of parents working around the time of a birth. These results are important because they demonstrate how inequalities emerge even at the outset when restricting the study sample to a sample of “currently working” parents. Column A reports the total number of parents listed on Washington birth certificates between 2010 and 2016. I then examine work history in two time periods. Column B reports the number of parents who had any pre-birth work history in the UI records, anytime from five quarters before a birth up to the quarter of birth. Column C reports the number of parents who worked right around the time of a birth, defined as working in the quarter before a birth and/or the quarter of birth. Columns D⁹ and E¹⁰ report labor force participation rates based on these two definitions, respectively, and Column F¹¹ estimates the share of parents with any work history who worked right around a birth.

⁹ Column D is calculated by dividing Column B by Column A.

¹⁰ Column E is calculated by dividing Column C by Column A.

¹¹ Column F is calculated by dividing Column C by Column B.

[Table 2.3 about here]

Table 2.3 reveals that perinatal labor force participation¹² is inconsistent and varies across parent subgroups. Labor force participation is higher among mothers than fathers; 70% of fathers had some work history in the UI data in the pre-birth period compared with 56% of mothers. Sixty-five percent of fathers and 46% of mothers worked in UI-eligible jobs in the quarter prior to birth and/or the quarter of birth and are therefore considered likely policy users and included in the main analytic sample for this study (Column C).

These results highlight differences in labor force participation that disproportionately exclude some parents from inclusion in the sample of working parents, before estimating paid leave eligibility. Latina, Asian, Native Hawaiian/Pacific Islander, and Native American/Alaska Native mothers were less likely to have work history in the UI data compared to White, Black, and multi-racial mothers. Of parents with any work history, Asian mothers were the most likely to work around the time of a birth, followed by White mothers (83%), multi-racial mothers (80%), Black mothers (78%), Latina mothers (75%), Native American/Alaska Native mothers (71%), and Native Hawaiian/Pacific Islander mothers (70%). Mothers with higher educational attainment were more likely to have any pre-birth work history in the UI data; among mothers with some work history those with higher educational attainment were also more likely to work right around a birth. Among mothers who had any work history, mothers working in higher-wage jobs were most likely to work around a birth compared to mothers working in lower-wage jobs. These rates varied across industries of employment as well. These results are important to keep

¹² Due to the nature of the employment records, these figures are an undercount of labor force participation for a number of reasons. Parents may be listed on birth certificates in the state of Washington but reside and work elsewhere or reside in Washington but work for employers located in other states. Parents may work under-the-table or for employers who are not included in the UI records. Therefore, these estimates should be interpreted as participation in work eligible for Unemployment Insurance. However, there is reason to believe that some working parents whose employment was not captured in the UI data may also not be able to qualify for paid leave -- due to not working in Washington State, for example .

in mind when interpreting findings described below. Because the main analytic sample for this paper is Column C, the population of parents working around the time of a birth, results below should be interpreted with the acknowledgment of which groups of parents are disproportionately excluded from this sample because they were not employed at the time of a birth.

Figure 2.1 simulates estimated paid leave eligibility under each state's policy for all mothers and fathers. States are ordered on the x-axis based on the overall share of parents who were estimated to be eligible under each policy regime. Red dots indicate the share of mothers estimated to be eligible for paid leave under each state's policy criteria, while blue dots present the same calculation for fathers. This figure demonstrates that state paid leave policies offer benefits to significantly different shares of the working parent population. Among mothers working around the time of a birth, eligibility for paid leave ranges from 97% under Oregon's policy to 58% under Delaware's policy – a 35 percentage point difference. In Oregon, Colorado, and California, almost all parents working around the time of a birth—more than 95%—would qualify for paid leave. In Connecticut, roughly 10% of fathers and 9% of mothers would not qualify. Under Massachusetts's policy, the percent of parents who would not be eligible increases to roughly 15% for fathers and almost 20% for mothers. Delaware's eligibility requirements are by far the most restrictive, resulting in only 58% of mothers and 64% of fathers being eligible. Delaware's policy also created the largest disparity between mothers and fathers—a gap of 6 percentage points.

[Figure 2.1 about here]

The following analyses focus on mothers, who are the most likely to claim paid leave and more likely to experience more perinatal employment instability compared to fathers (see

Chapter 1).¹³ Figures 2.2 and 2.3 examine how simulated eligibility for paid leave under different state policies varies across mothers' employment characteristics. First, Figure 2.2 examines simulated eligibility for paid leave among mothers across wage rate—the estimated hourly wage rate based on each mother's primary job in the pre-birth period. Dots represent the share of mothers estimated to be eligible under each state's policy design (represented by gray vertical columns) and are color-coded by wage quintile, from the first (representing the lowest-wage jobs) to the fifth (representing the highest-wage jobs).

These estimates illustrate stark disparities both within and among state policies. First, each state's policy results in significantly lower eligibility rates for mothers working in lower-wage jobs. Furthermore, states with more restrictive eligibility requirements result in the largest disparities in eligibility across wage rate. While Oregon, Colorado, and California have eligibility rates within roughly 10 percentage points regardless of wage rate, gaps widen under the policies of states with more restrictive eligibility requirements. Disparities in eligibility between mothers in the highest- and lowest-wage jobs ranged from 6 percentage points in Oregon to 45 percentage points in Massachusetts and Delaware. Notably, mothers working in the lowest-wage jobs in Oregon are more likely to be eligible for paid leave than mothers in the highest-wage jobs in Maryland, Washington, or Delaware. Across states, mothers working in the lowest-wage jobs (i.e., the first quintile) are particularly likely to be deemed ineligible for paid leave. For example, 20% of mothers in the lowest-wage jobs are estimated ineligible for leave under Connecticut's policy and half of these mothers are estimated ineligible under Massachusetts's policy. In Delaware, less than a third of mothers working in the lowest-wage jobs are estimated to be eligible for paid leave.

¹³ Results for fathers followed similar patterns and are available from the author upon request.

[Figure 2.2 about here]

Figure 2.3 plots paid leave eligibility estimates across the industry of mothers' main jobs pre-birth. Each industry is plotted in its own plot, with state policy regimes plotted along the x-axis. This graph illustrates that, because of differences in mothers' work histories by industry, different state policies produce different patterns in eligibility across industries. Some industries are relatively homogeneous with mothers tending to be highly connected to the labor force; in these industries, PFL policy differences matter less. For example, mothers who worked in information were more than 80% likely to qualify for paid leave under every state's policy regardless of state eligibility requirements. In contrast, eligibility rates for mothers working in accommodation and food services range from 36% under Delaware's policy to 97% under Oregon's. This graph illustrates how some state PFL policies produce relatively high and consistent PFL eligibility rates across industries, while others produce more unequal outcomes when disaggregated by industry.

[Figure 2.3 about here]

Figure 2.4 plots estimated PFL eligibility under the different state policy regimes across mothers' educational attainment. This figure reveals that all state policies result in lower estimated eligibility rates for mothers with lower educational attainment compared to those with higher educational attainment. However, the magnitude of the disparities in educational attainment vary significantly across policy designs. Under Oregon's policy, between 95% and 99% of mothers would qualify for paid leave regardless of educational attainment. In contrast, Massachusetts' and Delaware's policies both result in 24 percentage point gaps in eligibility between mothers with a high school education or less and mothers with a graduate degree. Under Massachusetts' policy, 92% of mothers with a graduate degree are eligible in contrast to 68% of

mothers with a high school education or less. Under Delaware’s rules, eligibility spans from 46% (mothers with a high school education or less) to 70% (mothers with a graduate degree). Again, state policy designs that are more restrictive overall tend to result in larger disparities in eligibility across mothers by educational attainment.

[Figure 2.4 about here]

Finally, Figure 2.5 plots estimated eligibility for paid family leave across mothers’ racial and ethnic identities. These results reveal a few key patterns. First, Asian mothers are consistently the most likely to qualify for paid family leave, followed by White mothers. Mothers identifying as Black, Native Hawaiian/Pacific Islander, Native American/Alaska Native, and Latina are disproportionately excluded from paid family leave across policy regimes. These disparities emerge because of differences in employment histories across racial and ethnic groups. State policies that are more generous overall are able to narrow racial/ethnic disparities across mothers. Racial and ethnic disparities in paid leave eligibility are relatively small under Oregon, Colorado, and California’s policies, but widen under policies that impose more restrictive requirements in order to qualify for paid family leave.

[Figure 2.5 about here]

To further show how policy design can shape eligibility across population sub-groups, Figures 2.6 and 2.7 simulate how paid leave eligibility rates change under hypothetical policy design scenarios. Rather than estimating the effects of specific states’ policies, these analyses explore how paid leave eligibility would change across continuous variation along the two most common types of eligibility requirement: eligibility based on earnings in the year prior to a birth (Figure 2.6) and eligibility based on hours worked in the year prior to a birth (Figure 2.7).

Figure 2.6 illustrates how a hypothetical earnings eligibility cutoff (along the x-axis)

would shape eligibility for paid family leave across parent subgroups. These results show how, while increasing the earnings eligibility cutoff of course results in fewer parents qualifying in each subgroup, the rate of this decline differs significantly across subgroups. Because the distribution of annual earnings differs between mothers working around the time of a birth and fathers working around the time of a birth, for example, more mothers than fathers are excluded from eligibility with each equivalent increase in the eligibility cutoff above \$5,000 (see Panel A).

Similar patterns are evident among mothers across wage quintile (Panel B). Increasing an earnings requirement to \$20,000 a year, for example, would result in over 90% eligibility for the top two quintiles and over 80% eligibility for the third quintile. In contrast, eligibility for the second wage quintile falls to approximately 60% and less than 30% of mothers in the lowest wage quintile would be eligible for PFL under such a policy. Panel C reports similar results across industry of employment.

A high share of mothers working in some industries (for example, Information) would qualify for a hypothetical policy with an earnings requirement up to \$20,000. However, because more mothers working in industries such as Accommodation and Food Services and Agriculture, Forestry, Fishing, and Hunting have lower earnings, a hypothetical earnings-based eligibility cutoff of \$20,000 would disqualify over half of mothers working in these industries. Examining eligibility differences across hypothetical earnings cutoffs by educational attainment (Panel D) reveals similar patterns.

Over 85% of mothers with a BA or more would qualify for PFL under a hypothetical policy with earnings threshold up to \$20,000. In contrast, such a policy would exclude roughly 30% of mothers with some college or an Associate's degree and nearly half of mothers with a high school education or less. Finally, Panel E reports the effects of these hypothetical eligibility

cutoffs across mother racial and ethnic identity. As a theoretical earnings-based eligibility requirement increases, racial disparities in eligibility for such a policy widen. Requiring higher earnings thresholds particularly disadvantages Native American/Alaska Native, Native Hawaiian/Pacific Islander, Black, and Latina mothers; among all these groups, roughly 40% of working mothers would be excluded by a \$20,000 eligibility requirement.

[Figure 2.6 about here]

Next, Figure 2.7 explores how a hypothetical hours eligibility cutoff would affect eligibility for PFL. Diverging eligibility rates across parent subgroups reveal that, similar to earnings eligibility cutoffs, increasing the number of hours required to qualify for paid leave tends to increase inequality across subgroups as the hours cutoff increases from zero to roughly 1500 hours. After roughly 1500 hours, eligibility rates across subgroups start to converge, as it becomes increasingly rare for parents to meet the requirement.

Panel A shows that eligibility rates based on a theoretical hours-based eligibility cutoff are relatively equal for mothers and fathers until approximately 500 hours, at which point fathers become more likely than mothers to have worked that amount. Panel B illustrates that hours-based eligibility requirements generate inequalities across wage quintile even at very low hours thresholds. Especially among mothers with the lowest wage rates (the first quintile), eligibility drops rapidly as hours-based requirements increase. Panel C shows how eligibility rates change across theoretical hours-based eligibility requirements by mothers' primary industry. Because mothers in certain industries (e.g. Accommodation and Food Services and Agriculture, Forestry, Fishing and Hunting) work fewer hours on average, their eligibility declines rapidly as hours requirements increase. In Panel D, the same exercise is repeated across educational attainment categories. Inequality in eligibility across educational attainment increases as a theoretical hours

threshold increases. Panel E repeats this analysis across mothers' racial and ethnic identity, showing that racial and ethnic inequalities widen as a theoretical hours threshold increases.

[Figure 2.7 about here]

Discussion and conclusion

This paper uses simulations with administrative microdata to explore the implications of state paid leave policy rules for eligibility among a population of likely policy users. Looking at parents of newborns in Washington State, I apply different states' eligibility requirements and report simulated eligibility rates for all parents and among mothers by subgroup. Then, I examine hypothetical policy scenarios by varying eligibility rule parameters continuously and reporting estimated eligibility rates for all parents and among mothers by subgroup. I find that the design of state PFL eligibility requirements has significant consequences for policy access and equity; examining simulated paid leave eligibility rates under different policy regimes and for different subpopulations reveals several key findings.

First, comparing working parents' eligibility rates under each state's paid family leave policy reveals that differences in labor market trajectories among parents produce significant disparities in paid leave eligibility across socioeconomic and racial lines. Under each state's eligibility policy, no matter how generous, differences in work history generate disparities in eligibility that result in lower eligibility rates for Black, Indigenous, and Latina mothers (vs. White and Asian mothers), mothers with lower educational attainment, and mothers working in lower-wage jobs.

However, disparities in PFL eligibility are not inevitable; differences in paid leave eligibility requirements dramatically shape overall and distributional effects of these policies on parents of newborns. While all of these policies except California's were passed within the span of the past decade, and these state policies are often discussed together, this analysis

demonstrates that along the dimension of eligibility they are actually quite different. When comparing across states, differences in state eligibility requirements result in different overall rates of eligibility for paid leave and also shape disparities in eligibility across groups. State policies that are more generous overall, allowing more parents to qualify for PFL, also typically result in smaller racial and socioeconomic disparities in eligibility across parent subgroups.

Finally, disparities in paid leave access emerge at the outset when identifying which parents are connected enough to the labor force to potentially claim PFL—or, in the case of this study, selecting the analytic sample (see Table 2.2). Parents, particularly mothers, experience significant employment instability around the time of a birth (Hill et al., 2021; Stanczyk, 2020; see also Chapter 1). As a result, many parents are not currently working when a child is born. Perinatal employment instability presents a challenge for policy accessibility and equity – especially because most states require workers to be currently employed in the state in order to claim leave. Of all mothers with some pre-birth work history in the UI data, 19% were not working around the time of a birth. This percentage was higher for mothers who were not White or Asian, mothers with lower educational attainment, and mothers working in lower-wage jobs. These findings highlight how, by operating as work-based programs, paid leave policies exclude a significant share of parents, even among those with some connection to the labor force. Importantly, these findings also highlight the promise of policies like Washington’s, which allow parents to qualify based on employment history even if they are not currently employed, to reduce disparities in leave access at this point in the pipeline.

Limitations

This analysis focuses on rates of eligibility for paid leave. However, these simulations of estimated eligibility do not fully capture *access* to paid leave. Eligibility is one element of access, but take-up of any policy is also determined by other factors. State outreach campaigns

may influence whether parents are aware of the program and/or understand whether they are eligible; many potential beneficiaries may not be aware of their eligibility (Goodman et al., 2020). State administrative procedures and employer compliance in implementation shape the level of administrative burden that applicants face, which can affect take-up (Herd & Moynihan, 2018). Other policy design features, such as wage replacement rates, length of allowed leave, and whether or not job protection is guaranteed, affect the economic costs and benefits that parents weigh when deciding to take leave, which can also influence take-up rates in ways that could disadvantage lower-wage workers. Therefore, while eligibility is a critical determinant of access, it is not the only relevant factor. Qualitative work could explore barriers to access among potential policy users.

Another important limitation is that this study focuses on parents of newborns and therefore only examines eligibility for one type of paid leave: bonding leave following the birth of a child. However, states also allow workers to take paid leave for other purposes, most commonly attending to one's own serious medical issues or caring for family members other than newborns. This analysis focuses on how employment trajectories before a birth affect eligibility for taking leave in a framework where a child's birth is a worker's qualifying event. However, this does not capture how state policy designs affect eligibility rates and disparities among workers who take leave for another reason. Future research should examine employment trajectories of workers who experience these other qualifying events to more fully explore how employment-based eligibility requirements affect accessibility and equity of paid leave policies.

This study also faces specific data limitations. First, the data focuses on parents in Washington State. As Table 2.3 demonstrates, parents in Washington are relatively similar to parents nationwide along some dimensions (education; age) but quite different in other ways

(race/ethnicity; earnings). Therefore, future work should extend this analysis to see if similar patterns apply given the particular population of parents in other states. In addition, the ESD data only captures UI-eligible employment, so the employment histories used to calculate paid leave eligibility do not include self-employment, informal work, and other types of non-UI-eligible jobs, which could possibly qualify a parent for paid leave under certain policies and certain conditions. It is therefore possible that I underestimate paid leave eligibility among parents who could use employment not reported in the ESD data to qualify. However, the population of interest (the denominator for all eligibility rates) is all parents who worked some number of hours according to the ESD data in the quarter prior to a birth or the quarter of a birth, restricting the sample to a population that is connected to the UI-eligible labor force in some way and therefore likely reducing the extent of this underestimation.

Research implications

These findings underscore the importance of studying variation in design of paid leave policies, pointing to fruitful directions for future research. State policy design and implementation affect not only who is eligible for paid leave (the focus of this study), but may also shape policy effectiveness and equity in other ways that future research could examine. For example, wage replacement rates shape household income directly and also affect the financial viability of taking paid leave based on the cut to income parents face by claiming leave, particularly for parents in lower-wage jobs. Or, if policies do not offer job protection, fear of job loss can be a barrier to families taking advantage of the policy, particularly for those who are economically vulnerable (Setty et al., 2016). Disparities in take-up may also be generated by differences in knowledge across families, which can be shaped by the strengths or weaknesses of state outreach campaigns.

This analysis also points to the value of linked, longitudinal administrative microdata,

which allow me to identify a potentially eligible population of paid leave claimants and trace pre-birth employment histories in a way that closely mirrors several states' eligibility requirements. The large sample size of the administrative records also allowed me to estimate paid leave eligibility among smaller subgroups of parents, including Native American and Alaska Native parents, Native Hawaiian and Pacific Islander parents, and parents working in specific industries. These groups would likely not be identifiable in survey datasets that only contain a sample of the population. These data have clear policy relevance and should be leveraged in support of future research on policy and family economic wellbeing.

Policy implications

Despite the popular notion that paid family leave is diffusing across states (Bipartisan Policy Center, 2022), policy designs differ significantly with important implications for potential beneficiaries. This analysis focuses on one dimension of policy variation: eligibility requirements based on employment histories. Among working parents, policy differences across ten states have significant implications for access to paid leave. While conditioning eligibility on employment necessarily generates some amount of inequality in who is eligible, states looking to narrow disparities in PFL eligibility could look to the policies of Oregon, Colorado, and California. In each of these states, less restrictive eligibility requirements significantly narrow gaps across race/ethnicity, educational attainment, and job characteristics.

Tables and figures

Table 2.1. Descriptive statistics of analytic sample compared to nationwide estimates

	Analytic sample using Washington birth records (births 2010-2016)			American Community Survey, parents with own children less than 1 year old (2010-2016)		
	All parents	Mothers	Fathers	All parents	Mothers	Fathers
Race/ethnicity						
% White	66.20%	66.05%	66.31%	60.57%	60.19%	60.92%
% Black	4.52%	4.23%	4.76%	10.81%	13.24%	8.64%
% Asian, Native Hawaiian, or Pacific Islander	10.47%	9.89%	10.93%	6.01%	5.49%	6.47%
% Native American/Alaska Native	1.15%	1.26%	1.05%	0.61%	0.72%	0.52%
% Two or more races	3.58%	3.93%	3.31%	2.15%	2.29%	2.02%
% Hispanic, Spanish, or Latinx, any race	14.08%	14.65%	13.64%	19.85%	18.07%	21.44%
Educational attainment						
% HS or less	30.37%	27.65%	32.56%	31.28%	26.94%	35.16%
% Some college/Associate's degree	32.08%	34.22%	30.36%	31.36%	33.67%	29.30%
% BA	23.42%	23.49%	23.36%	22.85%	23.70%	22.10%
% More than BA	14.13%	14.64%	13.72%	14.50%	15.70%	13.44%
Age						
Mean	30.58	29.28	31.57	31.08	29.63	32.37
Median	30.00	29.00	31.00	31.00	30.00	32.00
Annual earnings in year prior to birth						
Mean	61940.45	48166.13	72456.39	57784.63	42426.18	71492.20
Median	45894.66	35751.47	55651.21	41922.88	30483.01	53013.94

Notes: All racial groups exclude parents identifying as Hispanic, Spanish, or Latinx. Earnings from each data source have been adjusted for inflation and are reported in \$2023. American Community Survey statistics are drawn from one-year estimates for the years 2010 through 2016.

Sources: Author's analysis of records from Washington State Employment Security Department, Washington State Department of Health, and American Community Survey.

Table 2.2. Eligibility Requirements for State Paid Family and Medical Leave Laws

<i>State</i>	<i>Year enacted</i>	<i>Benefits available</i>	<i>Earnings and/or hours requirements</i>	<i>Base period definition relative to birth quarter</i>	<i>Additional notes</i>
California	2002	2004	Earned \$300 or more in wages in base period	First four of five quarters before	
New Jersey	2008	2009	Worked 20 weeks earning at least \$260 weekly, OR have earned a combined total of \$13,000 in base period	First four of five quarters before	Upper bound: Assume each \$260 in a quarter is a week's work Lower bound: Consider weekly earnings = quarterly earnings / 13
Rhode Island	2013	2014	Either (1) earned \$15,600 or more in wages in base period, or (2) all of the following: earned at least \$2,600 in one or more base period quarters, total base period taxable wages were at least one and one-half times highest quarter of earnings, and base period taxable wages equal at least \$5,200	First four of five quarters before	
Washington	2017	2020	Worked 820 or more hours in base period	First four of five quarters before OR four quarters before	
Massachusetts	2018	2021	Earned at least \$6,000 (as of 2023) in the last four completed calendar quarters and at least 30 times more than weekly benefit amounts	Last four completed calendar quarters	
Connecticut	2019	2022	Earned \$2,325 or more in the highest-earning quarter of the base period	First four of five quarters before	
Oregon	2019	2023	Earned \$1000 or more in wages in base period	Four quarters before	
Colorado	2020	2024	Must have earned at least \$2,500 in wages subject to premiums during the base period	First four of the last five quarters OR last four completed quarters	
Delaware	2022	2025	Must have been employed for at least 12 months by the employer the worker is requesting leave from and must have been employed for at least 1,250 hours of service with that employer during the previous 12-month period	Four quarters before	Workers who worked for the same employer in the 4 quarters prior to a birth and worked at least 1,250 hours with that employer
Maryland	2022	2025	Worked 680 or more hours in the year prior to birth	Four quarters before	

Notes: All eligibility requirements are circa 2023 except for Colorado, Maryland, and Delaware's policies which do not take effect until 2024 or 2025. All earnings data are also adjusted for inflation and converted to 2023 dollars. Current employment requirements are operationalized as working nonzero hours in the quarter before birth or the quarter of birth.

Sources: Author's compilation of state policy documentation (A Better Balance, 2023; Colorado Department of Labor, 2023; Connecticut Paid Leave, 2023; Delaware Department of Labor, 2023; Massachusetts Department of Family and Medical Leave, 2023; National Partnership for Women & Families, 2021; New Jersey Department of Labor and Workforce Development, 2023; Paid Leave Oregon, 2023; State of California Employment Development Department, 2023; State of Rhode Island Department of Labor and Training, 2023; Time to Care Act, n.d.; Washington State Employment Security Department, 2023a).

Table 2.3. Parent population by perinatal employment status

	A. Parents included on birth certificates	B. Parents with any pre-birth work history ¹⁴	C. Parents working around time of birth (study sample) ¹⁵	D. % of parents with any pre-birth work history	E. % of parents working around time of birth	F. Of parents with any pre-birth work history, % who worked around time of birth
All fathers	546,861	382,440	354,895	69.9%	64.9%	92.8%
All mothers	593,222	334,212	270,943	56.3%	45.7%	81.1%
Mothers by race/ethnicity						
White	360,991	215,379	178,181	59.7%	49.4%	82.7%
Black	25,767	14,680	11,397	57.0%	44.2%	77.6%
Asian	54,850	27,786	24,097	50.7%	43.9%	86.7%
Hawaiian/Pac. Isl.	7,142	3,688	2,571	51.6%	36.0%	69.7%
Native Am/AK Nat	8,980	4,730	3,401	52.7%	37.9%	71.9%
Two or more races	21,731	13,416	10,589	61.7%	48.7%	78.9%
Hispanic, Spanish, or Latina, any race	110,285	52,969	39,513	48.0%	35.8%	74.6%
Mothers by educational attainment						
High school or less	213,968	105,221	74,463	49.2%	34.8%	70.8%
Some college/Associate's degree	189,909	114,341	92,184	60.2%	48.5%	80.6%
BA	119,589	70,321	63,271	58.8%	52.9%	90.0%
More than BA	64,408	42,146	39,430	65.4%	61.2%	93.6%
Mothers by pre-birth wage quintile						
1 st	-	66,843	42,349	-	-	63.4%
2 nd	-	66,843	49,044	-	-	73.4%
3 rd	-	66,842	55,935	-	-	83.7%
4 th	-	66,842	60,590	-	-	90.6%
5 th	-	66,842	63,025	-	-	94.3%
Mothers by pre-birth industry of employment¹⁶						
Accommodation and Food Services	-	40,451	30,437	-	-	75.2%
Administration, Support, Waste Management & Remediation Services	-	19,785	14,523	-	-	73.4%
Educational Services	-	28,422	26,087	-	-	91.8%
Finance and Insurance	-	14,070	12,868	-	-	91.5%
Health Care and Social Assistance	-	74,739	65,222	-	-	87.3%
Professional, Scientific, Technical Services	-	18,738	16,681	-	-	89.0%
Retail Trade	-	44,238	34,992	-	-	79.1%

Notes: All racial groups exclude mothers identifying as Hispanic, Spanish, or Latina. Estimates disaggregated by pre-birth wage rate quintile are restricted to mothers who had any pre-birth employment history, so only columns relevant to this population are reported.

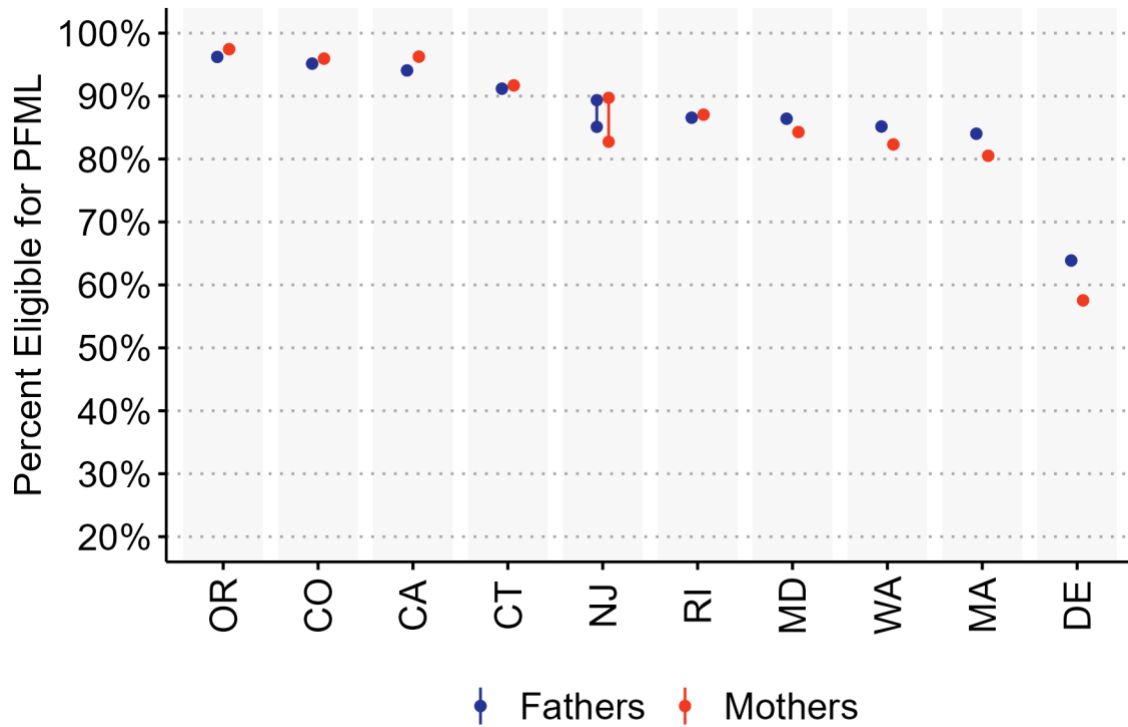
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

¹⁴ Includes all parents who worked nonzero hours in any of the five quarters before a birth and/or the quarter of birth (i.e., inclusive of all states' paid leave base periods).

¹⁵ Includes all parents who worked nonzero hours in the quarter before a birth and/or the quarter of birth.

¹⁶ Industries are included in this table if they represented more than 5% of the population of parents in the study sample.

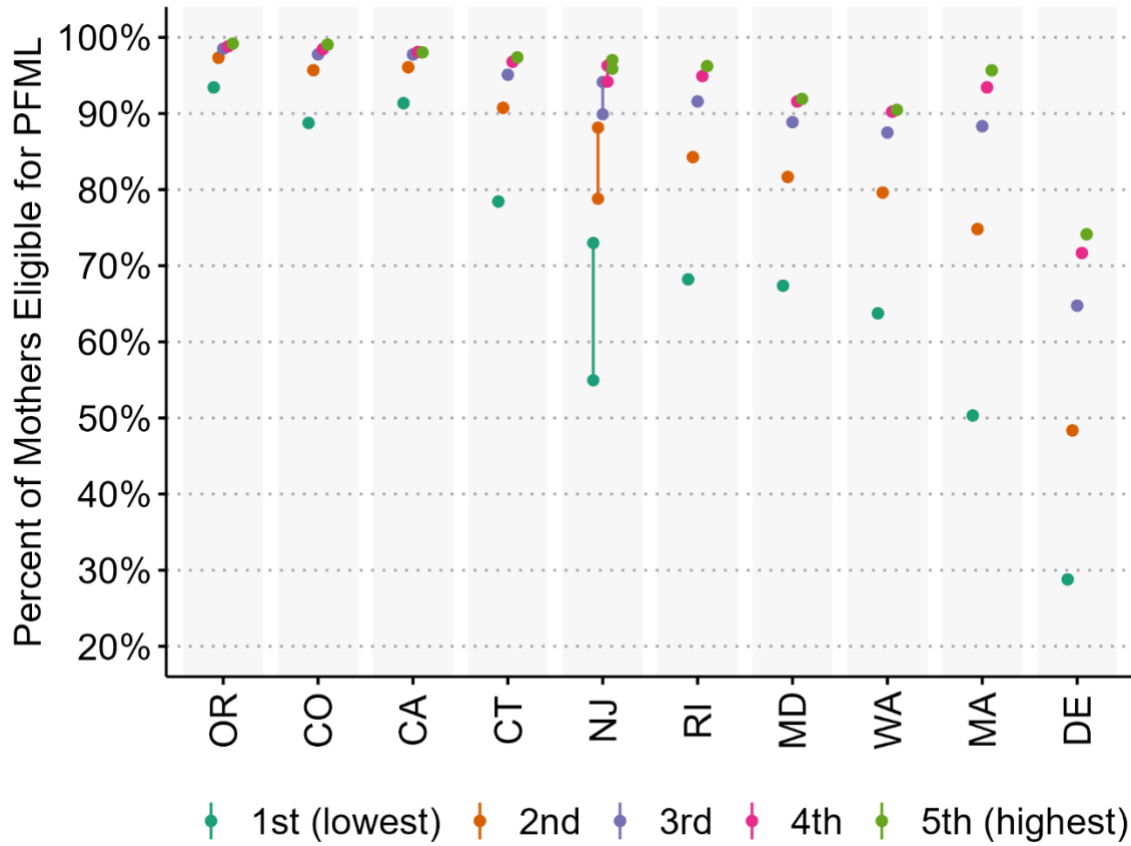
Figure 2.1. Estimated eligibility for paid leave among mothers vs. fathers



Notes: New Jersey estimates presented as an upper and lower bound based on assumptions about distributions of earnings over weeks of the quarter (see *Data and measures* section for more information).

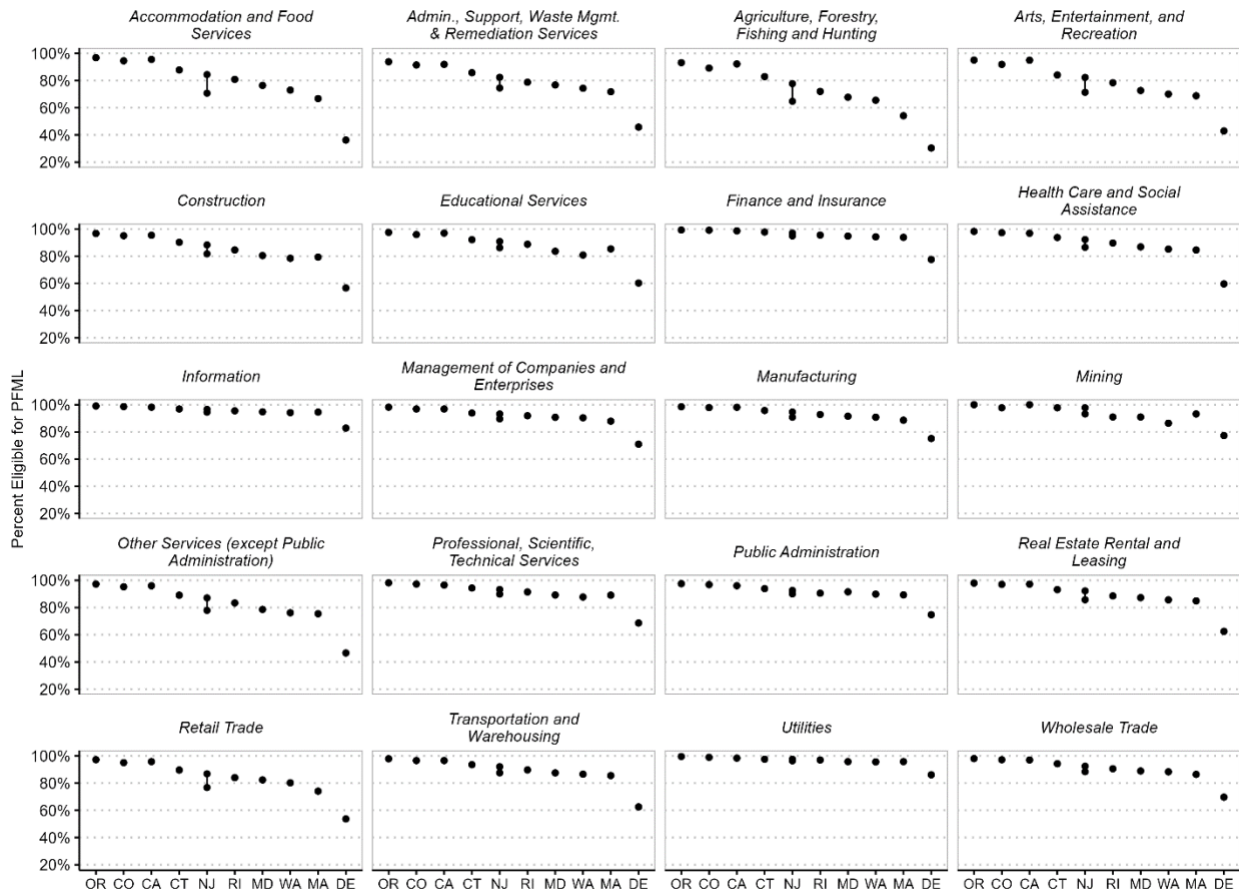
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Figure 2.2. Estimated eligibility for paid leave among mothers, by wage quintile in primary pre-birth job



Notes: Wage rate is calculated by dividing quarterly earnings by quarterly hours worked for the mother’s primary pre-birth job, the job for which the mother worked the most number of hours in the closest quarter to birth in which she was employed. New Jersey estimates presented as an upper and lower bound based on assumptions about distributions of earnings over weeks of the quarter (see *Data and measures* section for more information).
Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

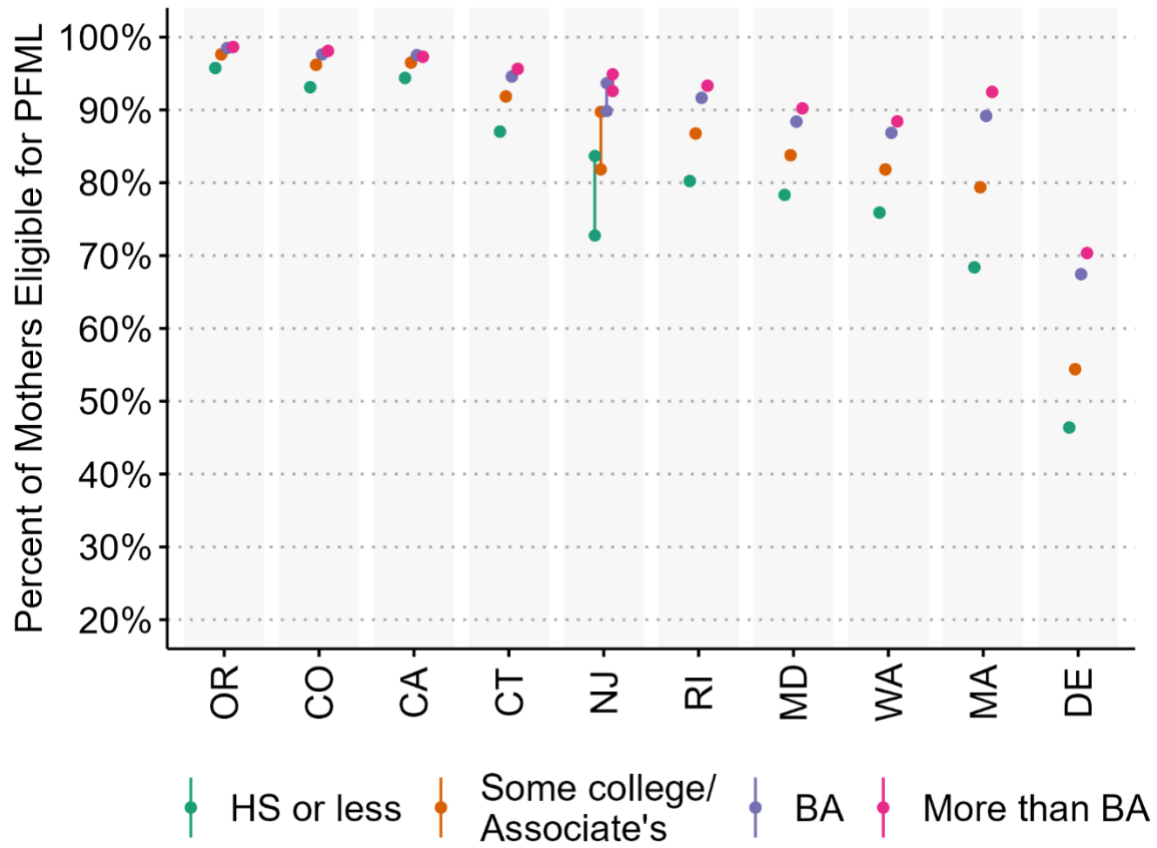
Figure 2.3. Estimated eligibility for paid leave among mothers, by industry of employment



Notes: Industry of employment represents the industry of the employer of the mother’s primary pre-birth job, the job for which the mother worked the most number of hours in the closest quarter to birth in which she was employed. New Jersey estimates presented as an upper and lower bound based on assumptions about distributions of earnings over weeks of the quarter (see *Data and measures* section for more information).

Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

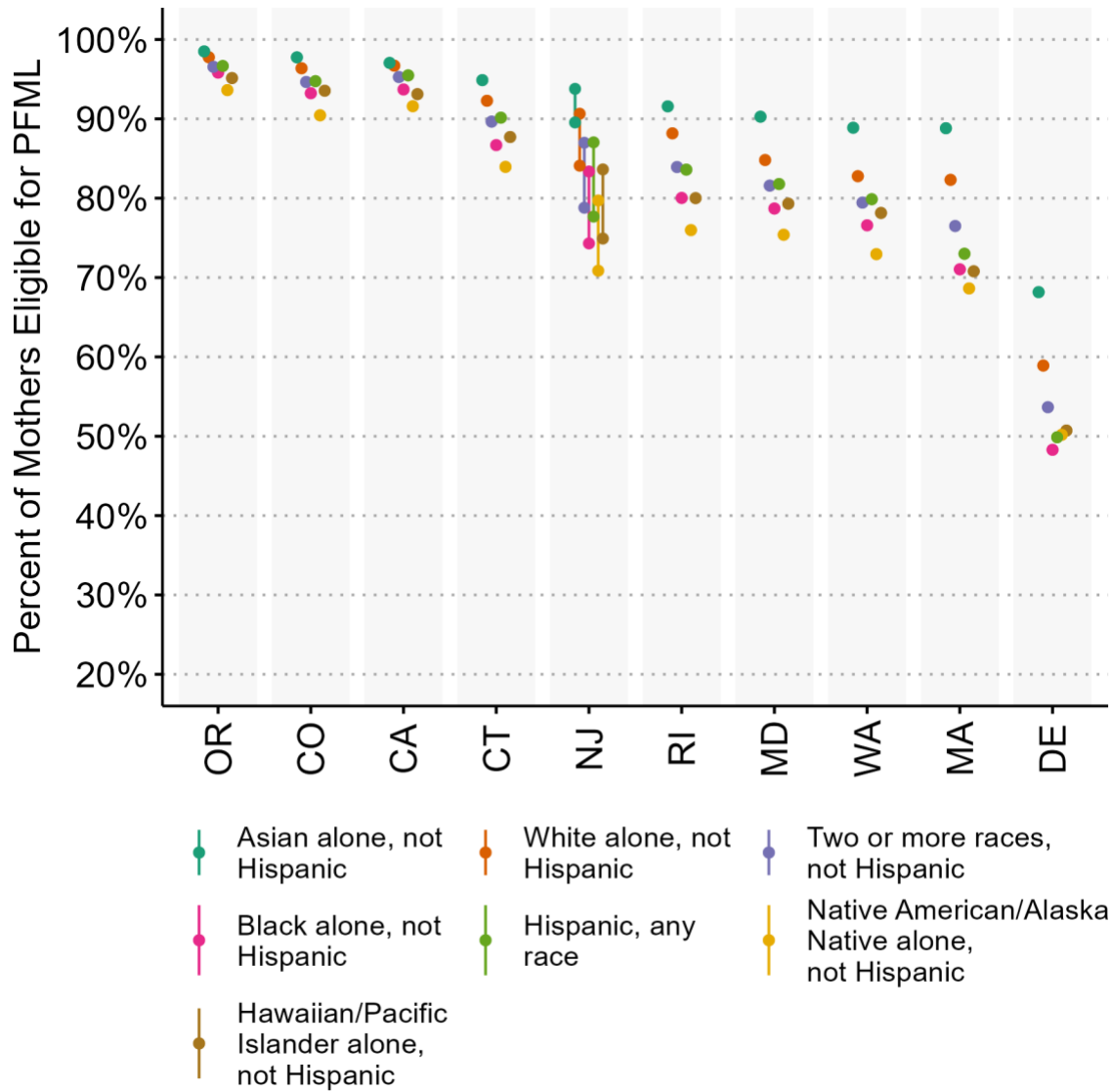
Figure 2.4. Estimated eligibility for paid leave among mothers, by educational attainment



Notes: New Jersey estimates presented as an upper and lower bound based on assumptions about distributions of earnings over weeks of the quarter (see *Data and measures* section for more information).

Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

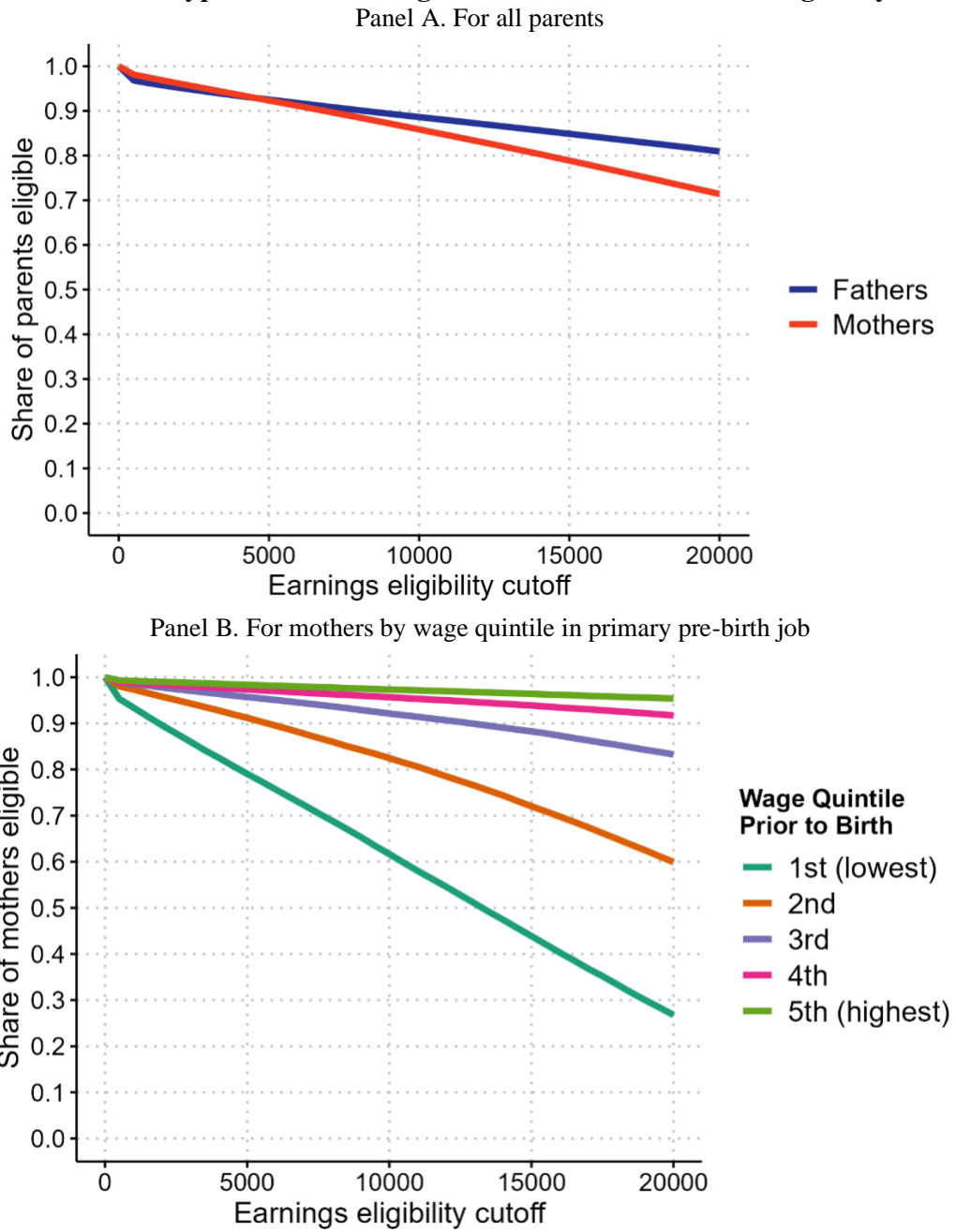
Figure 2.5. Estimated eligibility for paid leave among mothers, by race and ethnicity



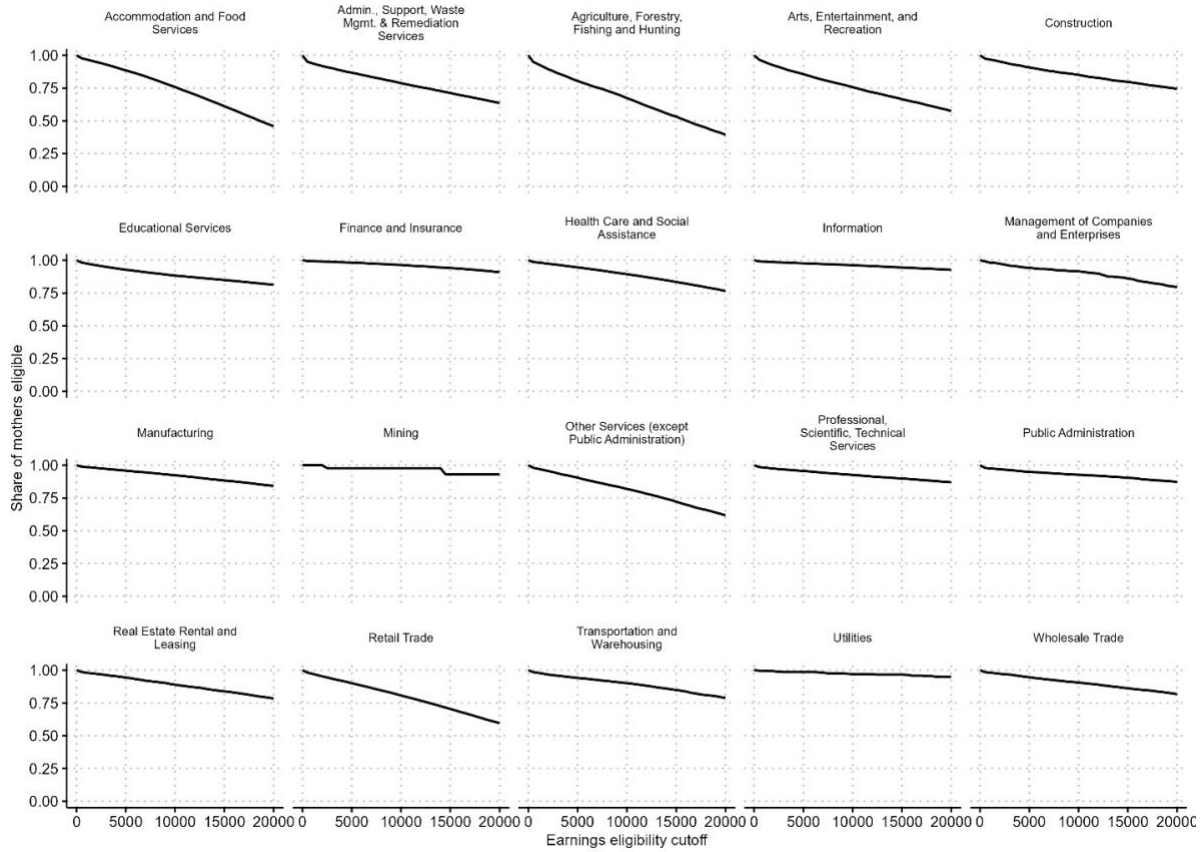
Notes: New Jersey estimates presented as an upper and lower bound based on assumptions about distributions of earnings over weeks of the quarter (see *Data and measures* section for more information).

Sources: Author’s analysis of records from Washington State Employment Security Department and Washington State Department of Health.

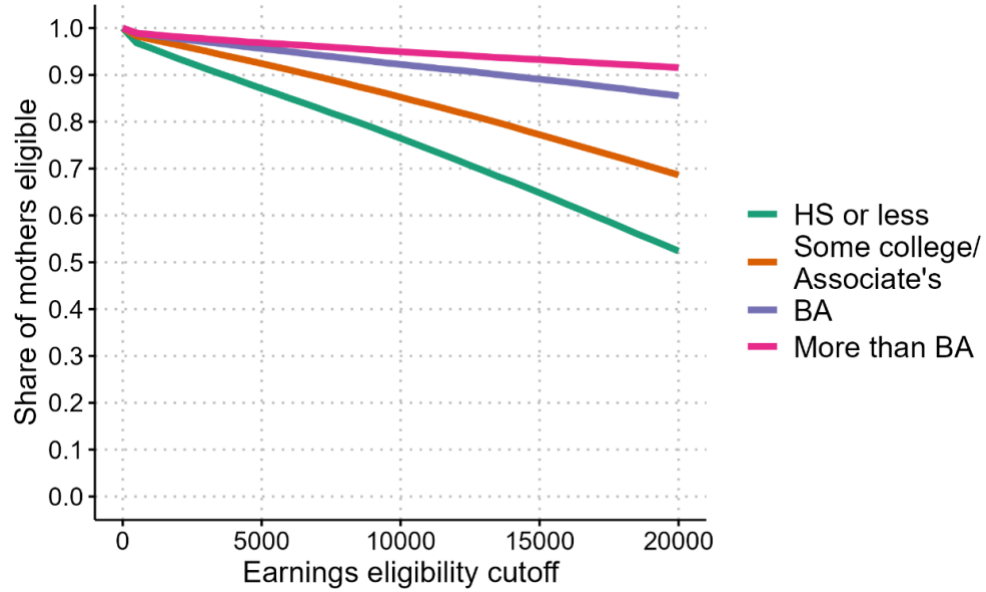
Figure 2.6. Effects of hypothetical earnings cutoffs on mothers' PFL eligibility



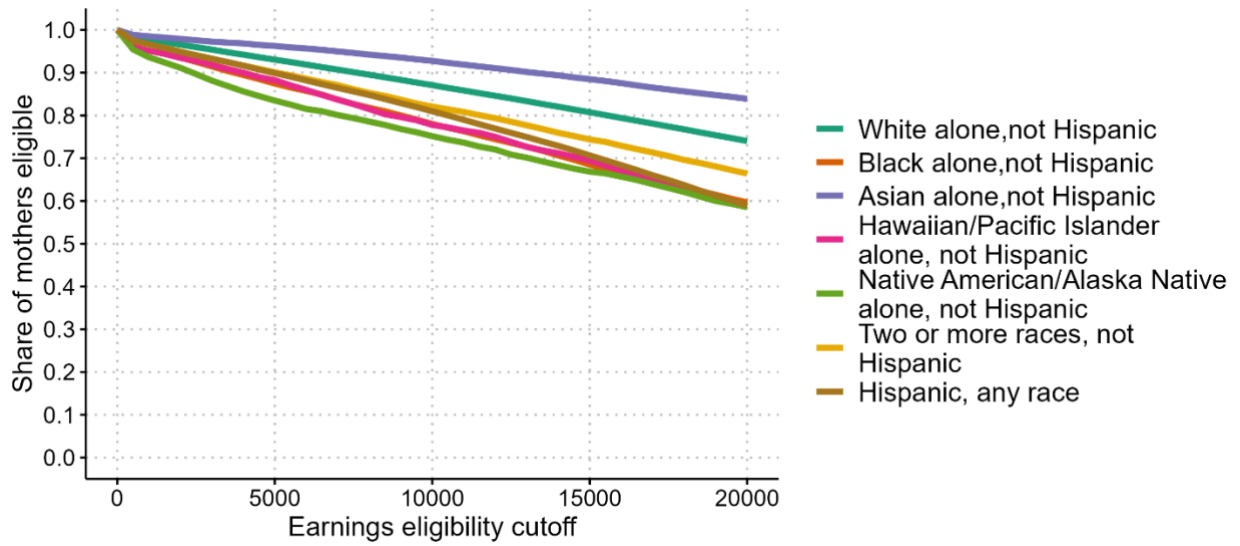
Panel C. For mothers by industry of primary pre-birth job



Panel D. For mothers by educational attainment



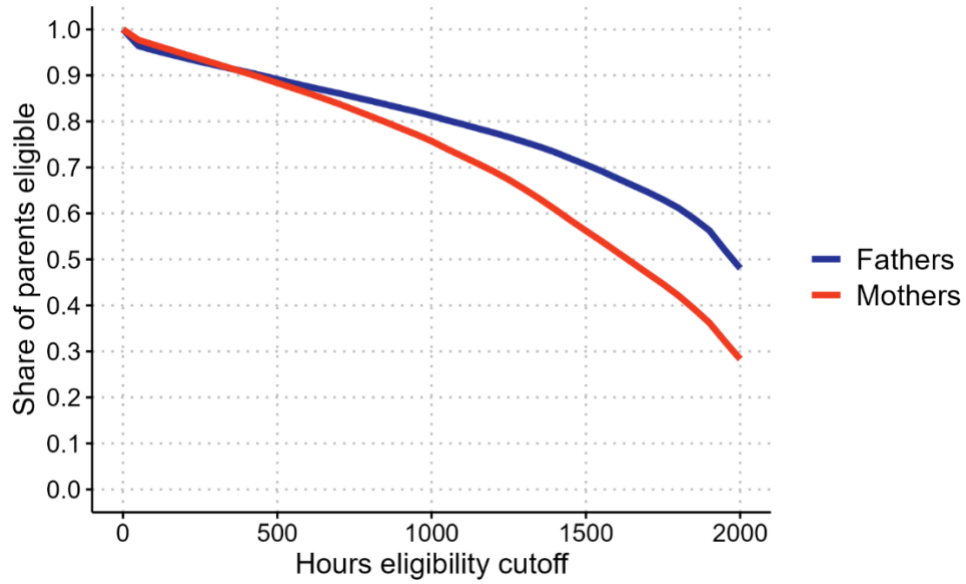
Panel E. For mothers by race/ethnicity



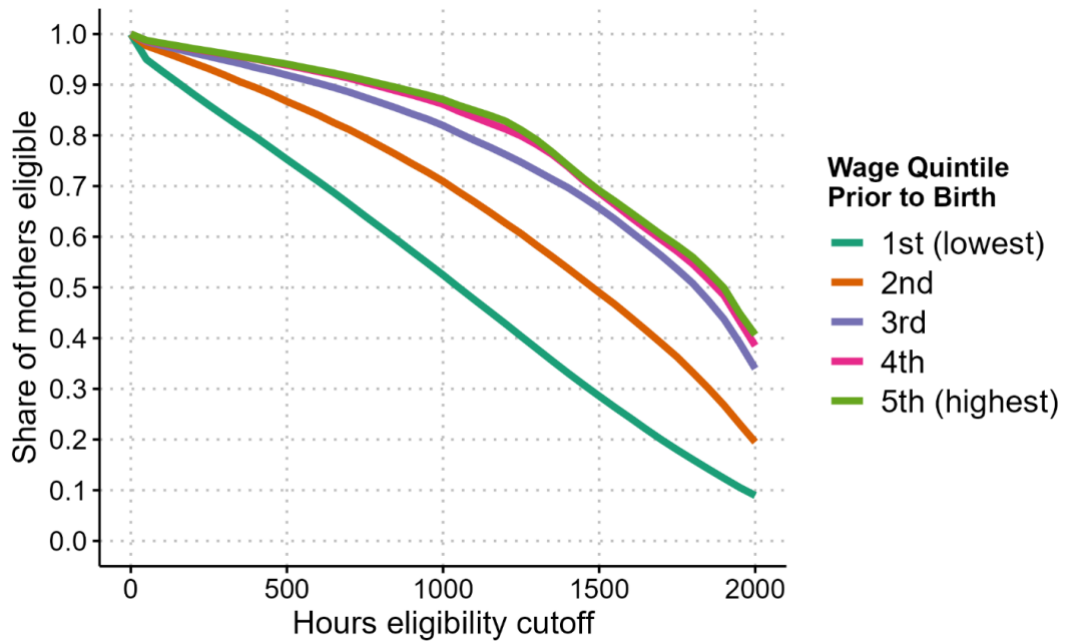
Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Eligibility rates are calculated assuming an earnings eligibility cutoff based on the last four quarters prior to a qualifying event (in this case, a birth).

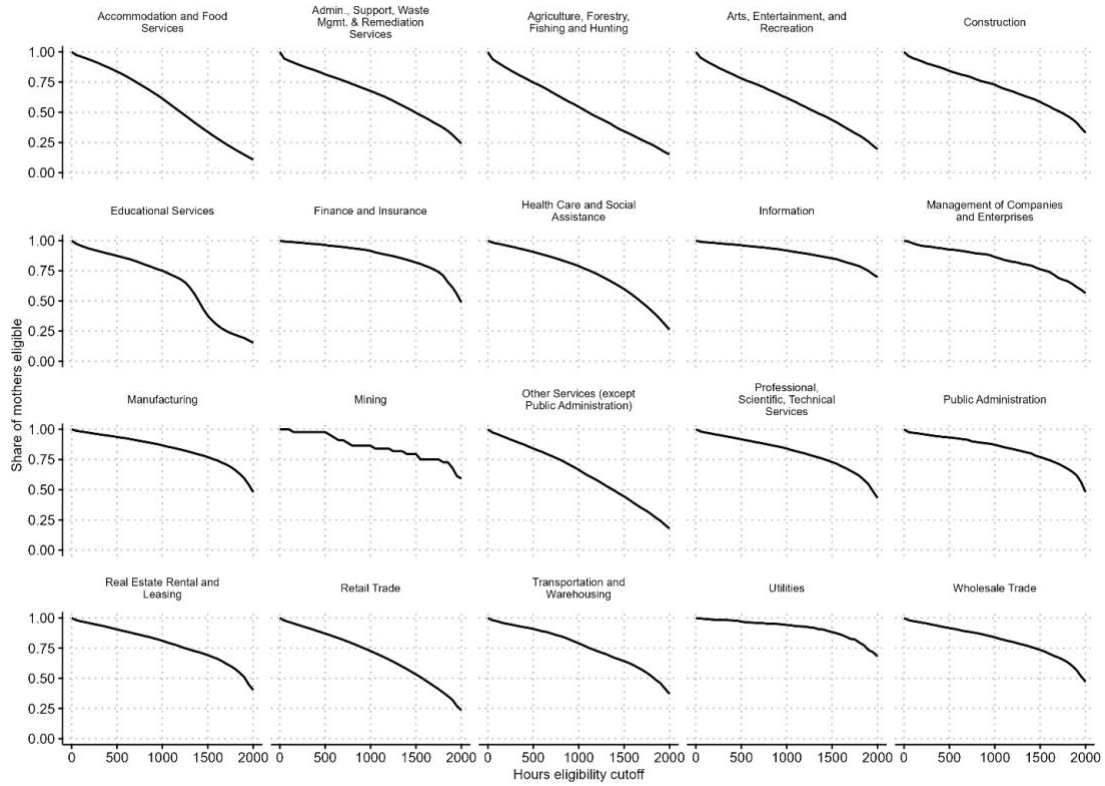
Figure 2.7. Effects of hypothetical hours cutoffs on mothers' PFL eligibility
Panel A. For all parents



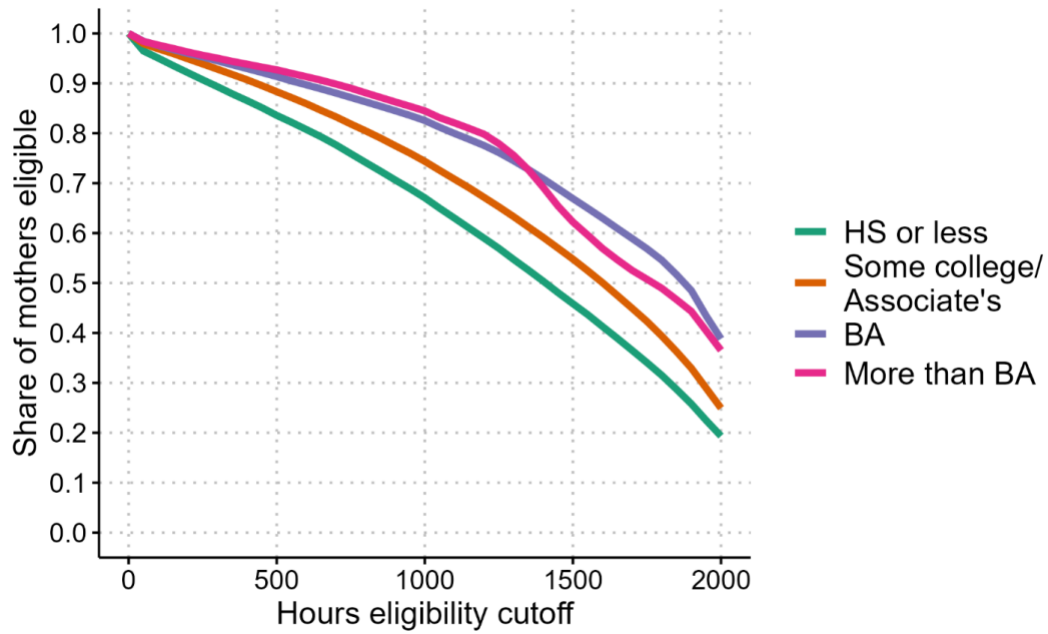
Panel B. For mothers by wage quintile in primary pre-birth job



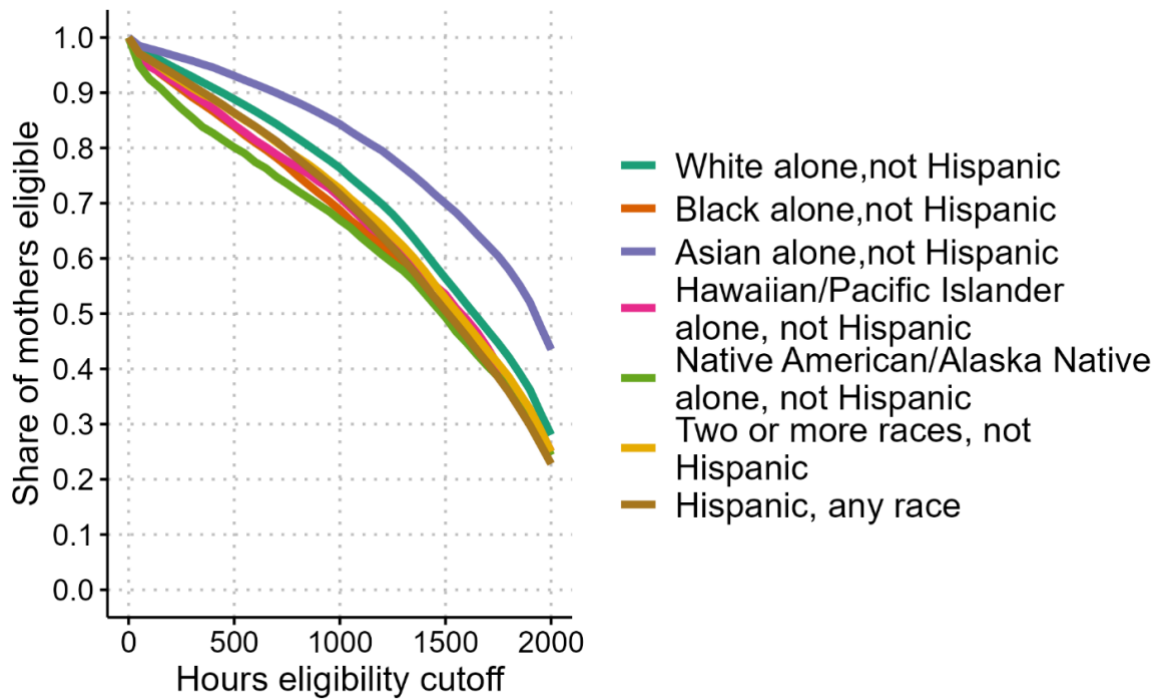
Panel C. For mothers by industry of primary pre-birth job



Panel D. For mothers by educational attainment



Panel E. For mothers by race/ethnicity



Sources: Author's analysis of records from Washington State Employment Security Department and Washington State Department of Health.

Notes: Eligibility rates are calculated assuming an hours eligibility cutoff based on the last four quarters prior to a qualifying event (in this case, a birth).

Chapter 3 : Paid leave and maternal employment: Evidence from Washington State

Introduction

Parents, particularly mothers, often experience unstable employment around the time a child is born, leading to volatility in earnings. For example, parents may take unpaid leave from work, work fewer hours, voluntarily leave a job, or even be fired. As a result, household income frequently falls around the birth of a child—precisely the time families need increased resources to cover expenses for the new child’s needs (Stanczyk, 2020). Furthermore, research suggests that employment changes related to childbirth affect parents unequally and are a persistent contributor to gender wage gaps (Glauber, 2018; Hill et al., 2021; Yu & Kuo, 2017). Paid family leave has emerged in policy discussions as a potentially promising way to smooth income disruptions and reduce employment instability while also supporting caregiving. Supporters argue that paid leave policies will also reduce inequalities by allowing more parents to afford time off and reducing the economic disparities produced by perinatal employment instability (Rossin-Slater, 2018).

As federal policymakers contemplate national paid leave policies, researchers and policy decisionmakers are looking to the states that have innovated in this area in the last two decades or so for lessons on the effects of such programs (Jacobs, 2018). Washington State was the sixth state to enact such a program, implementing a Paid Family and Medical Leave (PFML) policy that workers could use starting in 2020. Under PFML in Washington, anyone who works at least 820 hours in the state in a year prior to a qualifying event can take up to twelve weeks of paid leave to bond with a new child, attend to their own serious health condition, or care for a family member with a serious health condition. The policy provides parents of a newborn with up to 12

weeks of paid “bonding” leave. Mothers who give birth can also use up to 16 weeks of combined family and medical leave, because they are considered to have had two qualifying events in a year. Mothers with a serious pregnancy-related health condition, such as being put on bed rest or having a C-section, can receive up to 18 weeks of combined family and medical leave. Workers receive up to 90% of their pre-leave weekly wage during leave, up to a cap (which, for example, was \$1,456 per week in 2024). Any worker making less than 50% of the state’s average wage receives the maximum wage replacement rate (90%) (Washington State Employment Security Department, 2023a).

Most research studying the causal effects of paid leave policies on maternal employment around a birth has found that these policies increase parental earnings and employment, reduce household poverty, and support mothers in remaining at the same employer (Baum & Ruhm, 2016; Bedard & Rossin-Slater, 2016; Byker, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019). However, this literature has thus far been limited and relatively unvaried in its design and data. Prior research has largely focused on California (the first state to pass paid leave), and almost exclusively uses difference-in-difference designs to identify the causal effect of paid leave policies. Existing research also largely uses survey data, which have both advantages and limitations relative to administrative records. Some limitations of survey data that are relevant to this research include the potential for non-response and recall bias, the lack of adequate sample size to study smaller subgroups, and the inability to precisely identify eligibility for paid leave policies. Administrative records are beneficial for studying this topic because they are less subject to biases related to self-report, capture longitudinal employment trajectories in granular detail, and have sufficient sample size to study smaller subgroups.

To extend the current literature, this paper contributes new data, studies a new setting, and employs a causal inference strategy that has rarely been applied to this type of policy. The paper uses administrative data to conduct the first causal evaluation of Washington's PFML policy, building new evidence on state paid family and medical leave policies and the economic conditions of mothers around the time of a birth. The study first describes mothers' take-up of the new paid leave program, then employs a regression discontinuity design to estimate the causal effect of the policy on maternal employment outcomes.

The work focuses on two sets of research questions. First, descriptive analyses illuminate take-up of Paid Family and Medical Leave in Washington in the policy's first few years. What share of eligible mothers claimed paid medical and/or bonding leave? How did take-up rates of PFML vary across mother demographic and employment characteristics, and over time as the policy rolled out? Second, a regression discontinuity design estimates the causal effect of the PFML policy on mothers' employment outcomes, leveraging the policy's eligibility cutoff to compare outcomes among mothers whose work histories place them right above and below the cutoff. How did PFML use affect employment status, earnings and hours, and employer continuity among mothers of newborns in the quarters around the time of a birth?

This paper makes multiple contributions with relevance to paid leave research and policy. First, detailed program take-up estimates build research evidence on use of the policy and inequalities in access, with implications for practitioners hoping to increase equitable use of the program. The regression discontinuity analysis of maternal employment provides the first causal estimates of the impact of Washington State's policy, building on a small but growing literature of the effects of state paid leave programs. These estimates speak to the generalizability of prior findings by applying a new causal inference method, using a different type of data, and looking

at a new state context. Recently, state paid leave laws, combined with a growing awareness about the importance of care work in light of the Covid-19 pandemic, have inspired conversations about mandating paid family leave at the federal level. While momentum on federal reform has largely stalled, paid leave policies continue to receive attention at the state level, where most policy action is currently occurring. Therefore, building evidence on existing state policies offers useful lessons for current state efforts as well as potential future federal conversations. Finally, by using a new data resource that merges health insurance claims data to employment and leave program records, I demonstrate proof-of-concept of a new type of data that could be used for more research on the intersections of health, employment, and paid leave policy.

Background: Paid family and medical leave in the United States and in Washington State

U.S. workers who welcome a new child encounter a complex array of leave policies provided by employers, localities, states, and the federal government. Since 1993, eligible workers have been guaranteed up to twelve weeks of job-protected but unpaid leave through the federal Family and Medical Leave Act (FMLA). FMLA eligibility criteria is quite restrictive, however. Employees must have worked for a covered employer for at least twelve months, worked at least 1,250 hours for that employer, and be employed at a worksite where at least 50 employees work for the same firm within 75 miles. Estimates based on the FMLA Employee Survey suggest that roughly 44% of workers are ineligible due to either the worksite size requirement, tenure and hours requirement, or both (Brown et al., 2020). Furthermore, FMLA only provides unpaid leave, which many families cannot afford to take (Joshi et al., 2020). Research demonstrates that while expanding access to unpaid leave (such as FMLA) does increase leave-taking among both mothers and fathers, these changes are much larger for

college-educated and married mothers who are more likely to be able to afford to take unpaid leave (Han & Waldfogel, 2003).

In addition to unpaid leave provided through FMLA, some workers have access to paid leave as an employer-provided benefit. The Bureau of Labor Statistics estimates that 23% of workers had access to employer-provided paid family leave in 2021 (U.S. Bureau of Labor Statistics, 2021). There have been recent expansions to employer-provided leave; in 2020, for example, federal employees were guaranteed up to 12 weeks of paid leave through the Federal Employee Paid Leave Act. As with FMLA, however, leave policies that are contingent on employer provision create disparities in which parents are eligible for these programs. Of particular concern is evidence that working parents of color, particularly Hispanic parents, and parents working in lower-wage jobs are less likely to report having access to paid parental leave compared to White working parents and working parents earning higher wages (Gault et al., 2014).

Finally, thirteen states and Washington D.C. have passed and/or implemented laws guaranteeing eligible workers paid leave that can be used when welcoming a new child and/or to attend to one's own medical issues including those related to pregnancy and childbirth. California's paid family leave policy was the first of its kind, effective in 2004. Washington's policy began disbursing benefits starting in 2020. Under PFML in Washington, workers who have worked at least 820 hours in the four quarters prior to a qualifying event can take up to twelve weeks of paid leave. Qualifying events include the birth of a new child, attending to one's own serious health condition, caring for a family member with a serious health condition, or time with a family member in the military before or after deployment. The policy provides parents of a newborn with up to twelve weeks of paid "bonding" leave. In addition, mothers with a serious

health condition related to pregnancy can receive up to eighteen weeks of combined family and medical leave around a birth. Both employers and employees pay into the program to fund the benefits. Workers receive up to 90% of their pre-leave weekly wage during leave, with anyone making less than 50% of the state's average wage receiving the maximum wage replacement rate (Washington State Employment Security Department, 2023a).

Research on paid leave and its effects on maternal employment

Research demonstrates that mothers significantly reduce employment around the time of a birth, particularly in the first few months after a child is born (Florian, 2018; Han et al., 2011; Hotchkiss et al., 2008; Lu et al., 2017). Motivated in part by these findings, a growing body of research has studied the effects of state paid leave policies on economic and employment outcomes (Jacobs, 2018), with the potential to speak to whether these policies smooth perinatal employment disruptions. These studies focus on three main outcomes: leave taking, employment, and household income and poverty. I review each set of findings in more detail below.

Effects on leave taking

Research demonstrates that access to paid leave does indeed increase leave-taking among mothers and fathers, although mothers remain significantly more likely to take leave (Bartel et al., 2018; Baum & Ruhm, 2016; Bedard & Rossin-Slater, 2016; Rossin-Slater et al., 2013a). Multiple studies have estimated take-up rates of state paid leave programs, including assessing heterogeneity in which parents tend to use these policies. Bana et al. (2022) study use of California's paid family leave program between 2005 and 2014, finding that take-up increased during that period. Women took shorter bonding leaves than men, and women with lower earnings and working in smaller firms were less likely to take up the program. Elser et al. (2022) find lower uptake of leave among workers in blue-collar jobs when compared to those working

in white-collar jobs. Gaps in take-up may be driven by low awareness of benefits (Goodman et al., 2020).

Effects on employment

The provision of paid family leave also increases parental employment around and after a birth (Baum & Ruhm, 2016; Bedard & Rossin-Slater, 2016; Byker, 2016; Rossin-Slater et al., 2013a). Most of these studies have focused on California's policy. California's paid family leave policy was found to increase maternal employment rates 9 and 12 months after a birth, and to increase employment intensity during the second year after a birth (Baum & Ruhm, 2016). Rossin-Slater et al. (2013a), also studying California, find that the state's policy increased work hours of employed mothers of 1- to 3-year-old children by an average of 10% to 17%. Byker (2016) incorporates evidence from both California and New Jersey to find that paid family leave policies led to mothers reducing employment less around a birth when compared to mothers who gave birth in the pre-policy eras. Studying paid maternity leave available through Rhode Island's Temporary Disability Insurance (TDI) program, Campbell et al. (2017) apply a regression discontinuity design and find no effect of eligibility for TDI on employment, earnings, or earnings conditional on employment in the fourth quarter after birth and the one to two years following that first year. The authors argue that these results may be due to a lack of employment effects among mothers right around the employment history eligibility threshold. When applying an alternate research design incorporating mothers with more extensive employment histories and controlling for observable factors, they find positive and significant effects of the program on maternal employment – but are less confident that this design identifies the true causal effect of the policy.

Some prior research has found evidence that paid leave policies are also associated with increases in the likelihood that mothers will remain employed in the same job. Baum and Ruhm

(2016) find that California's paid leave policy increased job continuity among mothers working relatively few hours (i.e., less attached to the labor force). Evidence from California also suggests that increased benefit amounts are associated with increases in the probability that mothers return to their pre-leave firm, conditional on being employed (S. H. Bana et al., 2020). However, Campbell et al. (2017) find no effects on employer continuity.

In contrast to unpaid leave policies, whose benefits largely accrue to more highly educated and married mothers (Han et al., 2009), paid leave has appeared to increase employment and earnings most significantly for less-educated, lower-income, and unmarried mothers (Baum & Ruhm, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019).

Effects on household income & poverty

Provision of paid family leave has also been found to increase income and reduce household poverty around a birth, though there are fewer studies at the household level than at the individual parent or employee level. For example, Stanczyk (2019) finds quasi-experimental evidence that California's policy decreased families' risk of poverty and increased household income in the year after a birth. In cross-national research, increased leave generosity was also associated with a reduced probability of poverty, particularly for single mothers (Misra et al., 2012). Parents who took paid leave reported lower rates of public assistance use compared to parents who did not (Houser & Vartanian, 2012). A cross-sectional analysis of paid leave availability among low-income single women found that living in a state with paid leave was associated with a lower likelihood of material hardship following a birth (Ybarra et al., 2019).

Limitations of the current literature

Evidence on paid leave impacts on employment and economic circumstances suffers from three key limitations. First, researchers studying parental employment and paid leave have often relied on survey data (Baum & Ruhm, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019;

Ybarra et al., 2019), which use self-reported earnings and employment information. Survey data is subject to recall bias, social desirability bias, and non-response bias, which have been shown to be increasing in recent years (Meyer et al., 2015). There is evidence that these issues disproportionately affect data on low-income respondents and have become especially acute during the Covid-19 pandemic, posing serious problems for the study of employment and economic wellbeing during this time period (Rothbaum & Hokayem, 2021). Furthermore, surveys have smaller sample sizes that can prevent researchers from identifying precise time trends and conducting sub-group analyses, and they are often limited in the ability to follow individuals over time.

Second, past studies have almost exclusively used difference-in-difference or triple difference methods to estimate the causal effect of paid leave provision, comparing trends among parents eligible for the policy to trends among similar groups of ineligible parents, parents in other states, and/or parents at other time points (Bartel et al., 2018; Baum & Ruhm, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019; Stearns, 2015). These methods, while valuable, rely on strong assumptions about parallel trends among comparison groups in the absence of the policy, which cannot be empirically confirmed. For example, estimates from studies that rely on comparisons between states that passed paid leave policies and states that did not may be biased if trends in the different groups of states would have been different anyway, absent the policy. I am aware of one study applying a regression discontinuity design to study the effects of paid leave, which found no effect of paid parental leave access on employment among mothers making around \$12,000 a year, contradicting many of the difference-in-difference analyses (Campbell et al., 2017). The fact that this result contradicts most other findings on paid leave and

employment emphasizes the importance of using a range of identification strategies, beyond just difference-in-difference designs, to study this topic.

Finally, the majority of existing work has studied paid leave in early adopters of the policy, largely focused on California – the first state to implement such a program (Bartel et al., 2018; Baum & Ruhm, 2016; Bedard & Rossin-Slater, 2016; Rossin-Slater et al., 2013a; Stanczyk, 2019). Each state has a unique economic context, and paid leave policy design features differ across states. For example, states that passed paid leave policies before Washington all added family and medical leave to long-standing temporary disability insurance systems; Washington is more representative of the more recent group of states that have passed these policies independent of an existing disability program. Assessing the effects of paid leave programs across a variety of state policy contexts is critical, especially as paid leave programs are debated at the federal level.

The current study

I construct a novel administrative data resource by merging health insurance claims data on birth events to state employment records and paid leave program records. This rich dataset enables detailed descriptive analyses that describe use of Paid Family and Medical Leave in Washington in the policy's first few years. Next, I leverage the policy's eligibility cutoff to conduct a regression discontinuity design that estimates the causal effect of the PFML policy on mothers' employment outcomes in the year after a birth.

The administrative dataset used in this study provides more valid and reliable measures of quarterly employment for nearly all Washington workers compared to prior studies using survey data. Combined with PFML program data on leave use, these records illuminate trends and heterogeneity in mothers' employment patterns and leave use with detail and precision. Washington is one of few states that reports hours worked in Unemployment Insurance wage

reports, allowing analyses of paid leave eligibility and employment intensity that would not be possible using other states' Unemployment Insurance data. Quarterly data with large sample sizes can illuminate time trends, and rich information on mothers' demographic and employment characteristics allows for detailed subgroup analyses. These data align notably well with policy eligibility criteria, allowing the identification of PFML eligibility based on birth timing and employment history and making the regression discontinuity design possible. Finally, this study is the first to estimate impacts of a new generation of state paid leave programs, which were developed from scratch rather than as expansions of temporary disability insurance.

Data and measures

This study links three types of administrative records. First, health insurance records on birth-related insurance claims from the Washington State All Payer Claims Database (WA-APCD) identify a population of individuals who gave birth and the timing of that event through birth-related medical and inpatient stay claims records. These data allow me to narrow the analytic sample to a population of likely users of PFML in Washington. All workers could theoretically use PFML, but few will have a qualifying event in any given year; therefore, assessing this effect among a subset of mothers of newborns will represent a more meaningful and detectable effect size. Second, wage reports from the PFML program (PFML wage reports) and the Unemployment Insurance program (UI wage reports), both collected by the Washington Employment Security Department (ESD), report workers' employment histories and are used to calculate workers' eligibility for paid leave and to estimate employment outcomes. Finally, PFML claims data from the ESD PFML program report on paid leave claims and benefits received.

Washington All-Payer Claims Data

WA-APCD reports insurance claim-level data on claims made to health insurance payers

in Washington, including both public and private payers. WA-APCD captures health insurance claims from more than 30 commercial health care payers, Medicaid (including its five managed care plans), Medicare Advantage, and Medicare fee-for-service (added in 2019). The organization began collecting data in 2014 and is updated each quarter with new claims (Washington Health Care Compare, 2022). These records can be used to identify timing of childbirth using diagnosis and procedure codes related to delivery and those that specifically mention live births. Appendix Table 3.1 lists the diagnosis and procedure codes used to identify mothers who gave birth. Both medical claims data and inpatient stay data were used to identify mothers with birth-related insurance claims. I filter the sample to individuals who were listed as female and between the ages of 10 and 60 and who had a valid Social Security Number (SSN), which is required to link to the ESD data. Filtering out young children and male individuals reduces the chance of data errors resulting in improper inclusion in the study population, such as newborns being included because they were associated with birth-related codes. A birth event is any quarter in which a mother had one or more claims with the diagnostic codes in Appendix Table 3.1. In rare cases, mothers in the data have multiple consecutive quarters with birth-related claims. To maximize the likelihood of capturing the quarter in which a birth occurred, I restrict the sample to all birth quarters preceded by at least 4 quarters without birth-related claims.¹⁷ I compare counts of births generated using this method in WA-APCD data to Washington State Department of Health birth records, birth certificate-based administrative records that are considered quite reliable. An important limitation of the WA-APCD data is that they do not contain information on claims made by employees of firms that have self-funded insurance plans. This limitation is explored further below by comparing WA-APCD and DOH data.

¹⁷ This excludes roughly 3 percent of birth quarter observations.

ESD Wage Reports

Next, employment records from ESD provide detailed data at the job-quarter level on hours worked, wages earned, and employer characteristics for workers comprising a majority of workers in Washington. Wage reports are submitted quarterly by employers to ESD for the WA PFML and Unemployment Insurance programs (with separate reporting processes). These reports include person-job-level hours worked and wages earned among workers employed in Washington State and covered by each of the programs. The granularity of these data enables in-depth analysis of labor market trends and the effects of policies on the labor market.

While these records contain rich information, they also have important limitations, and each data source has its own unique advantages and disadvantages. First, the PFML program does not require the submission of SSNs, so the quality of this field is likely lower when compared to UI wage reports. Second, ESD PFML wage reports are believed to be less accurate in the early years of the program's implementation. Furthermore, there is an exclusion for employees covered by collective bargaining agreements that existed as of 2017 and that had not been renegotiated as of each quarter of data; employers are not required to report these data to ESD PFML records. UI wage reports, in contrast, are potentially less accurate at identifying eligibility for the PFML program because they are collected for the purposes of administering the UI program instead. I show a direct comparison between UI and PFML wage reports in the Appendix, with results reported in Appendix Tables 3.2 and 3.3. Given these discrepancies and the difficulty of identifying which data source represents "ground truth" of earnings and hours worked, I report results from both data sources throughout this analysis. However, because the UI wage reports are the more-established agency data source, these data are of more consistent quality throughout the study period. I therefore default to reporting results using the UI wage

reports throughout the paper. However, I note when results differ between UI and PFML wage reports.

ESD PFML Program Records

Data collected through the administration of the PFML program contains information on paid family and medical leave applications, claims, and program benefit receipt. I use these records to identify which mothers used paid leave in the quarters around a birth and the dollar value of benefit amounts received in each quarter. It is important to note that these records face the same data quality challenge regarding SSN as the ESD PFML wage reports; as a rule ESD does not require the reporting of SSN as part of administering the PFML program.

Measures

The data described above are used to calculate several quarterly employment outcome measures relative to the quarter of a birth. *Paid leave claiming* is a binary measure indicating whether each mother claimed paid family and/or medical leave in the quarters around a birth. Claiming leave was identified by selecting quarters with nonzero leave hours used as reported in the weekly PFML program database. *Employment status* is a binary indicator of whether each mother worked in the quarter of birth and each quarter following, for up to four quarters. *Hours and earnings levels* are continuous measures of quarterly hours worked and quarterly wages earned in the quarter of birth and each quarter following. *Employer continuity* measures whether mothers who were employed in the year following a birth continued to work for the same employer after the birth, and is defined according to four specifications. All specifications use the same definition of the pre-birth employer, which is the employer with the most hours worked in the most recent pre-birth quarter in which the mother worked. Specification 1 measures, among working mothers, whether the mother worked any hours for the main pre-birth employer in each quarter following a birth. Specification 2 measures, among all mothers regardless of

employment status, whether the mother worked any hours for the main pre-birth employer in each quarter following a birth. Specification 3 measures, among working mothers, whether each mother had the same main employer in a quarter following birth as the main pre-birth employer. Specification 4 measures, among all mothers regardless of employment status, whether each mother had the same main employer in each quarter as the main pre-birth employer. *Wage earnings plus program benefits* is a measure of income that encompasses both wage earnings as well as payments through the PFML program. I estimate *PFML eligibility* by first calculating each mother's hours worked in the policy's qualifying period. Parents can qualify based on hours worked in the four quarters prior to a birth, or if that work history does not meet the threshold may also qualify based on an alternate qualifying period, the first four of the five quarters prior to the birth. Eligibility, then, is a binary measure indicating whether the mother worked 820 or more hours in either qualifying period.

Descriptive analyses also assess heterogeneity across the following measures: *Mother race/ethnicity* and *mother age* are reported in the WA-APCD data. Age is reported quite consistently in the APCD records, and then used to subset the sample, so the analytic sample has no observations that are missing information on age. Mother race/ethnicity is more sporadically reported; race and Hispanic or Latinx¹⁸ ethnicity are reported for 74% of observations. When there is a discrepancy in reported race and ethnicity across records for an individual, I use the most frequently reported category. *Mother zip code* is identified in the WA-APCD data. I link each birth with the zip code observation for which the beginning of the insurance plan eligibility window is closest to the year of the birth. I match zip codes to counties and also link these to rural-urban continuum codes as created by the U.S. Department of Agriculture's Economic

¹⁸ Throughout this report, I refer to mothers who were identified as having Hispanic or Latinx ethnicity as "Latina."

Research Service (USDA, 2020). This information is used to report results by *county urbanicity*, (urban, suburban, and rural areas) and *region* of the state.¹⁹ *Wage rate quintile* is calculated by dividing earnings by hours in the main job pre-birth, for mothers who worked prior to a birth. This measure is then disaggregated by quintiles and used to assess heterogeneity across wage rate.

Analytic approach

I first estimate take-up rates of Washington PFML among mothers of newborns between 2020 and 2022, describing the use of this policy over time and across mothers as the policy rolled out during the pandemic. I report the share of mothers claiming PFML in each quarter relative to birth, for all mothers and across birth years. Then, I report overall take-up in the perinatal period across mother demographic and employment characteristics.

To assess the causal effect of PFML on maternal employment outcomes, I use a regression discontinuity approach that leverages the PFML program's eligibility structure. Because the PFML program has a discontinuous eligibility cutoff, I can compare mothers with pre-birth employment histories that place them just above and just below the 820-hour cutoff. A simple comparison of employment outcomes among all PFML-eligible mothers to outcomes among PFML-ineligible mothers would likely not identify the causal effect of PFML eligibility because eligible mothers are more strongly connected to the labor force and therefore likely have systematically different employment trajectories regardless of the policy. However, when comparing mothers whose work histories place them right around the cutoff, the assignment of PFML eligibility can be assumed to be as good as random. This method identifies the local

¹⁹ Future analyses will also report heterogeneity across *employer size*, calculated using ESD wage reports; *primary industry*, identified using the NAICS code of each mother's primary job prior to birth; and *wage rate*, calculated by dividing quarterly earnings by hours worked in the mother's primary job in the year before the birth.

average treatment effect of the policy and avoids the selection bias issues that often challenge policy evaluation studies.

Because PFML eligibility does not perfectly imply policy take-up, I use a fuzzy RDD approach to estimate the treatment-on-the-treated effect of actual PFML claiming. Eligibility can be thought of as an instrument for PFML claiming, with the estimation occurring in a two-stage least squares framework. The first stage is

$$(1) \widehat{PLClaim} = \beta_0 + \beta_1 Hours + \beta_2 Eligible,$$

where *Hours* represents hours worked in the qualifying period, *Eligible* is equal to 1 if $Hours \geq 820$ and 0 otherwise, and $\widehat{PLClaim}$ is the predicted probability of claiming leave based on hours and eligibility. The second stage is

$$(2) Y = \gamma_0 + \gamma_1 Hours + \gamma_2 \widehat{PLClaim},$$

where *Y* represents one of the employment outcomes described above. In addition to the two-stage least squares LATE estimate γ_2 , I also report the reduced form estimate, which is the coefficient α_2 in the equation

$$(3) Y = \alpha_0 + \alpha_1 Hours + \alpha_2 Eligible.$$

For binary outcomes, these estimates can be interpreted in a linear probability model framework.

Results

Descriptive statistics of analytic sample

First, I contextualize the analytic sample of mothers in the APCD data compared to other data sources on births in Washington. Tables 3.1 and 3.2 describe the study population as identified in the WA-APCD data, and compare it to the best available statewide data on individuals who gave birth, including information from the state's Health Care Authority and Department of Health (Health Care Authority First Steps Database Team, 2024; Washington State Department of Health, 2022). Table 3.1 shows the number of observations as the APCD

data are filtered to an analytic sample, then benchmarks how similar these counts are to other data sources capturing births in Washington. Column A shows the total number of person-quarters that had insurance claims related to a live birth, as defined by the diagnosis and procedure codes in Appendix Table 3.1. Column B filters this sample to the number of person-quarters that had a live birth-related claim and also had four quarters without a birth-related claim prior to that quarter; this filters out approximately 4% of person-quarter records in a given year. Next, Column C filters the sample to the number of person-quarters that also had a valid SSN, which is required to match to the ESD data. Therefore, Column C represents the analytic sample.

Columns D through F represent the most comparable counts available from other data sources. They are imperfectly comparable but represent the closest possible comparisons to understand what share of mothers the APCD captures. Column D is a count of the number of mothers who gave birth according to the state's Health Care Authority, including both live births and fetal deaths. This source is at the same level of analysis as the APCD data (mother level) but includes fetal deaths in contrast to the APCD. Column E reports on the number of live births reported by the Department of Health; this source only includes live births but is at the birth level rather than the mother level. Therefore, Column F approximates the number of women with live births by subtracting half the number of multiple births reported in each year. This approach is an approximation, and assumes that all multiple births are twins. These comparisons suggest that the best approximation of live birth-quarters in the APCD data captures approximately 62 to 67% of mothers who gave birth in Washington State. When the APCD data are filtered to usable observations (i.e., those not missing SSN), this estimated coverage rate falls to between 50 and 55%.

[Table 3.1 about here]

Table 3.2 explores how the composition of the population of mothers identified in WA-APCD data compares to that reported by HCA and DOH, according to observable characteristics. As described above and shown in Table 3.1, the population of mothers in the APCD is a subset of all mothers giving birth in Washington. Therefore, results in Table 3.2 help depict how this subpopulation compares to the broader population of mothers, according to the best available data. Panel A illustrates that the WA-APCD data contain a relatively larger share of Black, American Indian/Alaska Native, Latina, and Native Hawaiian/Pacific Islander mothers and relatively fewer White and Asian mothers when compared to DOH and HCA estimates. Panel B demonstrates that the population of mothers in the WA-APCD data skews notably younger than mothers in DOH records. For example, the mean age of mothers in the APCD data is approximately one year lower than in the HCA data (29 versus 30). The APCD data also contains a larger share of mothers in each age category under 30 when compared to DOH data. Panel C indicates that the WA-APCD data contains a larger share of births to mothers living in Eastern and Central Washington, whereas King, Snohomish, and Pierce counties, as well as the northwest counties on the Olympic Peninsula, are underrepresented compared to DOH data. Finally, Panel D compares the share of mothers with Medicaid-covered versus non-Medicaid-covered births in the APCD versus the HCA data, illustrating a dramatic difference. The percent of mothers with at least one birth-related claim billed to Medicaid was 23 percentage points higher in the APCD data when compared to the DOH estimate of the share of Medicaid births.

There are multiple potential reasons for the discrepancy between the APCD sample and the more comprehensive DOH/HCA records. Based on the scale of the gap and the nature of each potential discrepancy, however, I believe that the primary discrepancy between the

populations of mothers included in DOH/HCA and APCD data is exclusion of certain birth-related insurance claims based on the nature of the insurance plans. Specifically, APCD data excludes firms that have self-funded insurance plans. One estimate from 2022 suggested that approximately 65% of workers covered by employer-sponsored insurance plans are enrolled in a self-funded plan (Kaiser Family Foundation et al., 2022). The major discrepancy in the share of Medicaid births in the APCD data versus other sources further suggests that Medicaid is overrepresented in the APCD relative to other payment types. Therefore, I believe that the most substantial population that is missing from the APCD is mothers with employer-provided insurance plans that are self-funded by that employer. A few other discrepancies may also contribute to the gap between the APCD data and other estimates of the number of births in Washington. For example, in rare cases, delivery can be funded by self-pay by an individual, but this represented only 1.3% of births in Washington in 2022 (Kaiser Family Foundation, 2024). Also, home births may not generate insurance claims leading to these births not being included in the APCD data. From 2019 to 2020, between 2% and 3% of births in Washington were home births (Gregory et al., 2021). These are important limitations to keep in mind when considering generalizability of these findings.

[Table 3.2 about here]

Table 3.3 reports employment statistics in the quarters before and after a birth for the analytic sample – including employment rate, mean earnings, and mean hours worked. Employment, earnings, and hours drop in the quarters around a birth, particularly the quarter immediately after. For example, among mothers who gave birth in 2022, mean quarterly earnings fell by 59% between the quarter before birth and the quarter immediately after. The rate of working any number of hours fell 13 percentage points, and average hours worked fell by 48%.

These employment metrics do not return to pre-birth levels by the end of the study period (a year following the birth). These results largely mirror findings in Chapter 1 that mothers reduce employment around a birth and employment does not return to pre-birth levels by the end of the study period. However, there are a few differences between these findings and those in Chapter 1 that illuminate differences in the study populations in these two studies. For example, there is a larger percentage decline in earnings around a birth represented in Table 3.3 when compared to the results in Chapter 1, in part because the mothers in this analytic sample begin with lower earnings. This is because Medicaid-eligible mothers are more likely to be included in the APCD sample when compared to the DOH birth certificate data.

Findings in Table 3.3 further suggest that mothers who leave the labor force in the perinatal period have lower-than-average earnings. Mean earnings among working mothers (conditional on working nonzero hours) are much higher and rebound more rapidly following a birth. Furthermore, the mean and median wage rate among working mothers rises throughout the perinatal period as employment rate declines, suggesting that perinatal employment instability is disproportionately affecting women with lower-paying jobs.

Table 3.3, Panel E shows different measures of employer continuity in the quarters following a birth. Each specification measures employer continuity relative to the “main employer” in the pre-birth quarter closest to a birth in which the mother worked. The main employer is defined as the employer associated with the job with the most hours in that quarter. Importantly, the specifications have different denominators. Specifications 1 and 3 capture the share of mothers working for the same employer as a share of all working mothers. Specifications 2 and 4 capture the share of mothers working for the same employer, but instead as a share of all mothers, working and not. Therefore, Specifications 2 and 4 capture the two

phenomena of mothers leaving the labor force as well as mothers returning to an employer other than their main pre-birth employer. Employer continuity drops sharply from the quarter of birth to the quarter after. For example, while 95% of working mothers who gave birth in 2022 worked for their main pre-birth employer in the quarter of birth, only 85% of those who worked still worked for that same employer in the following quarter. Out of all mothers regardless of employment status, 88% still worked for their main pre-birth employer in the quarter of birth but only 60% still did in the quarter after. This drop-off is due to a combination of mothers changing employers and mothers leaving the labor force. Taken together, these findings suggest that mothers experience substantial employment instability in the perinatal period. These findings are similar to those in Chapter 1 and also echo the literature on economic conditions around a birth (Lu et al., 2017; Stanczyk, 2020).

[Table 3.3 about here]

PFML take-up

Between 25% and 32% of all mothers in Washington claimed paid family and/or medical leave through the state's program in the quarter of a birth or the quarter after (Table 3.4). Use of family leave peaks in the quarter after birth, while medical leave usage peaks in the quarter of a birth. Rates of any type of family leave use and bonding leave use were quite similar, revealing that almost all family leave claims among this population were for bonding leave. Take-up of medical leave has increased significantly as the policy rolled out between 2020 and 2022. For example, in 2020, 13% of mothers in the state used medical leave in the quarter in which they gave birth; by 2022, this percentage had increased by 15 percentage points, to 28%.

[Table 3.4 about here]

Table 3.5 displays these same rates among the subset of the population of mothers who were estimated to be eligible for PFML based on their work histories in the qualifying period.²⁰ These results reveal similar patterns to Table 3.4, but rates in this table are higher overall because the denominator is restricted to eligible mothers. Roughly a third of eligible mothers used bonding leave in the quarter of birth; this was quite consistent between 2020 and 2022. Fifty-six percent of eligible mothers used bonding leave in the quarter after birth in 2022, up from 45% for 2020 births. Roughly half of eligible mothers used medical leave in the quarter of birth. These findings demonstrate that a substantial share of eligible mothers are using leave through the state's program. By 2022, over half of eligible mothers were taking bonding leave in the quarter after a birth, and nearly half of eligible mothers were using medical leave in the quarter of a birth. However, these percentages still leave a significant portion of mothers who are eligible but do not take up the policy, reflecting opportunities for further outreach if the state wants to expand take-up of the program. These findings reflect previous findings in the literature that not all eligible potential participants use paid leave programs (Goodman et al., 2020)

[Table 3.5 about here]

Since nearly all family leave taken among this population is for bonding leave, analyses from this point forward focus on bonding and medical leave as the two main categories of PFML discussed. Table 3.6 explores differences in take-up rates across mother demographic characteristics among eligible mothers. This table reports, of mothers who worked at least 820 hours in the qualifying period before a birth, the share who used WA PFML. This table aggregates PFML use across each of the three years in the study (2020, 2021, and 2022) and

²⁰ Because this analysis relies on employment history data from the wage reports, results are reported separately using the UI and PFML wage reports.

reports the share of eligible mothers who used WA PFML in either the quarter of birth or the quarter after.

White mothers were most likely to take up bonding leave among all racial and ethnic groups. However, take-up rates were relatively comparable across racial groups except for Native Hawaiian/Pacific Islander mothers and American Indian/Alaska Native mothers, who were significantly less likely to use bonding leave. Fifty-two percent of eligible White mothers used bonding leave, in contrast to 40% of eligible Native Hawaiian or Pacific Islander mothers and 36% of eligible American Indian and Alaska Native mothers. Medical leave take-up was highest among Latina mothers and lowest for American Indian/Alaska Native mothers, followed by Native Hawaiian/Pacific Islander mothers. Take-up estimates for American Indian and Alaska Native mothers were significantly different using the UI wage reports and the PFML wage reports, suggesting that the UI wage reports estimated that significantly more American Indian/Alaska Native mothers were eligible for PFML when compared to the PFML wage reports. Take-up of bonding leave was highest for mothers aged 25-39 and lower for mothers both younger and older than this group. Take-up of medical leave increases with maternal age, peaking at age 35-39, before declining slightly.

Take-up of both types of leave is generally higher in more highly urbanized areas than in more rural areas. Mothers in the largest urban counties were 9 percentage points more likely to use bonding leave compared to mothers in small or remote rural counties (56% versus 47%), and 8 percentage points more likely to use medical leave than rural mothers (42% versus 34%). Analysis of take-up by region in Panel D, and by county in Panel E, shows that areas closest to the state's largest urban centers (including Seattle, Tacoma, and Olympia) tended to have higher take-up rates of paid leave, while more rural areas, especially in the east, north, and remote

northwest of the state, had lower rates of use of the program for both bonding and medical leave. Interestingly, when examining take-up of leave by county, Thurston County, which contains the state capital, Olympia, had the highest rate of take-up of bonding leave.

Panel F shows that large disparities in take-up emerge when examining take-up of PFML by wage rate. Eligible mothers working in the lowest-wage jobs (1st quintile) used the policy only 30% of the time, compared to 67% of mothers working in the highest-wage jobs. There were similarly large disparities in take-up of medical leave by wage rate quintile. Only one-fifth of eligible mothers in the lowest-wage jobs took medical leave, compared to 49% of mothers in the highest-wage jobs.

[Table 3.6 about here]

Regression discontinuity results

First, I address the identifying assumptions of a regression discontinuity design. An important potential threat to validity of regression discontinuity analyses is manipulation of the assignment variable (in this case, hours worked in the base period) such that parents non-randomly select into the “just eligible” group. Therefore, it is important to examine the density of this variable around the cutoff to look for evidence of discontinuous density. Figure 3.1 displays histograms produced using the **rddensity** package in R (Cattaneo et al., 2024) representing the density of the assignment variable around the cutoff, with a local polynomial density estimator plotted according to Cattaneo et al. (2020). Visually, these graphs convey that there is no evidence of a discontinuity in density around the cutoff, and a McCrary density test did not find evidence of a difference in density around the eligibility cutoff ($p=0.71$) (McCrary, 2008). This provides suggestive evidence for a lack of manipulation but does not conclusively disprove manipulation.

[Figure 3.1 about here]

Next, I test whether there is evidence of significant differences in other observable characteristics around the cutoff. Using local linear regression estimates with a MSE-optimal bandwidth according to Calocino, Cattaneo, and Titiunik (2014) and the **rdrobust** package (Calonico et al., 2023), I test whether there are any discontinuities in race/ethnicity and age around the eligibility threshold. Table 3.7 displays these results. There is evidence that there is a statistically significant decrease (3.5 percentage point decrease, $p=0.01$) in the share of mothers who are Black around the eligibility threshold when using the UI wage reports. However, this finding is not statistically significant when using the PFML wage reports. There is no evidence of significant discontinuities in the share of mothers identifying as other racial/ethnic identities, or mother age, at the cutoff. Because there is only one statistically significant finding in this analysis, and only for one data source, I believe this does not represent persuasive evidence of manipulation and is more likely due to chance.

[Table 3.7 about here]

Next, I examine the “first stage” of the fuzzy RD setup: whether crossing the eligibility threshold induces a significant change in taking leave through the PFML program. Eligibility as measured by working 820 or more hours in the policy’s base period is correlated with PFML use but does not perfectly imply PFML take-up for multiple reasons. First, errors in employment or insurance claims data submission or processing can mean that a worker’s hours in the data, relative to a birth event, do not accurately identify eligibility for PFML as determined by agency staff. Second, many workers are eligible for PFML but do not take up the policy. Table 3.8 descriptively examines whether there is a discontinuity in paid leave take-up around the eligibility cutoff. This table presents rates of any PFML, bonding, and medical leave use in the

quarter of birth or the quarter after across binned groupings of the assignment variable. Table 3.8 illustrates that the proportion of mothers claiming paid leave does indeed jump significantly at the 820-hour mark. This is true for both bonding and medical leave. Twelve percent of mothers who worked between 720 and 819 hours in the qualifying period before a birth used PFML in the quarter of birth, compared to 28% of mothers who worked 820-919 hours. Use of bonding leave jumped 10 percentage points in the quarter of birth, and 12 percentage points in the quarter after, between the 720-819- and 820-919-hour groups. Between the 720-819 and 820-919 groups, use of medical leave jumped 8 percentage points in the quarter of birth and 4 percentage points in the quarter after.

[Table 3.8 about here]

Table 3.9 estimates these effects more formally in a regression discontinuity model framework, again using local linear regression estimates (with an order of 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). This table presents coefficient estimates and confidence intervals from regression discontinuity estimates of the first stage of the RD model—that is, the estimated effect of crossing the eligibility threshold on the probability of PFML use in the quarter of a birth and the four quarters after. Point estimates can be interpreted (as in a linear probability model) as the percentage point change in the predicted rate of PFML claiming resulting from crossing the 820-hour threshold.

Eligibility for PFML (i.e., crossing the 820-hour threshold) induces a positive and statistically and substantively significant increase in claiming of both bonding and medical leave in the quarter of birth and the quarter after. Crossing the eligibility threshold increases the likelihood of using any PFML by 11 percentage points in the birth quarter and 9 percentage points in the quarter after. Crossing the threshold induces an 8 percentage point change in the

probability of bonding leave taking in both quarters. In the case of medical leave, crossing the threshold leads to a 4 percentage point change in the probability of using leave in the quarter of birth and a 3 percentage point change in the quarter after.

Examining the effects of threshold crossing on PFML use three quarters out from a birth presents an interesting potential puzzle. The coefficients indicating the effect of being just-eligible (i.e., crossing the 820-hour threshold) on PFML use are negatively signed in the third quarter after birth. This result is statistically significant when using the PFML wage reports; using the UI wage reports it is not statistically significant but still negative in magnitude. Using the PFML wage reports, I estimate that crossing the threshold to become eligible for PFML in the birth quarter is associated with a roughly 2 percentage point decrease in the probability of taking leave in the 3rd quarter after a birth. This finding reflects an important reality of this policy: the fact that eligibility for the policy is not a static trait, but may change in each quarter as employment histories evolve. The group of mothers who were just-ineligible at the time of a birth are quite close to the eligibility threshold, and therefore fairly likely to have crossed it (I find that roughly 15-20% of them do) by the third quarter out. So, there is some evidence that in the third quarter after a birth, more of the just-ineligible mothers approaching the eligibility threshold claim PFML than the just-eligible mothers. There is more consistent evidence of this negative effect for bonding leave, which can be taken somewhat flexibly following a child's birth and need not be taken immediately. This makes sense; it appears as though mothers who were just-ineligible at the time of a birth may be using the policy down the road, when mothers who were previously just-eligible may have used up their annual leave allotment. This result implies caution in interpreting employment effects (presented below) in these later quarters; they

may be affected by the fact that some of the mothers in the “control group” are later treated by the policy.

[Table 3.9 about here]

Figures 3.2 through 3.7 show visual representations of the models in Table 3.9. The dots in these figures show binned averages of the outcome in question (PFML use in each quarter relative to a birth) across a 5-hour interval of the assignment variable. The red lines represent results from the local linear regression models reported in Table 10. The black vertical line demarcates the eligibility cutoff (820 hours). Figures 3.2 and 3.3 show that more work history in the quarters before a birth is associated with steadily increasing use of PFML in the birth quarter and quarter after.²¹ Full-time work throughout the year would result in 2,080 hours worked in the qualifying period. Nearly three-quarters of mothers who worked full time throughout the qualifying period took PFML in the quarter of birth and in the quarter after. For use of leave farther out from a birth (i.e., six months or more after a birth), the pattern is a bit less straightforward. PFML use increases through about 1,500 hours worked in the qualifying period, then declines and increases again.

[Figures 3.2 and 3.3 about here]

The patterns of take-up by mother work history are quite similar for bonding leave as for all types of leave (Figures 3.4 and 3.5). Figures 3.6 and 3.7 present corresponding figures for use of medical leave. As mothers’ work history increases, use of medical leave in the quarter of a birth and the quarter after steadily rises. Right above the eligibility threshold, approximately 15% of mothers used medical leave in the quarter of birth and approximately 10% used it in the quarter after. However, among mothers who worked full time in the year before a birth, an

²¹ Figure 2 presents results using UI wage reports; Figure 3 presents results using PFML wage reports.

average of nearly 50% took medical leave in the quarter of birth and nearly 40% in the quarter after. As with other types of leave, results for quarters farther out from a birth event were less consistent. Many 5-hour intervals of the assignment variable have no mothers taking leave, and leave take-up is much lower in general. These figures highlight inequalities in take-up of leave by labor force attachment. Even among eligible mothers (all points to the right of the vertical line), mothers who worked more in the year prior to a birth were significantly more likely to use leave. This pattern is consistent in the quarters around a birth for both bonding and medical leave.

[Figures 3.4 and 3.5 about here]

[Figures 3.6 and 3.7 about here]

Tables 3.10 and 3.11 report the main results of the effect of PFML eligibility on quarterly employment outcomes using UI and PFML wage report data, respectively. Tables 3.12 and 3.13 do the same but for employment outcomes aggregated across multiple quarters. In each of these tables, three sets of models are reported: the reduced-form models, estimating the effect of threshold crossing on employment outcomes (first column); the first-stage models, estimating the effect of threshold crossing on using PFML (second column); and the 2SLS models, estimating the effect of claiming PFML on the employment outcomes (third column). The variable capturing PFML use in the fuzzy models is a binary indicator of taking any PFML in the quarter of birth or the quarter after. All of these models use local linear regression estimates (order of 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014) and estimates calculated using the **rdrobust** package (Calonico et al., 2023).

Figures 3.8 through 3.23 visualize results from the reduced form estimates of threshold crossing on quarterly employment outcomes. Figures 3.24 and 3.25 visualize results from the

models depicted in Table 3.12 and Table 3.13. The points in the figures represent binned averages of each outcome across 5-hour intervals of the assignment variable, and the red lines represent the local linear regression lines corresponding to the RD estimates in the tables.

Employment status (worked any hours). Evidence of the effect of threshold crossing on working any hours is mixed and inconclusive, and estimates using the UI and PFML wage reports differ substantially. When using the UI wage reports, the reduced form estimates are small (all 0.03 or smaller) and differently-signed depending on the quarter. There is a small negative effect in the quarter of birth that is marginally significant, suggesting that eligibility for PFML was associated with a 3 percentage point decrease in the probability of working any hours in the quarter of a birth.²² However, effects in all other quarters are statistically insignificant. The 2SLS estimates are larger in magnitude but very imprecisely estimated and not statistically significant. Using PFML wage reports, however (see Table 3.11), finds a significant negative effect of PFML eligibility on the likelihood of working any hours one²³ and four quarters after a birth. Again, the 2SLS estimates have a larger magnitude due to positive estimates of the first stage, but are imprecisely estimated and the only coefficient that remains significant is the effect on employment 4 quarters after a birth.

When examining outcomes aggregated across quarters, results are similar. Using the UI wage reports, reduced form coefficient estimates of the effect of PFML eligibility on working any hours in quarter of a birth and/or the one or two quarters after are small, of mixed signs, and statistically insignificant. When using PFML wage reports, I find a marginally significant negative effect of PFML eligibility on working any hours in the quarter of birth through the two

²² The statistical significance of this result is not robust to alternate choices of polynomial order or the use of robust, bias-corrected standard errors through the **rdrobust** package.

²³ The statistical significance of this result is not robust to alternate choices of polynomial order.

quarters after. PFML eligibility is associated with a 4 percentage point increase in the probability of working any amount in this time frame.²⁴ However, all 2SLS estimates (using either data source) are statistically insignificant. Taken together, these findings present suggestive and weak evidence that eligibility for PFML may have reduced the probability of mothers working any hours in some quarters around a birth, among mothers around the eligibility threshold. This could mean the policy is working as intended if mothers are replacing work hours with leave hours.

Hours worked. Table 3.10, using the UI wage reports, finds a marginally significant negative effect of PFML eligibility on hours worked in the quarter of a birth.²⁵ PFML eligibility was associated with a 9-hour decrease in quarterly work hours in the quarter of a birth. In subsequent quarters, the reduced form estimates were not statistically significant, and differently signed. The PFML wage reports find more consistently negatively-signed effects of PFML eligibility on hours worked, although the effect is only (marginally) statistically significant for the third quarter following a birth.²⁶ The 2SLS estimates using both datasets are larger in magnitude because of positive first stage estimates, but imprecisely estimated. When examining multiple quarters bundled together, both data sources estimate negative effects of PFML eligibility on hours worked in the quarter of birth through one or two quarters after. Only one coefficient is statistically significant, though: using the UI wage reports, PFML eligibility is associated with a 14-hour decrease in work hours in the quarter of birth and the quarter after combined.²⁷ Taken together, these findings provide some limited evidence of small negative effects of PFML eligibility on hours worked. However, these results are marginally statistically

²⁴ The statistical significance of this result is not robust to the choice of polynomial order or the use of robust bias-corrected standard errors through the **rdrobust** package.

²⁵ The statistical significance of this result is not robust to alternate choices of polynomial order or the use of robust bias-corrected standard errors through the **rdrobust** package.

²⁶ The statistical significance of this result is not robust to alternate choices of polynomial order.

²⁷ The statistical significance of this result is not robust to alternate choices of polynomial order or the use of robust bias-corrected standard errors through the **rdrobust** package.

significant, not consistent across data sources, and/or not robust to alternate specifications (see footnotes). Therefore, the evidence of negative effects on hours worked is quite limited.

Wages from work. Using the UI wage reports, reduced form estimates of the effect of PFML eligibility on wages are differently signed in each quarter and not statistically significant. Using the PFML wage reports finds a marginally significant negative effect in the quarter of birth; PFML eligibility is associated with a \$633 decrease in wages in the quarter of a birth. Estimates of the effect of PFML eligibility across multiple quarters around a birth are negatively signed but statistically insignificant across both data sources. Taken together, these findings suggest some evidence that PFML eligibility was associated with short-term reductions in wages from work. This could mean the policy was working as intended if mothers reduced work earnings and replaced work with paid leave.

Wages plus program benefits. Next, I examine the effect of PFML eligibility on wages from work plus PFML program benefits. Estimates using the UI wage reports find no statistically significant estimates and different signs depending on the quarter. PFML wage report results are all negatively signed, and the estimate in the third quarter after a birth is marginally significant, estimating that PFML eligibility is associated with a \$511 decrease in wages plus PFML program benefits in the third quarter after a birth.²⁸ Taken together, the preponderance of this evidence suggests that PFML eligibility did not significantly change mothers' earnings including wages plus PFML benefits.

Continuity with same employer. Tables 3.10 and 3.11 provide evidence that PFML eligibility may have promoted employer continuity. Looking at Specification 1, of mothers who were working following a birth, estimates with the UI wage reports find that PFML eligibility

²⁸ The statistical significance of this result is not robust to alternate choices of polynomial order or the use of robust bias-corrected standard errors through the **rdrobust** package.

was associated with a 7 percentage point increase in the probability of working some number of hours for the same employer in the quarter after a birth. PFML wage reports find a similar effect, finding that PFML eligibility is associated with an 8 percentage point increase in the probability of working some hours for the same employer in the quarter after a birth, conditional on working in that quarter.²⁹ Analysis with the PFML wage reports also finds that PFML eligibility is associated with a 5 percentage point increase in employer continuity in the third quarter after a birth, conditional on employment in that quarter.³⁰ Next, Specification 2 assesses the outcome of employment for the pre-birth employer among all mothers regardless of employment status. Estimates of the effect of PFML eligibility on this outcome are similar in magnitude and direction to estimates for Specification 1. However, only one estimate is statistically significant, and marginally so (using the PFML wage reports finds that PFML eligibility is associated with a 6 percentage point increase in the likelihood of working for the same employer as before the birth).³¹ Specifications 3 and 4 examine employer continuity outcomes that test whether mothers had the same “main job” (job with the most hours) in each quarter following a birth as they did in the quarter before a birth. These estimates are small in magnitude, differently-signed, and not statistically significant across both data sources. Taken together, these results provide relatively consistent evidence that PFML eligibility promoted continuing work with the same employer in the short term after a birth, conditional on working.

[Tables 3.10, 3.11, 3.12, and 3.13 about here]

[Figures 3.8 through 3.25 about here]

²⁹ These findings, including magnitude and statistical significance, are largely robust to alternate polynomial order specifications and robust, bias-corrected standard errors through **rdrobust**.

³⁰ The statistical significance of this result is robust to alternate polynomial order specifications but not to the use of robust, bias-corrected standard errors through **rdrobust**.

³¹ This result is similar in magnitude and remains statistically significant when using alternate polynomial order specifications and robust, bias-corrected standard errors through **rdrobust**.

These treatment effect estimates are calculated using a subset of observations; only mothers in the bandwidth are incorporated. Therefore, to explore the generalizability of these findings, it is important to understand how mothers in the bandwidth compare to mothers more broadly. Table 3.14 investigates how mothers captured in the RD analysis (i.e., within the RD bandwidth) differ from other mothers in the sample. This table compares mothers whose employment histories placed them below, within, or above the bandwidth, reporting on demographic and employment statistics for these three populations. The bandwidth is estimated empirically and is slightly different for each regression model. Therefore, the bandwidths used to subset mothers into these groups are the average bandwidths across all models using the same dataset.

[Table 3.14 about here]

These results find some key differences between mothers in the bandwidth and those whose work histories placed them below or above the bandwidth. Mothers in the bandwidth were more likely to be Latina and less likely to be White when compared to mothers whose work histories placed them below the bandwidth. Mothers in the bandwidth are younger, on average, than mothers outside of the bandwidth. Notably, 33% of mothers in the bandwidth are between 18 and 24 years old – compared to only 23% of mothers below the bandwidth and only 19% of mothers above the bandwidth. In contrast, mothers in the bandwidth were significantly less likely to be aged 30 or older. Geographic disparities by bandwidth category are relatively small, except that more mothers with work histories below the bandwidth live out of state – which is as expected given that these mothers are significantly less likely to have work histories in Washington-based employment records.

Employment statistics in Table 3.14 illustrate significant differences in rate of working any hours and working full time, as well as average hours worked; mothers in the bandwidth work significantly more than those below the bandwidth and mothers above the bandwidth work significantly more than those in the bandwidth. Very few mothers in the bandwidth work full time (less than 10% in each quarter through six months after a birth), and mothers above the bandwidth experience more dramatic changes to work intensity in the perinatal period. This is, in some sense, by definition, because the bandwidth is defined by work history. However, the fact that the population in the bandwidth is significantly different in terms of employment patterns may have important implications for the generalizability of these findings.

Mothers in the bandwidth tend to also have higher earnings in each quarter in the perinatal period, which is not surprising given higher work hours. The median working mother in the bandwidth had a lower average wage rate than the median working mother with work hours above the bandwidth. Across each specification of employer continuity, and in each quarter in the year following a birth, mothers in the bandwidth had higher rates of employer continuity than mothers below the bandwidth; in turn, mothers with work histories above the bandwidth had higher rates of employer continuity than mothers in the bandwidth.

Discussion and conclusion

This study used administrative data from multiple sources and a quasi-experimental research design to examine the effect of access to paid leave on leave-taking and employment among new mothers in Washington. A majority of eligible Washington mothers who give birth between 2020 and 2022 use PFML at some point during the perinatal period. Use of family leave is most common in the quarter after a birth, and almost all mothers who use family leave around the birth of a newborn use bonding leave rather than other types of caregiving leave. In the first three years that PFML is available in Washington, 32% of mothers use paid family and/or

medical leave at some point in the two-year period surrounding a birth. Twenty-eight percent of mothers and 58% of eligible mothers use family leave. Twenty-two percent of mothers and 42% of eligible mothers use medical leave. Take-up increases between 2020 and 2022 as the policy rolls out, especially for medical leave. While only 34% of eligible mothers who gave birth in 2020 use leave for their own health conditions sometime in the perinatal period, that percent increases to 56% for births occurring in 2022.

Analysis of policy take-up by mother characteristics reveals some important disparities. For example, results suggest that eligible Native Hawaiian/Pacific Islander and American Indian/Alaska Native mothers are less likely to take up paid bonding and medical leave than mothers identified with other racial and ethnic groups. Take-up is more equitable among Black, Latina, White, Asian, and Multiracial mothers. Younger mothers (under 25) and older mothers (40 plus) are less likely to take up bonding leave than mothers aged 25-39, while use of medical leave in the quarters around a birth generally increases with mother age. Mothers in more urban areas are more likely to take up both types of leave. There are sharp disparities by wage rate; only 30% of eligible mothers in the lowest-wage jobs take up bonding leave compared to 67% of mothers in the highest-wage jobs. Similar inequalities emerge for medical leave; 21% of eligible mothers in the lowest wage rate quintile use medical leave compared to 49% in the highest.

First-stage results reveal a sharp discontinuity in take-up of leave around the eligibility threshold. First-stage estimates are consistently positive, similar in magnitude, and statistically significant. Crossing the eligibility threshold is associated with approximately a 10 percentage point increase in the probability of using PFML in the quarter of birth and/or the quarter after. However, take-up continues to increase for mothers who have more extensive work histories in

the qualifying period, revealing disparities in policy use among eligible mothers by labor force attachment.

Regression discontinuity analyses of the local treatment effect of PFML eligibility on mothers around the eligibility threshold find mixed and somewhat inconclusive results. There is some evidence that eligibility for PFML has small negative effects on employment status and intensity (i.e., hours worked) in the short term. I do not find the positive effects on medium-term employment status and intensity that have been reported in some other studies (Byker, 2016; Rossin-Slater et al., 2013b). However, there was largely no evidence of an effect of PFML eligibility on total earnings (including wages plus PFML benefits). This null finding could be viewed as a policy success, suggesting that mothers, on average, were able to spend more paid time off, attending to either their new babies or their own health, without incurring a reduction in income. Furthermore, there is relatively consistent evidence, among mothers who are employed following a birth, that PFML eligibility in the birth quarter is associated with an increase in the likelihood of working for the same employer as before the birth.

It is possible that these results reflect heterogeneous treatment effects among mothers in the bandwidth. The effects of paid leave on maternal employment are theoretically ambiguous (Rossin-Slater et al., 2013a), especially in the quarters right around a birth. Assuming that access to PFML leads to an increase in uptake of leave, which I find in the first stage, mothers may replace work hours with leave hours, and work hours and wages could fall among eligible mothers relative to ineligible mothers in the short term. In the medium term, mothers who took more leave may work less if their leave was not job-protected and/or employers perceive a loss of job skills or employability relative to mothers who worked more consistently through the perinatal period (Rossin-Slater, 2018). In this case, there might be a negative effect of PFML

eligibility on employment. On the other hand, the policy could prevent mothers who would have otherwise stopped working from losing their jobs entirely, promoting employer continuity. In this case, work hours of mothers who have access to leave might be lower or the same in the quarter(s) a mother is taking leave, but higher in subsequent quarters, relative to the control group without PFML access. Future research should assess whether there is evidence of heterogeneity in treatment effects.

Limitations

It is possible that results may not generalize outside the bandwidth to the broader population of mothers who are eligible for paid leave. One of the limitations of regression discontinuity in a policy evaluation context is that it only estimates the local treatment effect among observations right around the eligibility cutoff. For example, I find that mothers in the bandwidth are significantly more likely to be 18-24 years old. Some of these mothers may be students whose employment experiences and policy use may not generalize to non-student mothers. Student status is not observable in these data so it cannot be examined empirically. Ideally, a causal design could compare employment outcomes among all eligible mothers, including those with more extensive work histories. However, this would require a design that compared outcomes before and after the policy's implementation. Because the availability of PFML benefits coincided with the beginning of the Covid-19 pandemic, a comparison between pre- and post-policy eras would need to grapple with many confounding factors that could affect parental employment. In the case of a hypothetical difference-in-differences design, for example, the co-occurrence of the pandemic and the policy rollout suggests that a parallel trends assumption may not be reasonable. Therefore, this paper is constrained to a regression discontinuity design, which necessarily only estimates a causal effect for mothers within the bandwidth. While this is a limitation, I argue that it is still valuable to study this group of

mothers, who are less strongly connected to the labor force and may be particularly vulnerable to employment instability.

This analysis is also limited by the fact that PFML eligibility status can change during the study period, as mentioned above. It is important to contextualize findings about effects in the third and fourth quarters after a birth with findings in the PFML wage reports that eligibility for PFML at the time of a birth was associated with a *lower* rate of PFML use in the third quarter after a birth. Therefore, coefficient estimates in quarters 3 and 4 may not represent the medium-term effect of PFML eligibility as determined in the quarter of a birth, but instead could also reflect the short-term effects of higher PFML take-up in the control group in these quarters.

Finally, this analysis is limited in the outcomes that can be examined using these administrative data. While these records have detailed information about employment histories, they cannot capture other important components of household wellbeing, such as household-level earnings and income, poverty status, material hardship, and time use. Previous research has also found evidence of positive effects of paid leave policies on outcomes such as physical and mental health (Doran et al., 2020; Stearns, 2015; Van Niel et al., 2020), which are not captured in this analysis. Examining these outcomes would present a more holistic picture of this policy's effects, but are beyond the scope of the data examined in this paper.

Implications for research

This study demonstrates proof-of-concept that health insurance records can be merged to state employment data to provide useful insights into contemporary labor policies. This paper demonstrates the utility of merging health insurance claims data to employment and paid leave program records to study take-up and employment effects of a state-level paid leave policy. This use of administrative data represents a significant contribution to the literature. Merging in the insurance claims data is key because it identifies a population of potential users of the policy,

which, combined with employment history information, can be used to determine eligibility. Often, policy research studies only have information on people who take up a policy, so they cannot (1) estimate take-up rates or (2) compare “treated” policy users to a control group. Sometimes, take-up rates are approximated by comparing the population using a policy to aggregate counts of potential policy users from another data source (S. Bana et al., 2022). In contrast, this study is able to identify a population in administrative microdata that has a need for leave (a birth) and then estimate, at the individual level, eligibility for the policy based on employment history. This data allows me to estimate take-up rates at the individual level and estimate the local average treatment effect of PFML in Washington.

However, this type of analysis with administrative data also creates complications. For example, while both the PFML wage reports and the UI wage reports have advantages, it is difficult to determine which most closely mirrors the “ground truth” employment trajectories we are interested in. Furthermore, the APCD data have significant advantages; they provide rich medical and demographic information. However, as demonstrated in Tables 3.1 and 3.2, they do not represent all births in the state. Future research should continue to explore the possibilities of these records to build policy-relevant knowledge, while carefully interpreting these data and acknowledging their limitations.

Implications for policy

A significant share of mothers of newborns are using Washington’s Paid Family and Medical Leave program to take paid time off to bond with children and care for their own medical conditions. While over two-thirds of eligible mothers took up the policy, take-up was not universal, pointing to areas where the state could focus energy to expand access. For example, this analysis revealed disparities in eligibility across racial, geographic, and socioeconomic lines such that Indigenous mothers, mothers living in rural areas, and mothers

working in lower-wage jobs were significantly less likely to use the policy even if they were eligible. These populations could be a focus of future outreach and engagement.

Tables and figures

Table 3.1. Number of individuals giving birth: APCD sample compared to statewide data

Birth year	Number of births in APCD: Full count and restrictions to create analytic sample			Comparable counts from other data sources		
	A. APCD: Number of person-quarters with live birth-related claims	B. Person-quarters with live birth-related claims at least 4 quarters since previous live birth claim(s)	C. Analytic sample: Person-quarters with live birth-related claims, at least 4 quarters since previous live birth claim(s), and valid SSN	D. HCA: individuals who gave birth	E. DOH: Number of live births	F. DOH: Estimated number of individuals who had a live birth
2019	56,705	54,705	43,964	82,709	84,918	83,678
2020	55,945	53,920	43,715	80,819	83,101	81,877
2021	56,832	54,679	44,866	81,486	83,899	82,681
2022	54,192	51,958	41,468	80,814	83,314	82,096

Notes: APCD numbers are filtered to all mothers with at least one live birth-related insurance claim. Column C restricts the APCD sample to mothers who will be included in the analytic sample because they have a valid SSN, allowing matching to other data sources, and had at least four quarters since the last birth event recorded in the data. HCA data (Column D) includes all mothers giving birth, including both live births and fetal deaths. DOH data in Column E includes only live births but is at the birth level rather than the mother level; since multiple births are counted multiple times in this column it is not the same unit of analysis as the APCD. Therefore, in Column F I approximate a conversion of the DOH data to the mother level by subtracting half of the number of multiple births recorded in each year in that data source. This assumes that all multiple births were twins. The number of multiple births was not available in 2022 DOH data, so I applied the 2019-2021 average multiple birth rate to 2022. There may be other differences between the HCA and DOH data sources that cause discrepancies between them.

Source: Author's analysis of data from WA-APCD; Washington State Health Care Authority (2024); Washington State Department of Health (2022).

Table 3.2. Births by mother characteristics, APCD vs. other state data sources

	A. APCD	B. DOH Live Births Data		C. HCA Individuals Who Gave Birth Data	
	Estimate	Estimate	Difference (APCD - DOH)	Estimate	Difference (APCD - HCA)
A. Racial/ethnic identity					
Share American Indian or Alaska Native alone, not Hispanic or Latina	0.023	0.013	0.010	0.012	0.011
Share Asian alone, not Hispanic or Latina	0.041	0.108	-0.067	0.113	-0.072
Share Black or African American alone, not Hispanic or Latina	0.090	0.049	0.041	0.049	0.041
Share Hispanic or Latina, any race	0.248	0.197	0.051	0.204	0.044
Share Multiracial or other, not Hispanic or Latina	0.034	0.047	-0.013	0.045	-0.011
Share Native Hawaiian or Pacific Islander alone, not Hispanic or Latina	0.047	0.015	0.032	0.016	0.031
Share White alone, not Hispanic or Latina	0.517	0.571	-0.054	0.562	-0.045
B. Age					
Mean age	28.994	-	-	29.999	-1.005
Share less than 18	0.011	0.007	0.004	0.007	0.004
Share 10-17	0.011	0.007	0.004	-	-
Share 18-19	0.033	0.023	0.010	-	-
Share 20-24	0.198	0.155	0.043	-	-
Share 25-29	0.295	0.275	0.020	-	-
Share 30-34	0.279	0.32	-0.041	-	-
Share 35-39	0.148	0.18	-0.032	-	-
Share 40-44	0.033	0.037	-0.004	-	-
Share 45 plus	0.003	0.003	0.000	-	-

Table 3.2, cont. Births by mother characteristics, APCD vs. other state data sources

	A. APCD	B. DOH Live Births Data		C. HCA Individuals Who Gave Birth Data	
	Estimate	Estimate	Difference (APCD - DOH)	Estimate	Difference (APCD - HCA)
C. Region					
East (Ferry, Stevens, Pend Oreille, Lincoln, Spokane, Adams, Whitman, Garfield, Asotin)	0.129	0.089	0.040	-	-
King County	0.234	0.281	-0.047	-	-
North (Whatcom, Skagit, San Juan, Island)	0.054	0.052	0.002	-	-
North central (Okanogan, Chelan, Douglas, Grant)	0.048	0.038	0.010	-	-
Northwest (Clallam, Jefferson, Mason, Kitsap)	0.045	0.051	-0.006	-	-
Pierce County	0.126	0.132	-0.006	-	-
Snohomish County	0.102	0.115	-0.013	-	-
South central (Kittitas, Yakima, Benton, Franklin, Walla Walla, Columbia)	0.108	0.101	0.007	-	-
Southwest (Wahkiakum, Cowlitz, Clark, Skamania, Klickitat)	0.087	0.084	0.003	-	-
West (Grays Harbor, Pacific, Thurston, Lewis)	0.067	0.057	0.010	-	-
D. Insurance coverage					
Medicaid	0.682	-	-	0.456	0.226
Non Medicaid	0.318	-	-	0.544	-0.226

Notes: APCD numbers are filtered to all mothers with at least one live birth who had a valid SSN and at least four quarters since the last birth-related claim (i.e., the analytic sample). Race or Hispanic ethnicity were missing for 26% of APCD observations; those observations are excluded from race/ethnicity analysis of APCD data this table. HCA data (Column B) includes all mothers giving birth, including both live births and fetal deaths; the inclusion of fetal deaths differs from the filtering of the APCD sample. DOH data in Column C includes only live births but is at the birth level rather than the mother level; since multiple births are counted multiple times in this column it is not the same unit of analysis as the APCD. Medicaid coverage in the APCD microdata refers to any birth that had one or more Medicaid claims.

Sources: Author's analysis of WA-APCD data; Health Care Authority First Steps Database Team (2024); Washington State Health Care Authority (2022).

Table 3.3. Perinatal employment statistics of mothers in APCD sample

	UI WAGE REPORTS				PFML WAGE REPORTS			
	Birth year				Birth year			
	2019	2020	2021	2022	2019	2020	2021	2022
Panel A. QUARTERLY EMPLOYMENT STATUS								
Employment rate (share with nonzero hours)								
4 before	0.54	0.55	0.52	0.52		0.51	0.51	0.52
3 before	0.54	0.55	0.52	0.54		0.53	0.51	0.54
2 before	0.53	0.53	0.50	0.53		0.51	0.50	0.53
1 before	0.49	0.48	0.47	0.49		0.47	0.47	0.49
Birth	0.44	0.41	0.42	0.43	0.41	0.40	0.41	0.43
1 after	0.40	0.34	0.35	0.36	0.38	0.34	0.35	0.37
2 after	0.42	0.39	0.41	0.43	0.41	0.39	0.41	0.43
3 after	0.42	0.41	0.43		0.41	0.41	0.43	0.44
4 after	0.42	0.42	0.44		0.41	0.42	0.44	
Panel B. QUARTERLY EARNINGS								
Mean earnings (all mothers, including non-workers)								
4 before	5350.94	5858.37	5822.13	5902.32		5333.59	5678.06	5891.58
3 before	5510.27	6024.87	5892.36	6280.76		5638.86	5814.46	6211.68
2 before	5342.06	5644.76	5769.62	6169.10		5466.13	5728.56	6136.93
1 before	5265.38	5376.40	5751.10	5941.72		5291.64	5726.03	5963.89
Birth	3815.02	3778.52	3972.31	3944.11	3681.23	3872.80	4086.19	4152.87
1 after	3023.77	2559.42	2481.05	2408.13	3007.61	2665.33	2600.65	2550.08
2 after	4228.53	4236.15	4312.42	4394.12	4095.83	4246.76	4295.81	4447.16
3 after	4503.39	4741.18	4884.85		4392.05	4752.42	4900.46	5104.20
4 after	4625.07	4864.04	5046.94		4563.20	4894.61	5070.08	
Mean earnings among working mothers								
4 before	9994.85	10705.13	11177.39	11343.42		10448.96	11102.24	11374.76
3 before	10113.70	10861.81	11435.04	11684.35		10626.04	11404.71	11584.99
2 before	10081.92	10717.08	11489.56	11591.25		10644.21	11535.29	11557.13
1 before	10639.18	11271.30	12204.57	12041.77		11301.18	12232.36	12069.60
Birth	8676.40	9298.98	9545.37	9079.59	9076.92	9683.65	9852.79	9551.96
1 after	7639.62	7530.29	7138.76	6734.22	7964.48	7876.34	7438.54	6969.41
2 after	10112.77	10790.30	10403.31	10263.15	10063.67	10871.18	10404.08	10317.38
3 after	10793.61	11597.59	11418.35		10762.61	11689.86	11431.01	11671.26
4 after	11092.50	11647.21	11477.31		11145.99	11758.40	11523.51	
Median earnings among working mothers								
4 before	7970.87	8535.56	8850.96	9040.98		8097.70	8710.32	8921.37
3 before	8054.90	8579.27	8962.04	9319.75		8213.01	8846.88	9101.85
2 before	7893.73	8339.72	8964.35	9182.53		8122.20	8853.81	8973.87
1 before	8235.08	8678.82	9335.44	9325.21		8571.85	9221.86	9208.48
Birth	5825.81	6109.59	6292.09	6149.44	5859.24	6301.91	6493.45	6412.70
1 after	5141.11	4403.05	4064.51	3794.36	5208.93	4633.51	4171.23	3853.69
2 after	7631.56	8044.40	7752.33	7788.40	7464.27	8032.01	7684.80	7787.80
3 after	8139.92	8738.22	8800.01		7965.26	8723.16	8689.79	9002.51
4 after	8460.61	8900.00	8787.16		8318.70	8798.06	8695.99	

Table 3.3 cont. Perinatal employment statistics of mothers in APCD sample

	UI WAGE REPORTS				PFML WAGE REPORTS			
	Birth year				Birth year			
	2019	2020	2021	2022	2019	2020	2021	2022
Panel C. HOURS WORKED								
Mean hours worked (all mothers, including non-workers)								
4 before	194.8	201.3	185.3	189.2		185.6	182.5	189.4
3 before	197.2	203.6	183.2	195.8		192.2	181.9	195.8
2 before	185.0	182.1	176.4	186.1		177.2	175.8	187.5
1 before	176.9	165.7	169.4	177.1		163.5	169.4	179.1
Birth	114.0	101.7	105.0	109.1	109.9	105.7	110.8	114.8
1 after	93.0	68.7	66.7	67.1	93.7	74.6	73.5	73.0
2 after	133.8	123.4	127.0	130.5	130.8	124.9	129.1	134.0
3 after	139.7	138.1	144.9		136.4	139.2	146.9	151.8
4 after	140.7	142.5	149.3		138.3	143.9	151.1	
Mean hours among working mothers								
4 before	363.9	367.8	355.7	363.6		363.6	356.7	365.7
3 before	361.9	367.1	355.6	364.2		362.2	356.7	365.2
2 before	349.2	345.7	351.3	349.6		345.0	354.1	353.1
1 before	357.5	347.3	359.5	359.0		349.2	362.0	362.5
Birth	259.3	250.3	252.4	251.1	270.9	264.3	267.1	264.1
1 after	235.0	202.1	191.9	187.5	248.2	220.5	210.2	199.5
2 after	320.0	314.3	306.4	304.8	321.4	319.8	312.6	310.9
3 after	334.8	337.9	338.7		334.3	342.3	342.7	347.2
4 after	337.5	341.3	339.4		337.7	345.7	343.5	
Median hours among working mothers								
4 before	399.0	402.0	388.5	399.0		400.0	390.0	402.0
3 before	397.0	402.0	390.0	393.0		400.0	391.0	393.0
2 before	385.0	378.0	388.0	375.0		378.0	391.0	383.0
1 before	392.0	384.0	397.0	395.0		388.0	400.0	401.0
Birth	238.0	226.0	227.0	228.5	248.0	244.0	245.0	245.0
1 after	201.0	159.0	145.0	138.0	216.0	174.0	163.0	151.0
2 after	336.0	327.0	315.0	306.0	337.0	336.0	323.0	313.0
3 after	359.0	366.0	363.0		360.0	371.5	371.0	382.0
4 after	362.0	369.0	364.0		362.0	375.0	372.0	
Panel D. WAGE RATE								
Mean wage rate among working mothers								
4 before	29.39	32.23	36.08	33.02		30.62	33.28	37.18
3 before	31.75	30.60	34.61	41.33		30.69	37.48	43.15
2 before	30.97	34.73	36.00	34.72		32.69	36.00	40.41
1 before	32.61	36.23	38.56	34.21		34.83	36.90	46.00
Birth	45.05	53.87	65.03	47.62	40.81	49.04	61.17	57.53
1 after	71.93	70.97	81.35	108.60	54.56	60.14	75.36	96.76
2 after	37.74	42.32	51.34	64.59	35.85	41.24	44.31	62.66
3 after	35.95	36.77	43.35		35.72	39.02	42.70	64.10
4 after	39.06	35.03	46.00		38.27	42.41	43.12	

Table 3.3 cont. Perinatal employment statistics of mothers in APCD sample

	UI WAGE REPORTS				PFML WAGE REPORTS			
	Birth year				Birth year			
	2019	2020	2021	2022	2019	2020	2021	2022
Panel D. WAGE RATE, cont.								
Median wage rate among working mothers								
4 before	19.66	20.80	22.48	22.59		19.94	21.92	22.07
3 before	19.88	20.96	22.80	22.71		20.24	22.29	22.12
2 before	20.34	21.63	22.90	23.24		21.09	22.40	22.45
1 before	20.99	22.64	23.43	23.70		22.15	22.77	22.91
Birth	22.35	24.67	25.07	24.66	21.60	23.83	24.05	23.78
1 after	21.97	24.01	24.17	23.53	21.03	23.11	22.71	22.23
2 after	21.94	23.53	23.66	24.12	21.28	22.92	22.76	23.00
3 after	22.45	23.46	23.56		21.78	22.76	22.83	23.49
4 after	22.88	23.55	23.62		22.33	22.78	22.73	
Panel E. EMPLOYER CONTINUITY								
Share with any work hours with main employer from quarter before birth (of all working)								
Birth	0.96	0.96	0.96	0.95	0.96	0.97	0.96	0.95
1 after	0.87	0.89	0.87	0.85	0.87	0.90	0.88	0.86
2 after	0.80	0.84	0.81	0.77	0.80	0.85	0.82	0.79
3 after	0.74	0.78	0.73		0.75	0.79	0.74	0.72
4 after	0.69	0.72	0.66		0.70	0.74	0.68	
Share with any work hours with main employer from quarter before birth (of all mothers)								
Birth	0.85	0.81	0.84	0.84	0.84	0.81	0.84	0.84
1 after	0.68	0.61	0.61	0.60	0.67	0.61	0.62	0.61
2 after	0.68	0.67	0.70	0.69	0.65	0.67	0.69	0.69
3 after	0.65	0.65	0.67		0.61	0.65	0.67	0.66
4 after	0.62	0.63	0.64		0.58	0.63	0.64	
Share with same main employer from quarter before birth (of all working)								
Birth	0.82	0.88	0.89	0.88	0.93	0.95	0.95	0.93
1 after	0.75	0.81	0.78	0.76	0.84	0.88	0.86	0.82
2 after	0.71	0.77	0.73	0.70	0.77	0.82	0.79	0.75
3 after	0.67	0.71	0.66		0.72	0.76	0.71	0.69
4 after	0.63	0.66	0.60		0.67	0.70	0.65	
Share with same main employer quarter before birth (of all mothers)								
Birth	0.83	0.80	0.83	0.83	0.83	0.80	0.84	0.84
1 after	0.65	0.58	0.59	0.58	0.66	0.60	0.61	0.60
2 after	0.66	0.65	0.67	0.67	0.65	0.66	0.68	0.68
3 after	0.62	0.63	0.65		0.60	0.64	0.65	0.66
4 after	0.59	0.61	0.62		0.57	0.62	0.63	

Notes: All earnings and wage rate statistics are adjusted for inflation and reported in \$2023. Blank cells represent quarters in which data was not available for all mothers in that year due to the time range of data availability. Wage rate is calculated by dividing wages earned by hours worked for the primary job in each quarter, defined as the job for which a worker worked the most hours in that quarter.

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.4. Take-up of PFML, all mothers regardless of eligibility

	Birth year		
	2020	2021	2022
Share took any type of PFML			
4 before		0.014	0.017
3 before		0.009	0.009
2 before		0.006	0.006
1 before		0.016	0.016
Birth	0.249	0.277	0.322
1 after	0.245	0.278	0.319
2 after	0.060	0.073	0.092
3 after	0.022	0.023	0.025
4 after	0.016	0.017	0.017
Share took any type of family leave			
4 before		0.010	0.011
3 before		0.006	0.005
2 before		0.002	0.002
1 before		0.002	0.001
Birth	0.158	0.152	0.130
1 after	0.215	0.243	0.273
2 after	0.053	0.067	0.087
3 after	0.020	0.020	0.024
4 after	0.012	0.012	0.013
Share took bonding leave			
4 before		0.009	0.010
3 before		0.005	0.004
2 before		0.001	0.001
1 before		0.001	0.001
Birth	0.157	0.151	0.129
1 after	0.215	0.242	0.272
2 after	0.053	0.066	0.086
3 after	0.019	0.020	0.023
4 after	0.011	0.011	0.013
Share took medical leave			
4 before		0.006	0.008
3 before		0.003	0.005
2 before		0.004	0.005
1 before		0.014	0.014
Birth	0.132	0.174	0.275
1 after	0.095	0.124	0.176
2 after	0.009	0.010	0.008
3 after	0.003	0.003	0.003
4 after	0.004	0.005	0.004

Notes: Take-up rate estimated as share of mothers with nonzero hours of paid leave through the WA PFML program. Bonding claims are a subset of family leave. Blank cells represent quarters in which not all mothers giving birth in that year had access to the policy.

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.5. Take-up of PFML, eligible mothers

	UI wage reports			PFML wage reports		
	Birth year			Birth year		
	2020	2021	2022	2020	2021	2022
Share took any type of PFML						
4 before		0.020	0.026		0.021	0.027
3 before		0.014	0.015		0.015	0.016
2 before		0.012	0.011		0.012	0.012
1 before		0.035	0.031		0.036	0.032
Birth	0.525	0.609	0.664	0.544	0.628	0.678
1 after	0.514	0.609	0.662	0.541	0.629	0.675
2 after	0.124	0.159	0.203	0.137	0.163	0.209
3 after	0.045	0.047	0.053	0.047	0.049	0.055
4 after	0.030	0.034	0.034	0.032	0.035	0.035
Share took any type of family leave						
4 before		0.014	0.016		0.015	0.017
3 before		0.009	0.008		0.010	0.009
2 before		0.004	0.004		0.004	0.004
1 before		0.004	0.003		0.004	0.004
Birth	0.332	0.332	0.301	0.339	0.343	0.310
1 after	0.452	0.532	0.565	0.479	0.550	0.578
2 after	0.110	0.144	0.188	0.122	0.149	0.193
3 after	0.040	0.042	0.049	0.042	0.043	0.050
4 after	0.023	0.025	0.026	0.024	0.026	0.026
Share took bonding leave						
4 before		0.013	0.015		0.014	0.015
3 before		0.008	0.006		0.008	0.007
2 before		0.002	0.002		0.002	0.002
1 before		0.003	0.002		0.003	0.002
Birth	0.331	0.331	0.300	0.338	0.342	0.308
1 after	0.451	0.531	0.564	0.478	0.549	0.577
2 after	0.109	0.144	0.188	0.121	0.148	0.192
3 after	0.039	0.041	0.048	0.041	0.042	0.050
4 after	0.022	0.023	0.024	0.022	0.024	0.025
Share took medical leave						
4 before		0.008	0.013		0.008	0.013
3 before		0.006	0.009		0.006	0.009
2 before		0.008	0.008		0.008	0.008
1 before		0.031	0.028		0.032	0.029
Birth	0.279	0.385	0.490	0.305	0.397	0.500
1 after	0.200	0.273	0.359	0.214	0.281	0.364
2 after	0.019	0.021	0.022	0.020	0.021	0.023
3 after	0.006	0.007	0.007	0.006	0.007	0.007
4 after	0.008	0.011	0.011	0.009	0.011	0.011

Notes: Take-up rate estimated as share of mothers with nonzero hours of paid leave through the WA PFML program. Bonding claims are a subset of family leave. Mothers were considered eligible if they worked 820 or more hours in the base period/alternate base period relative to a birth. Blank cells represent quarters in which not all mothers giving birth in that year had access to the policy.

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.6. Take-up of PFML among eligible mothers, by mother characteristics

	UI wage reports		PFML wage reports	
	Type of leave		Type of leave	
A. Race/ethnicity	Bonding	Medical	Bonding	Medical
American Indian or Alaska Native, not Hispanic or Latina	0.359	0.261	0.509	0.377
Asian, not Hispanic or Latina	0.485	0.375	0.510	0.403
Black or African American, not Hispanic or Latina	0.474	0.370	0.504	0.410
Hispanic or Latina, any race	0.489	0.385	0.521	0.420
Multiracial or other, not Hispanic or Latina	0.497	0.380	0.531	0.412
Native Hawaiian or Pacific Islander, not Hispanic or Latina	0.397	0.325	0.426	0.357
White, not Hispanic or Latina	0.517	0.372	0.543	0.400
B. Age				
10-17	0.273	0.212	0.269	0.192
18-19	0.300	0.208	0.333	0.235
20-24	0.447	0.311	0.481	0.340
25-29	0.559	0.404	0.588	0.434
30-34	0.600	0.455	0.623	0.481
35-39	0.593	0.461	0.602	0.485
40-44	0.533	0.457	0.547	0.475
45 plus	0.455	0.358	0.426	0.383
C. Urbanicity				
Large metropolitan county	0.563	0.418	0.586	0.446
Small metropolitan county	0.531	0.404	0.565	0.441
Large rural county	0.503	0.358	0.540	0.393
Small or remote rural county	0.470	0.335	0.487	0.362
D. Region				
East (Ferry, Stevens, Pend Oreille, Lincoln, Spokane, Adams, Whitman, Garfield, Asotin)	0.536	0.406	0.558	0.429
King	0.569	0.431	0.585	0.454
North (Whatcom, Skagit, San Juan, Island)	0.525	0.391	0.549	0.426
North central (Okanogan, Chelan, Douglas, Grant)	0.514	0.362	0.557	0.400
Northwest (Clallam, Jefferson, Mason, Kitsap)	0.520	0.363	0.559	0.409
Pierce	0.552	0.423	0.586	0.459
Snohomish	0.581	0.416	0.603	0.442
South central (Kittitas, Yakima, Benton, Franklin, Walla Walla, Columbia)	0.541	0.412	0.572	0.448
Southwest (Wahkiakum, Cowlitz, Clark, Skamania, Klickitat)	0.540	0.380	0.568	0.404
West (Grays Harbor, Pacific, Thurston, Lewis)	0.555	0.399	0.591	0.431
E. County				
Adams	0.435	0.319	0.446	0.338
Asotin	0.523	0.352	0.564	0.385
Benton	0.546	0.400	0.581	0.437
Chelan	0.534	0.365	0.587	0.412
Clallam	0.472	0.350	0.535	0.411
Clark	0.566	0.390	0.588	0.413
Columbia	0.455	0.364	0.450	0.300
Cowlitz	0.478	0.356	0.519	0.390
Douglas	0.554	0.366	0.446	0.338

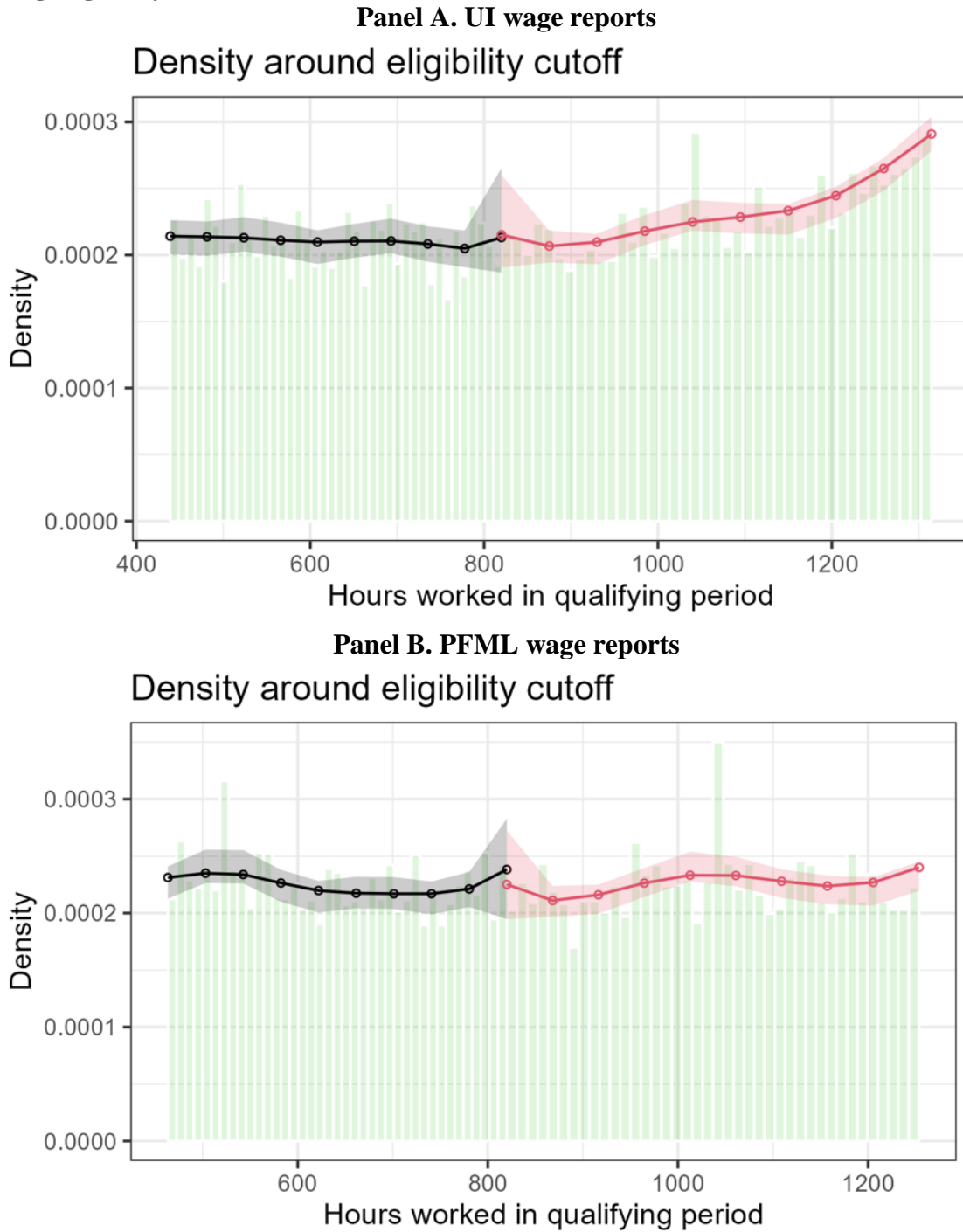
Table 3.6, cont. Take-up of PFML among eligible mothers, by mother characteristics

E. County, cont.	UI wage reports		PFML wage reports	
	Type of leave		Type of leave	
	Bonding	Medical	Bonding	Medical
Ferry	0.485	0.333	0.500	0.385
Franklin	0.511	0.273	0.553	0.303
Garfield	0.500	0.389	0.533	0.333
Grant	0.514	0.382	0.546	0.407
Grays Harbor	0.513	0.365	0.560	0.400
Island	0.468	0.300	0.488	0.339
Jefferson	0.479	0.323	0.494	0.388
King	0.569	0.431	0.585	0.454
Kitsap	0.545	0.374	0.575	0.414
Kittitas	0.532	0.319	0.564	0.364
Klickitat	0.468	0.325	0.521	0.324
Lewis	0.479	0.349	0.525	0.384
Lincoln	0.556	0.429	0.577	0.462
Mason	0.512	0.357	0.557	0.398
Okanogan	0.418	0.292	0.452	0.335
Pacific	0.556	0.385	0.566	0.396
Pend Oreille	0.420	0.261	0.482	0.321
Pierce	0.552	0.423	0.586	0.459
San Juan	0.571	0.393	0.520	0.400
Skagit	0.509	0.377	0.530	0.408
Skamania	0.448	0.345	0.522	0.348
Snohomish	0.581	0.416	0.603	0.442
Spokane	0.546	0.417	0.568	0.441
Stevens	0.471	0.324	0.510	0.354
Thurston	0.596	0.428	0.625	0.459
Wahkiakum	0.467	0.533	0.412	0.412
Walla Walla	0.490	0.407	0.524	0.443
Whatcom	0.548	0.424	0.579	0.463
Whitman	0.557	0.410	0.530	0.404
Yakima	0.547	0.434	0.576	0.468
F. Wage rate quintile				
1 st (lowest)	0.301	0.209	0.355	0.263
2 nd	0.437	0.314	0.463	0.339
3 rd	0.528	0.405	0.551	0.425
4 th	0.630	0.473	0.657	0.511
5 th (highest)	0.668	0.493	0.681	0.513

Notes: Mothers were considered eligible if they worked 820 or more hours in the base period and/or the alternate base period relative to a birth. Race and/or Hispanic ethnicity were missing for 26% of birth observations; those observations are excluded from analysis of race and ethnicity in this table. Wage rate quintile is calculated by dividing wages by hours worked for the primary job (the job with the most hours) in the quarter the mother worked closest to the birth.

Sources: Author's analysis of data from WA-APCD and ESD.

Figure 3.1. Density of assignment variable (hours worked in PFML qualifying period) along eligibility threshold



Notes: McCrary density test found no evidence of a discontinuity in density ($p=0.7078$ with PFML wage reports; $p=0.7968$ with UI wage reports).

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.7. Estimates of differences in mother characteristics around cutoff point

	UI wage reports					PFML wage reports				
	Coefficient	Std. Error	P-value	95% confidence interval Lower Upper		Coefficient	Std. Error	P-value	95% confidence interval Lower Upper	
Share White, not Hispanic or Latina	0.031	0.026	0.233	-0.020	0.081	0.004	0.021	0.858	-0.037	0.045
Share Asian, not Hispanic or Latina	0.010	0.008	0.177	-0.005	0.026	0.007	0.007	0.305	-0.007	0.022
Share Black, not Hispanic or Latina	-0.035*	0.014	0.012	-0.062	-0.008	-0.007	0.013	0.575	-0.033	0.018
Share American Indian/ Alaska Native, not Hispanic or Latina	0.000	0.006	0.971	-0.012	0.012	0.000	0.006	0.969	-0.011	0.011
Share Hispanic or Latina, any race	0.014	0.018	0.418	-0.020	0.049	-0.01	0.018	0.573	-0.046	0.026
Share Native Hawaiian/Pacific Islander, not Hispanic or Latina	-0.002	0.009	0.795	-0.020	0.015	0.002	0.009	0.819	-0.016	0.020
Age	-0.153	0.251	0.542	-0.644	0.339	-0.113	0.273	0.678	-0.650	0.423

. = p<0.10; * = p<0.05; ** = p<0.01; *** = p<0.001

Notes: All coefficients are local linear regression estimates (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). All earnings and wage rate statistics are adjusted for inflation and reported in \$2023.

Sources: Author’s analysis of data from WA-APCD and ESD.

Table 3.8. Take-up of PFML by hours worked in qualifying period

Hours worked in qualifying period	UI wage reports						PFML wage reports					
	Share taking leave						Share taking leave					
	Any PFML		Bonding		Medical		Any PFML		Bonding		Medical	
	Birth quarter	1 quarter after	Birth quarter	1 quarter after	Birth quarter	1 quarter after	Birth quarter	1 quarter after	Birth quarter	1 quarter after	Birth quarter	1 quarter after
[120,220)	0.013	0.015	0.008	0.013	0.007	0.005	0.018	0.023	0.010	0.020	0.013	0.009
[220,320)	0.020	0.019	0.012	0.016	0.012	0.010	0.031	0.029	0.017	0.024	0.019	0.013
[320,420)	0.026	0.028	0.015	0.025	0.015	0.013	0.039	0.039	0.021	0.033	0.023	0.019
[420,520)	0.042	0.049	0.022	0.039	0.023	0.022	0.066	0.070	0.033	0.058	0.038	0.032
[520,620)	0.051	0.060	0.028	0.052	0.033	0.027	0.086	0.099	0.049	0.086	0.049	0.043
[620,720)	0.086	0.090	0.049	0.073	0.048	0.038	0.100	0.106	0.053	0.088	0.064	0.050
[720,820)	0.121	0.132	0.066	0.113	0.077	0.057	0.141	0.157	0.074	0.134	0.088	0.071
[820,920)	0.279	0.267	0.173	0.235	0.150	0.105	0.334	0.323	0.203	0.281	0.187	0.131
[920,1020)	0.340	0.321	0.197	0.267	0.201	0.136	0.383	0.363	0.221	0.308	0.240	0.147
[1020,1120)	0.394	0.360	0.226	0.309	0.229	0.157	0.431	0.397	0.245	0.338	0.254	0.174
[1120,1220)	0.441	0.413	0.249	0.351	0.255	0.183	0.472	0.444	0.274	0.379	0.273	0.189
[1220,1320)	0.501	0.497	0.281	0.424	0.305	0.211	0.546	0.529	0.299	0.451	0.337	0.232
[1320,1420)	0.512	0.543	0.284	0.474	0.314	0.217	0.544	0.580	0.306	0.504	0.334	0.234
[1420,1520)	0.547	0.569	0.305	0.497	0.332	0.237	0.568	0.601	0.313	0.528	0.350	0.250
[1520,1620)	0.583	0.589	0.328	0.513	0.360	0.256	0.613	0.623	0.337	0.543	0.393	0.270
[1620,1720)	0.640	0.613	0.364	0.528	0.386	0.271	0.660	0.645	0.363	0.554	0.417	0.296
[1720,1820]	0.663	0.644	0.361	0.562	0.416	0.295	0.682	0.661	0.372	0.577	0.429	0.309

Notes: The qualifying period is defined relative to the birth quarter in this analysis. Mothers were eligible for PFML if they worked more than 820 hours in the qualifying period.

Sources: Author’s analysis of data from WA-APCD and ESD.

Table 3.9. Estimates of the effect of threshold crossing on use of PFML

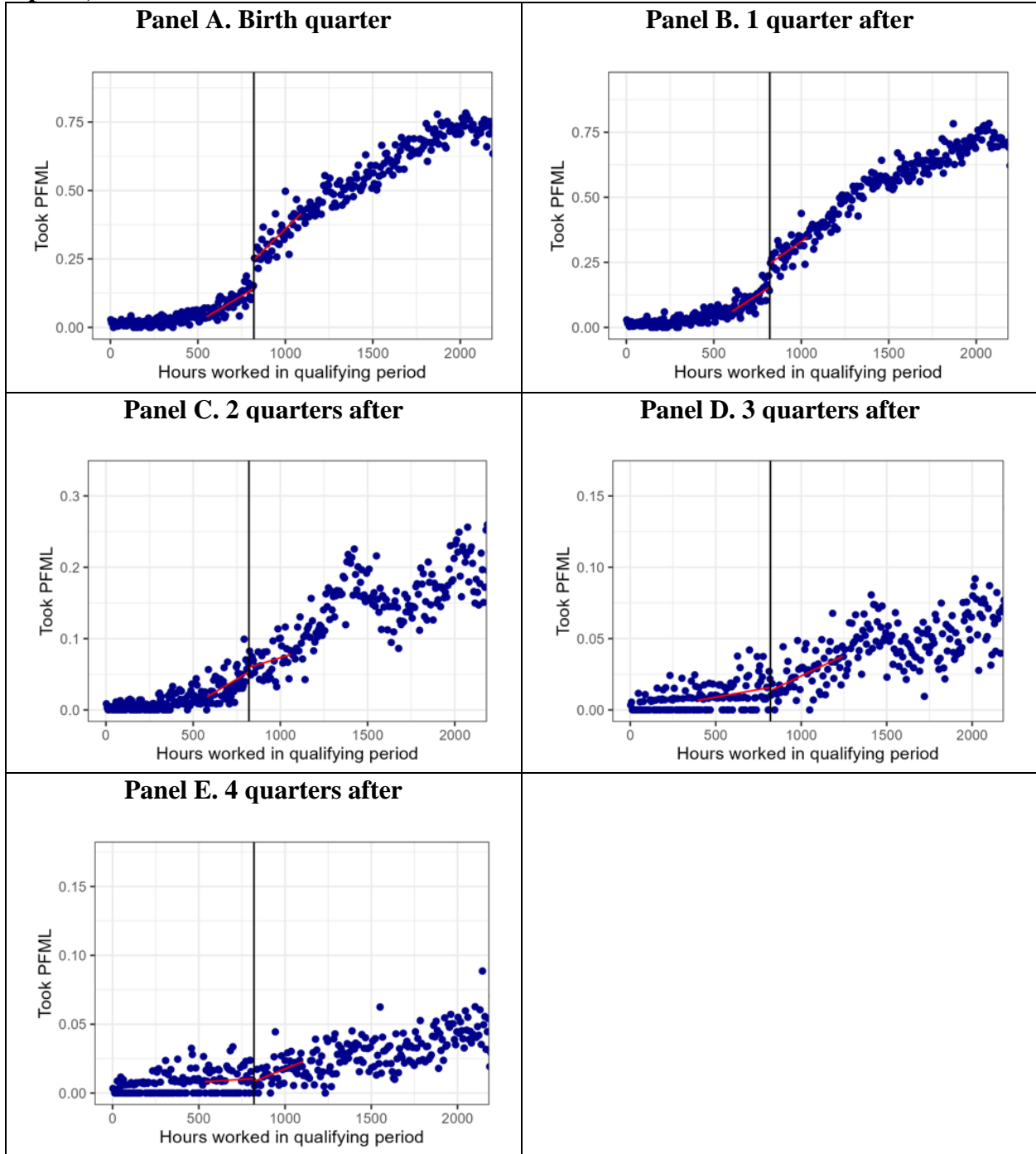
	UI wage reports					PFML wage reports				
	Coefficient	Std. Error	P-value	95% confidence interval		Coefficient	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper
Took any PFML										
Birth quarter	0.106***	0.015	0.000	0.076	0.137	0.119***	0.021	0.000	0.077	0.160
1 after	0.086***	0.018	0.000	0.051	0.120	0.085***	0.024	0.000	0.037	0.133
2 after	0.004	0.010	0.677	-0.015	0.024	-0.006	0.013	0.666	-0.031	0.020
3 after	-0.003	0.004	0.384	-0.011	0.004	-0.019**	0.006	0.002	-0.032	-0.007
4 after	-0.003	0.004	0.415	-0.010	0.004	-0.008	0.005	0.119	-0.018	0.002
Took bonding leave										
Birth quarter	0.079***	0.011	0.000	0.057	0.102	0.102***	0.014	0.000	0.074	0.130
1 after	0.078***	0.017	0.000	0.045	0.112	0.066**	0.023	0.004	0.021	0.112
2 after	0.004	0.010	0.719	-0.016	0.023	-0.010	0.013	0.416	-0.035	0.014
3 after	-0.006	0.004	0.181	-0.014	0.003	-0.015**	0.005	0.005	-0.026	-0.005
4 after	-0.006	0.003	0.113	-0.012	0.001	-0.007.	0.004	0.063	-0.014	0.000
Took medical leave										
Birth quarter	0.038**	0.013	0.003	0.013	0.064	0.053**	0.017	0.002	0.020	0.085
1 after	0.025*	0.012	0.033	0.002	0.047	0.037**	0.013	0.006	0.010	0.063
2 after	0.001	0.003	0.757	-0.005	0.006	0.004	0.004	0.258	-0.003	0.011
3 after	0.000	0.002	0.999	-0.003	0.003	-0.003	0.003	0.297	-0.008	0.002
4 after	0.002	0.002	0.392	-0.002	0.005	0.001	0.003	0.663	-0.004	0.007

. = p<0.10; * = p<0.05; ** = p<0.01; *** = p<0.001

Notes: All coefficients are local linear regression estimates (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter.

Sources: Author’s analysis of data from WA-APCD and ESD.

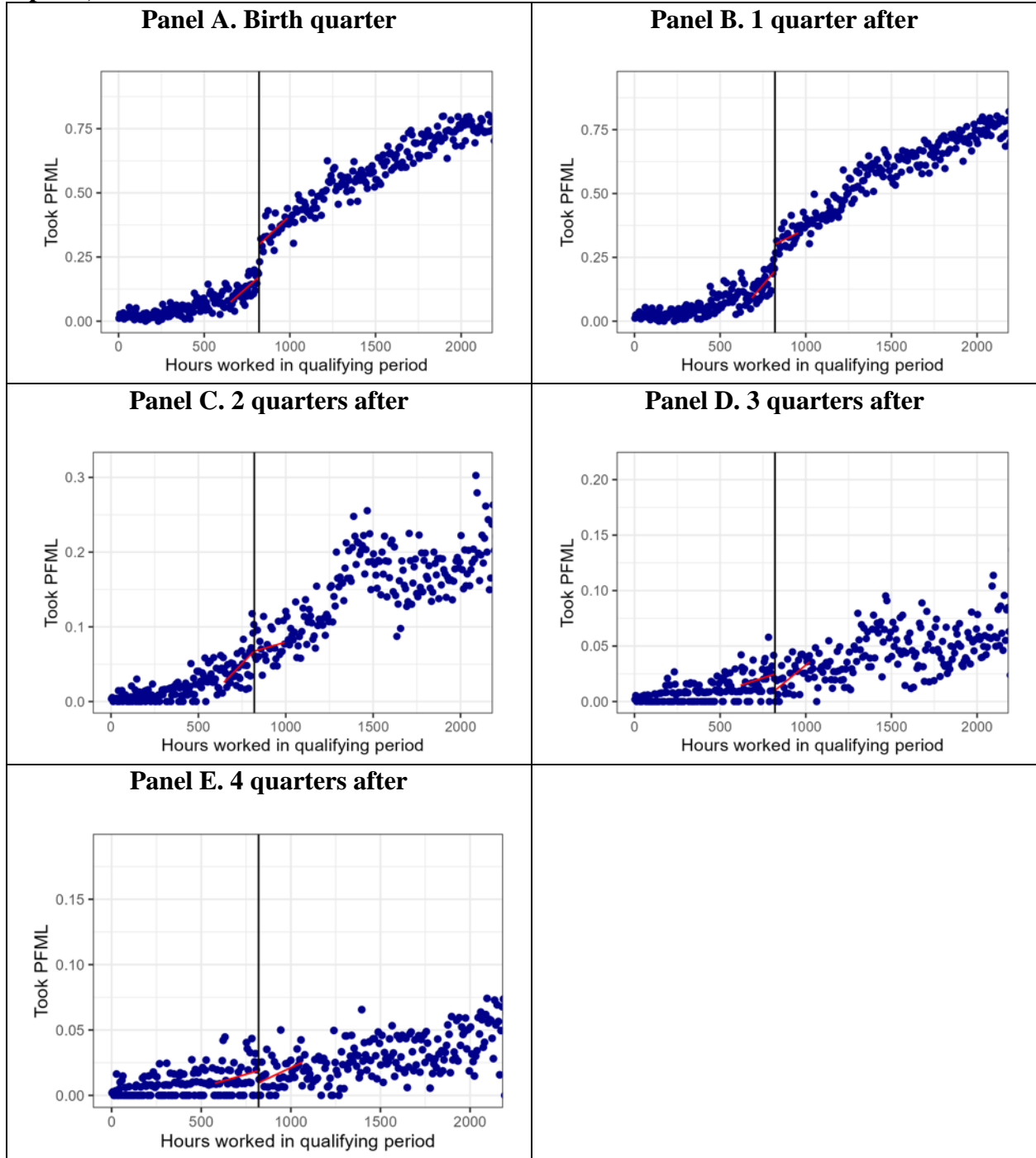
Figure 3.2. Any PFML take-up by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

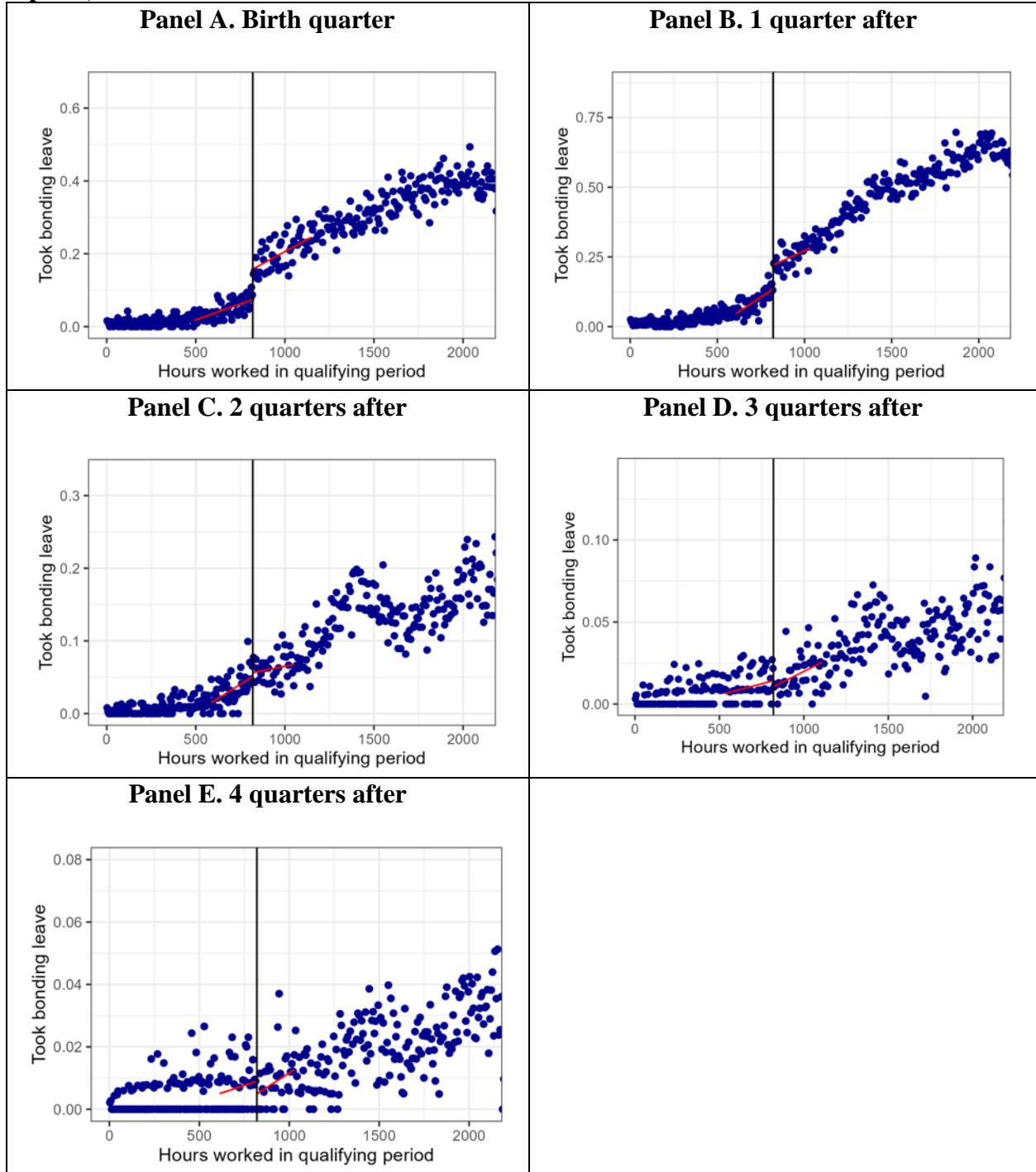
Figure 3.3. Any PFML take-up by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

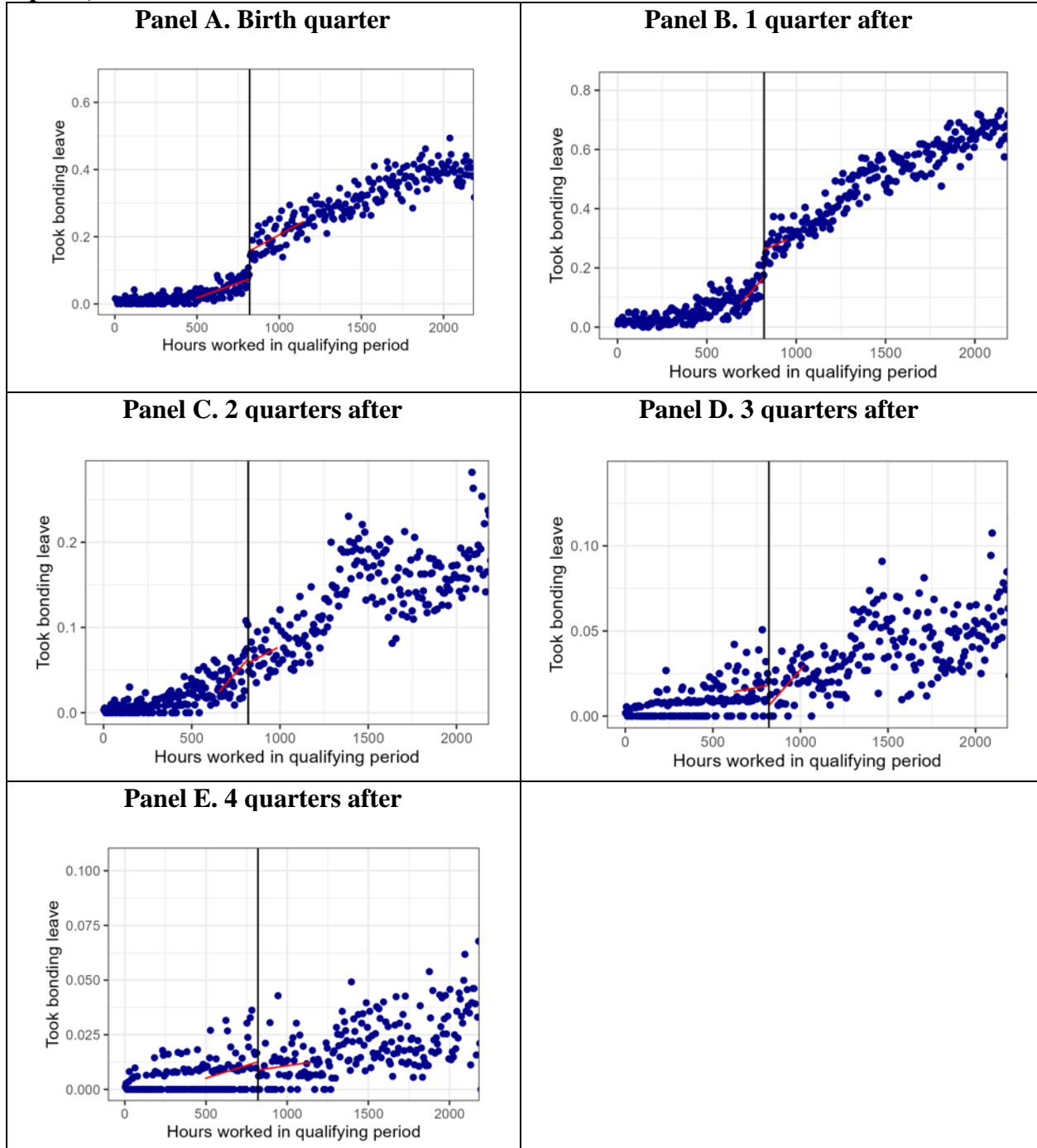
Figure 3.4. Bonding leave take-up by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

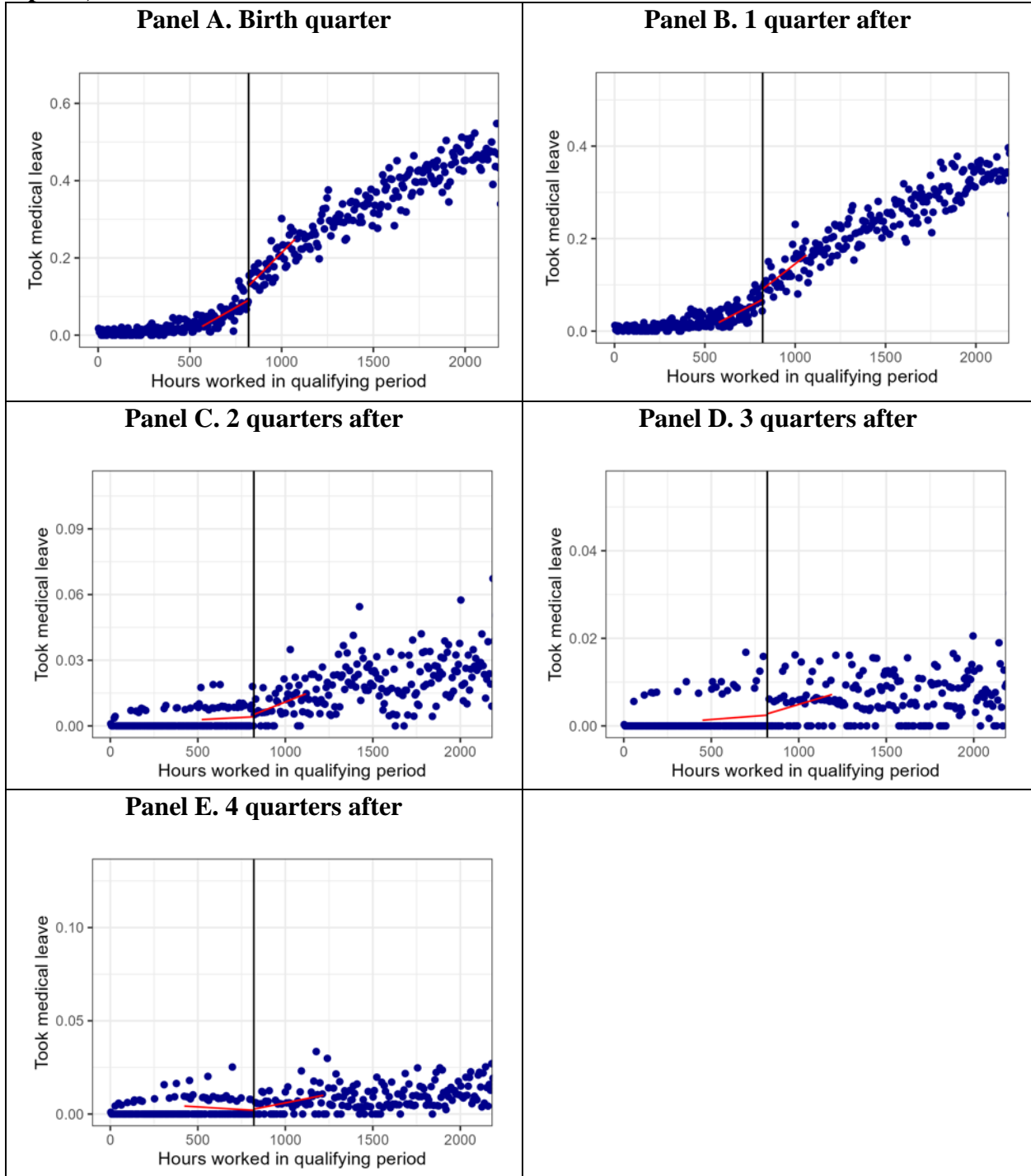
Figure 3.5. Bonding leave take-up by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

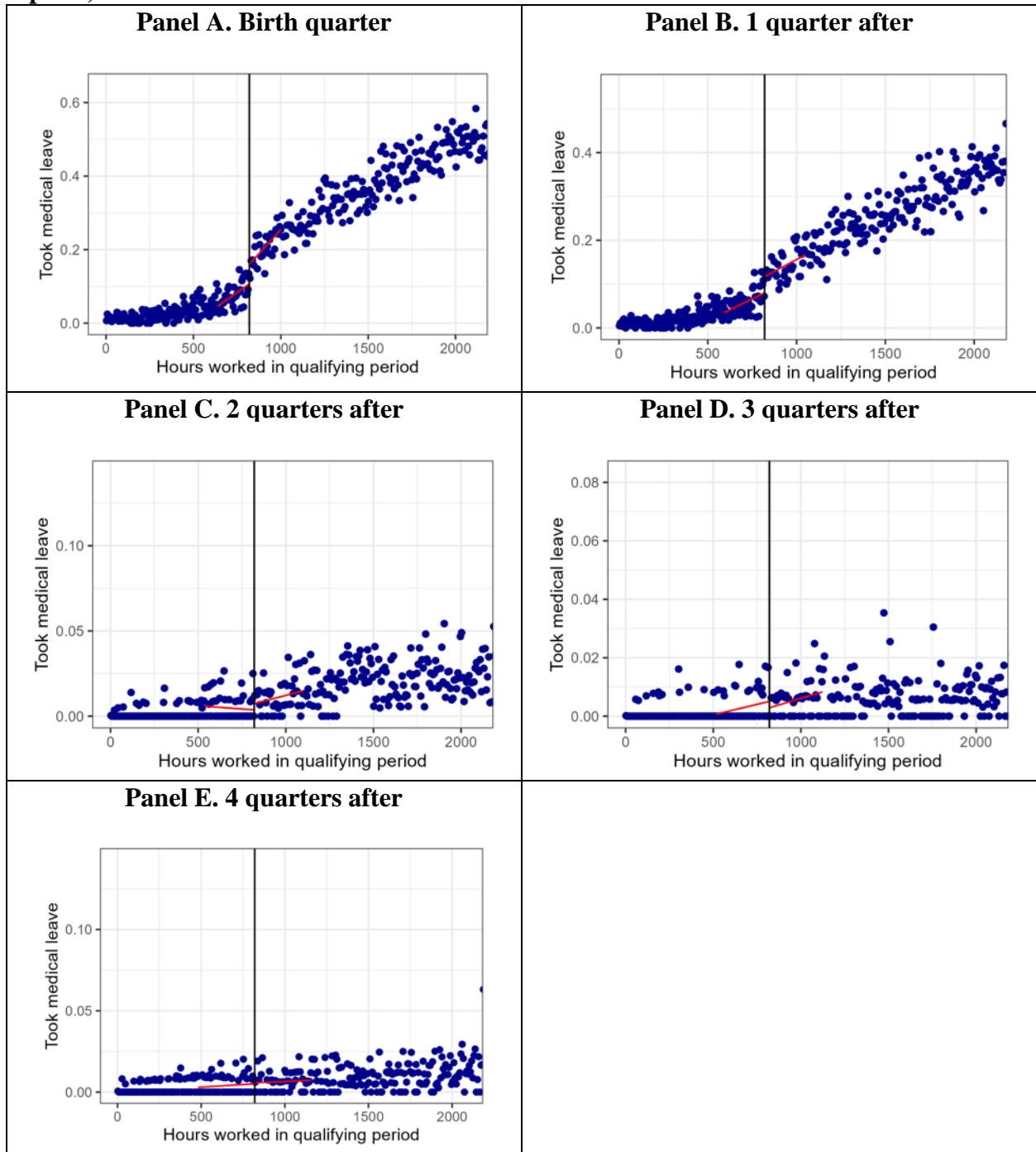
Figure 3.6. Medical leave take-up by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

Figure 3.7. Medical leave take-up by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.10. Estimates of the effect of threshold crossing on quarterly employment outcomes (using UI wage reports)

OUTCOME	Reduced form					First stage					2SLS estimate				
	Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper				Lower	Upper
Employment status															
Birth	-0.030.	0.017	0.080	-0.063	0.004	0.100***	0.016	0.000	0.069	0.130	-0.291	0.212	0.169	-0.706	0.123
1 after	-0.028	0.018	0.127	-0.063	0.008	0.099***	0.017	0.000	0.067	0.131	-0.261	0.210	0.212	-0.672	0.149
2 after	0.012	0.020	0.541	-0.028	0.053	0.098***	0.018	0.000	0.062	0.134	0.120	0.223	0.592	-0.318	0.557
3 after	0.008	0.020	0.693	-0.031	0.047	0.098***	0.019	0.000	0.061	0.134	0.029	0.226	0.898	-0.414	0.473
4 after	-0.013	0.020	0.508	-0.052	0.026	0.099***	0.016	0.000	0.067	0.131	-0.128	0.202	0.526	-0.525	0.269
Hours worked															
Birth	-9.118.	6.870	0.089	-22.584	4.348	0.099***	0.017	0.000	0.066	0.132	-93.342	76.109	0.148	-242.513	55.828
1 after	-6.332	4.477	0.157	-15.107	2.442	0.099***	0.016	0.000	0.068	0.131	-60.327	50.305	0.230	-158.924	38.270
2 after	2.200	6.085	0.718	-9.726	14.125	0.098***	0.018	0.000	0.063	0.134	23.337	73.197	0.750	-120.127	166.802
3 after	-1.331	6.211	0.830	-13.504	10.841	0.099***	0.017	0.000	0.065	0.133	-9.742	76.247	0.898	-159.183	139.700
4 after	0.920	6.659	0.890	-12.132	13.972	0.099***	0.016	0.000	0.068	0.131	3.308	73.338	0.964	-140.432	147.048
Wages from work															
Birth	-474.013	358.392	0.186	-1176.448	228.423	0.102***	0.015	0.000	0.073	0.131	-1947.837	3033.526	0.521	-7893.440	3997.765
1 after	-145.504	176.003	0.408	-490.463	199.455	0.102***	0.015	0.000	0.073	0.131	-1502.427	1742.858	0.389	-4918.367	1913.513
2 after	194.744	207.975	0.349	-212.880	602.369	0.099***	0.016	0.000	0.068	0.131	1763.613	2092.906	0.399	-2338.407	5865.634
3 after	-153.123	245.433	0.533	-634.162	327.916	0.099***	0.016	0.000	0.067	0.131	-1324.232	2475.636	0.593	-6176.390	3527.926
4 after	112.491	236.099	0.634	-350.255	575.237	0.100***	0.015	0.000	0.070	0.130	1427.203	2207.776	0.518	-2899.958	5754.363
Earnings from work + PFML payments															
Birth	-242.029	385.979	0.531	-998.534	514.476	0.101***	0.015	0.000	0.071	0.131	404.595	3183.896	0.899	-5835.727	6644.917
1 after	32.505	198.800	0.870	-357.136	422.146	0.104***	0.014	0.000	0.076	0.132	1251.050	1856.825	0.500	-2388.260	4890.361
2 after	184.468	214.380	0.390	-235.709	604.646	0.099***	0.017	0.000	0.067	0.132	1669.568	2156.157	0.439	-2556.421	5895.557
3 after	-193.106	248.726	0.438	-680.600	294.388	0.099***	0.016	0.000	0.068	0.131	-1573.266	2479.206	0.526	-6432.420	3285.888
4 after	120.051	231.095	0.603	-332.887	572.988	0.100***	0.015	0.000	0.070	0.130	1363.636	2214.653	0.538	-2977.005	5704.277
Same employer (specification 1): Share with any work hours with main employer from quarter before birth (of all working)															
Birth	0.014	0.021	0.499	-0.027	0.056	0.099***	0.018	0.000	0.064	0.133	0.089	0.125	0.477	-0.156	0.333
1 after	0.067*	0.032	0.039	0.003	0.130	0.101***	0.015	0.000	0.071	0.131	0.371.	0.206	0.072	-0.033	0.775
2 after	0.049.	0.029	0.093	-0.008	0.107	0.098***	0.018	0.000	0.063	0.134	0.411.	0.237	0.082	-0.053	0.875
3 after	0.037	0.029	0.204	-0.020	0.095	0.097***	0.019	0.000	0.059	0.134	0.410	0.308	0.184	-0.194	1.014
4 after	0.027	0.030	0.377	-0.033	0.086	0.098***	0.018	0.000	0.062	0.134	0.204	0.265	0.441	-0.316	0.724

. = p<0.10; * = p<0.05; ** = p<0.01; *** = p<0.001

Table 3.10, cont. Estimates of the effect of threshold crossing on quarterly employment outcomes (using UI wage reports)

OUTCOME	Reduced form					First stage					2SLS estimate				
	Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper				Lower	Upper
Same employer (specification 2): Share with any work hours with main employer from quarter before birth (of all mothers)															
Birth	0.014	0.015	0.344	-0.015	0.043	0.097***	0.019	0.000	0.059	0.134	0.125	0.101	0.217	-0.073	0.323
1 after	0.037	0.029	0.204	-0.020	0.093	0.100***	0.015	0.000	0.070	0.130	0.195	0.186	0.294	-0.169	0.559
2 after	0.040	0.025	0.119	-0.010	0.089	0.098***	0.018	0.000	0.063	0.134	0.309	0.220	0.160	-0.122	0.739
3 after	0.034	0.028	0.230	-0.021	0.089	0.097***	0.019	0.000	0.060	0.134	0.343	0.294	0.243	-0.233	0.919
4 after	0.031	0.027	0.247	-0.022	0.085	0.099***	0.018	0.000	0.063	0.134	0.186	0.255	0.466	-0.314	0.686
Same employer (specification 3): Share with same main employer from quarter before birth (of all working)															
Birth	-0.016	0.022	0.471	-0.059	0.027	0.098***	0.020	0.000	0.058	0.138	0.155	0.237	0.513	-0.309	0.619
1 after	-0.012	0.023	0.604	-0.057	0.033	0.099***	0.017	0.000	0.065	0.133	-0.072	0.188	0.700	-0.441	0.296
2 after	0.035	0.027	0.198	-0.018	0.088	0.097***	0.019	0.000	0.060	0.134	0.238	0.225	0.290	-0.203	0.680
3 after	0.025	0.029	0.386	-0.032	0.082	0.097***	0.019	0.000	0.060	0.134	0.14	0.226	0.535	-0.302	0.583
4 after	-0.024	0.032	0.448	-0.087	0.039	0.098***	0.018	0.000	0.063	0.134	-0.163	0.226	0.470	-0.605	0.279
Same employer (specification 4): Share with same main employer quarter before birth (of all mothers)															
Birth	-0.014	0.020	0.484	-0.055	0.026	0.098***	0.020	0.000	0.059	0.137	0.101	0.213	0.636	-0.317	0.519
1 after	-0.021	0.022	0.356	-0.065	0.023	0.097***	0.019	0.000	0.061	0.134	-0.146	0.221	0.507	-0.579	0.286
2 after	0.028	0.026	0.291	-0.024	0.079	0.097***	0.019	0.000	0.061	0.134	0.172	0.203	0.397	-0.226	0.570
3 after	0.021	0.028	0.466	-0.035	0.076	0.098***	0.018	0.000	0.062	0.134	0.115	0.207	0.580	-0.292	0.521
4 after	-0.031	0.033	0.358	-0.096	0.035	0.098***	0.018	0.000	0.063	0.134	-0.188	0.227	0.408	-0.633	0.257

. = p<0.10; * = p<0.05; ** = p<0.01; *** = p<0.001

Notes: Treatment status in the first stage and fuzzy model is represented by taking any hours of PFML in the quarter of birth and/or the quarter after. All coefficients are local linear regression estimates (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). All earnings and wage rate statistics are adjusted for inflation and reported in \$2023.

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.11. Estimates of the effect of threshold crossing on quarterly employment outcomes (using PFML wage reports)

OUTCOME	Reduced form					First stage					2SLS estimate				
	Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper				Lower	Upper
Employment status															
Birth	-0.023	0.018	0.210	-0.059	0.013	0.142***	0.016	0.000	0.112	0.173	-0.168	0.132	0.203	-0.428	0.091
1 after	-0.041*	0.020	0.039	-0.080	-0.002	0.111***	0.021	0.000	0.070	0.151	-0.338	0.232	0.144	-0.792	0.115
2 after	-0.025	0.019	0.190	-0.062	0.012	0.110***	0.021	0.000	0.069	0.151	-0.229	0.227	0.313	-0.675	0.216
3 after	-0.027	0.020	0.185	-0.067	0.013	0.110***	0.021	0.000	0.069	0.151	-0.279	0.230	0.226	-0.730	0.173
4 after	-0.056*	0.024	0.021	-0.104	-0.008	0.120***	0.019	0.000	0.082	0.158	-0.426*	0.205	0.038	-0.827	-0.024
Hours worked															
Birth	-9.045	6.100	0.138	-21.001	2.911	0.129***	0.017	0.000	0.096	0.163	-71.905	43.840	0.101	-157.831	14.020
1 after	-3.183	4.912	0.517	-12.810	6.443	0.118***	0.019	0.000	0.080	0.157	-2.606	48.307	0.957	-97.287	92.074
2 after	-5.264	6.124	0.390	-17.267	6.739	0.122***	0.019	0.000	0.085	0.159	-31.794	60.040	0.596	-149.471	85.883
3 after	-14.544.	7.881	0.065	-29.992	0.903	0.124***	0.018	0.000	0.088	0.159	-117.357.	68.571	0.087	-251.754	17.041
4 after	-7.575	7.418	0.307	-22.113	6.964	0.116***	0.020	0.000	0.077	0.155	-63.959	75.683	0.398	-212.295	84.376
Wages from work															
Birth	-633.224.	327.14	0.053	-1274.40	7.95	0.126***	0.018	0.000	0.090	0.161	-3196.47	2177.81	0.142	-7464.90	1071.96
1 after	-305.124.	175.88	0.083	-649.84	39.59	0.117***	0.020	0.000	0.078	0.156	-1069.567	1737.46	0.538	-4474.93	2335.80
2 after	-154.122	256.53	0.548	-656.91	348.67	0.129***	0.017	0.000	0.095	0.163	-1419.741	1752.76	0.418	-4855.09	2015.61
3 after	-411.206	300.47	0.171	-1000.12	177.71	0.127***	0.018	0.000	0.092	0.161	-3034.579	2065.77	0.142	-7083.42	1014.26
4 after	-291.605	310.99	0.348	-901.14	317.93	0.12***	0.019	0.000	0.083	0.158	-1950.044	2405.15	0.417	-6664.06	2763.97
Earnings from work + PFML payments															
Birth	-243.273	365.31	0.505	-959.26	472.72	0.140***	0.016	0.000	0.109	0.171	2056.498	1728.63	0.234	-1331.55	5444.55
1 after	-33.778	215.05	0.875	-455.26	387.71	0.139***	0.016	0.000	0.107	0.170	-152.233	1464.26	0.917	-3022.13	2717.66
2 after	-302.899	275.23	0.271	-842.35	236.55	0.132***	0.017	0.000	0.099	0.165	-1774.83	1706.65	0.298	-5119.81	1570.15
3 after	-511.113.	306.09	0.095	-1111.04	88.82	0.133***	0.017	0.000	0.100	0.165	-3120.623.	1890.90	0.099	-6826.71	585.46
4 after	-343.928	315.17	0.275	-961.66	273.80	0.12***	0.019	0.000	0.082	0.157	-2306.446	2456.46	0.348	-7121.02	2508.13
Same employer (specification 1): Share with any work hours with main employer from quarter before birth (of all working)															
Birth	0.007	0.016	0.659	-0.025	0.039	0.100***	0.024	0.000	0.053	0.146	0.187	0.154	0.224	-0.115	0.489
1 after	0.077*	0.035	0.030	0.007	0.146	0.122***	0.019	0.000	0.085	0.159	0.328	0.212	0.122	-0.087	0.743
2 after	0.025	0.027	0.352	-0.028	0.079	0.101***	0.023	0.000	0.056	0.147	0.625.	0.335	0.062	-0.032	1.282
3 after	0.051.	0.031	0.098	-0.010	0.112	0.098***	0.024	0.000	0.051	0.145	1.113.	0.581	0.055	-0.026	2.251
4 after	0.014	0.030	0.650	-0.045	0.072	0.102***	0.023	0.000	0.056	0.147	0.427	0.337	0.205	-0.233	1.086

. = p<0.10; * = p<0.05; ** = p<0.01; *** = p<0.001

Table 3.11, cont. Estimates of the effect of threshold crossing on quarterly employment outcomes (using PFML wage reports)

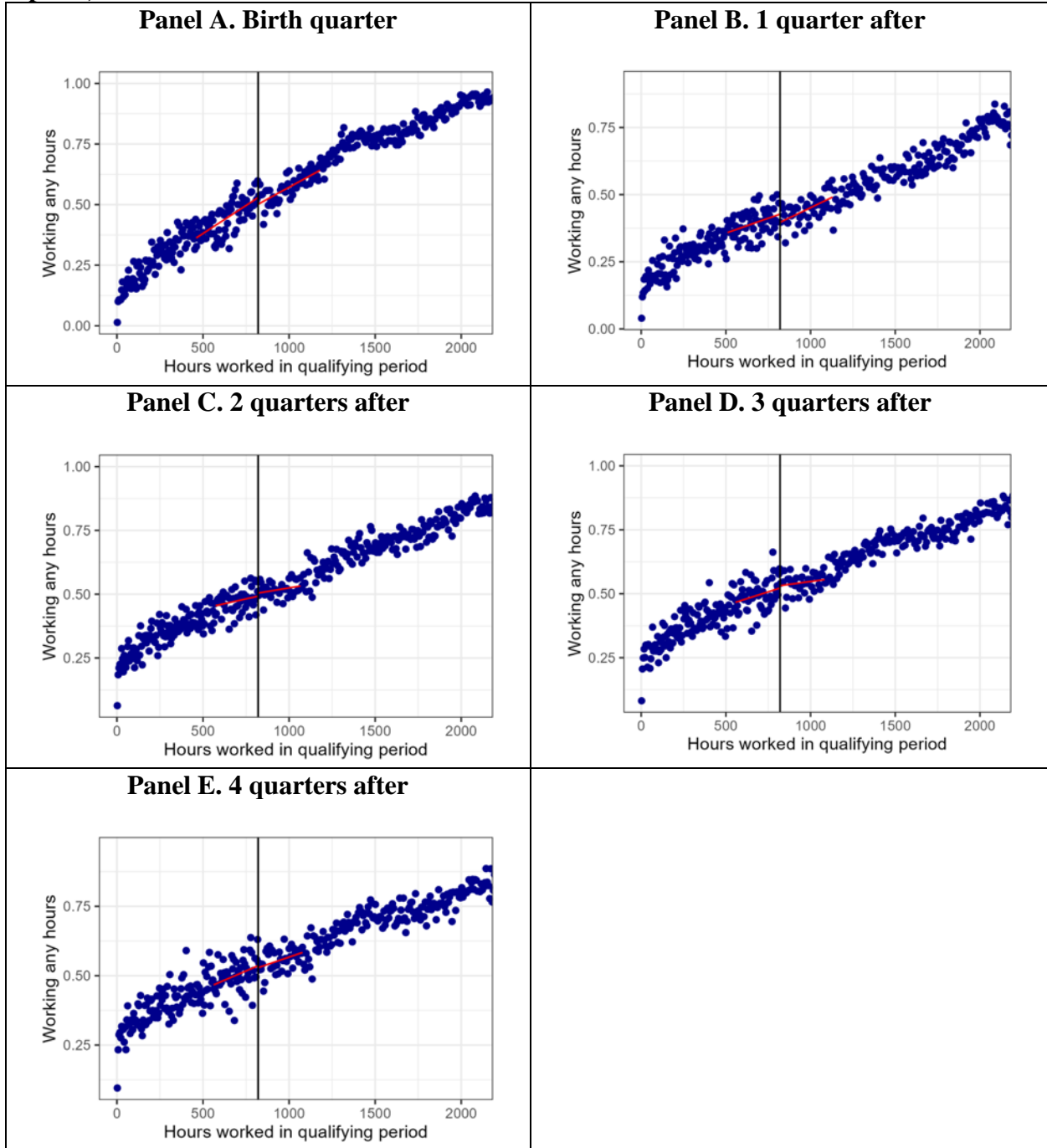
OUTCOME	Reduced form					First stage					2SLS estimate				
	Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper				Lower	Upper
Same employer (specification 2): Share with any work hours with main employer from quarter before birth (of all mothers)															
Birth	0.007	0.014	0.595	-0.020	0.034	0.100***	0.024	0.000	0.053	0.146	0.180	0.135	0.183	-0.085	0.444
1 after	0.060	0.032	0.057	-0.002	0.122	0.106***	0.022	0.000	0.063	0.149	0.596	0.361	0.099	-0.112	1.304
2 after	0.038	0.027	0.158	-0.015	0.091	0.102***	0.023	0.000	0.057	0.147	0.765*	0.333	0.022	0.112	1.419
3 after	0.042	0.031	0.170	-0.018	0.102	0.097***	0.024	0.000	0.050	0.145	1.197	0.622	0.054	-0.023	2.417
4 after	0.032	0.032	0.307	-0.030	0.094	0.102***	0.023	0.000	0.056	0.147	0.548	0.351	0.118	-0.139	1.236
Same employer (specification 3): Share with same main employer from quarter before birth (of all working)															
Birth	-0.019	0.022	0.381	-0.062	0.024	0.105***	0.022	0.000	0.061	0.148	0.112	0.225	0.619	-0.329	0.552
1 after	-0.022	0.024	0.373	-0.070	0.026	0.115***	0.020	0.000	0.075	0.154	-0.062	0.199	0.754	-0.452	0.327
2 after	0.017	0.027	0.523	-0.036	0.071	0.106***	0.022	0.000	0.064	0.149	0.318	0.273	0.244	-0.217	0.854
3 after	0.017	0.027	0.542	-0.037	0.070	0.101***	0.023	0.000	0.056	0.147	0.341	0.279	0.222	-0.206	0.889
4 after	-0.031	0.030	0.296	-0.089	0.027	0.109***	0.021	0.000	0.068	0.150	-0.178	0.255	0.484	-0.677	0.321
Same employer (specification 4): Share with same main employer quarter before birth (of all mothers)															
Birth	-0.018	0.021	0.395	-0.060	0.024	0.105***	0.022	0.000	0.062	0.148	0.096	0.212	0.650	-0.319	0.512
1 after	-0.024	0.024	0.302	-0.071	0.022	0.112***	0.020	0.000	0.072	0.152	-0.068	0.211	0.748	-0.482	0.346
2 after	0.024	0.027	0.384	-0.030	0.078	0.105***	0.022	0.000	0.062	0.148	0.372	0.270	0.169	-0.158	0.902
3 after	0.012	0.027	0.661	-0.041	0.065	0.104***	0.022	0.000	0.060	0.148	0.298	0.260	0.253	-0.213	0.808
4 after	-0.024	0.029	0.405	-0.081	0.033	0.111***	0.021	0.000	0.071	0.152	-0.153	0.231	0.508	-0.606	0.300

. = p<0.10; * = p<0.05; ** = p<0.01; *** = p<0.001

Notes: Treatment status in the first stage and fuzzy model is represented by taking any hours of PFML in the quarter of birth and/or the quarter after. All coefficients are local linear regression estimates (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). All earnings and wage rate statistics are adjusted for inflation and reported in \$2023.

Sources: Author's analysis of data from WA-APCD and ESD.

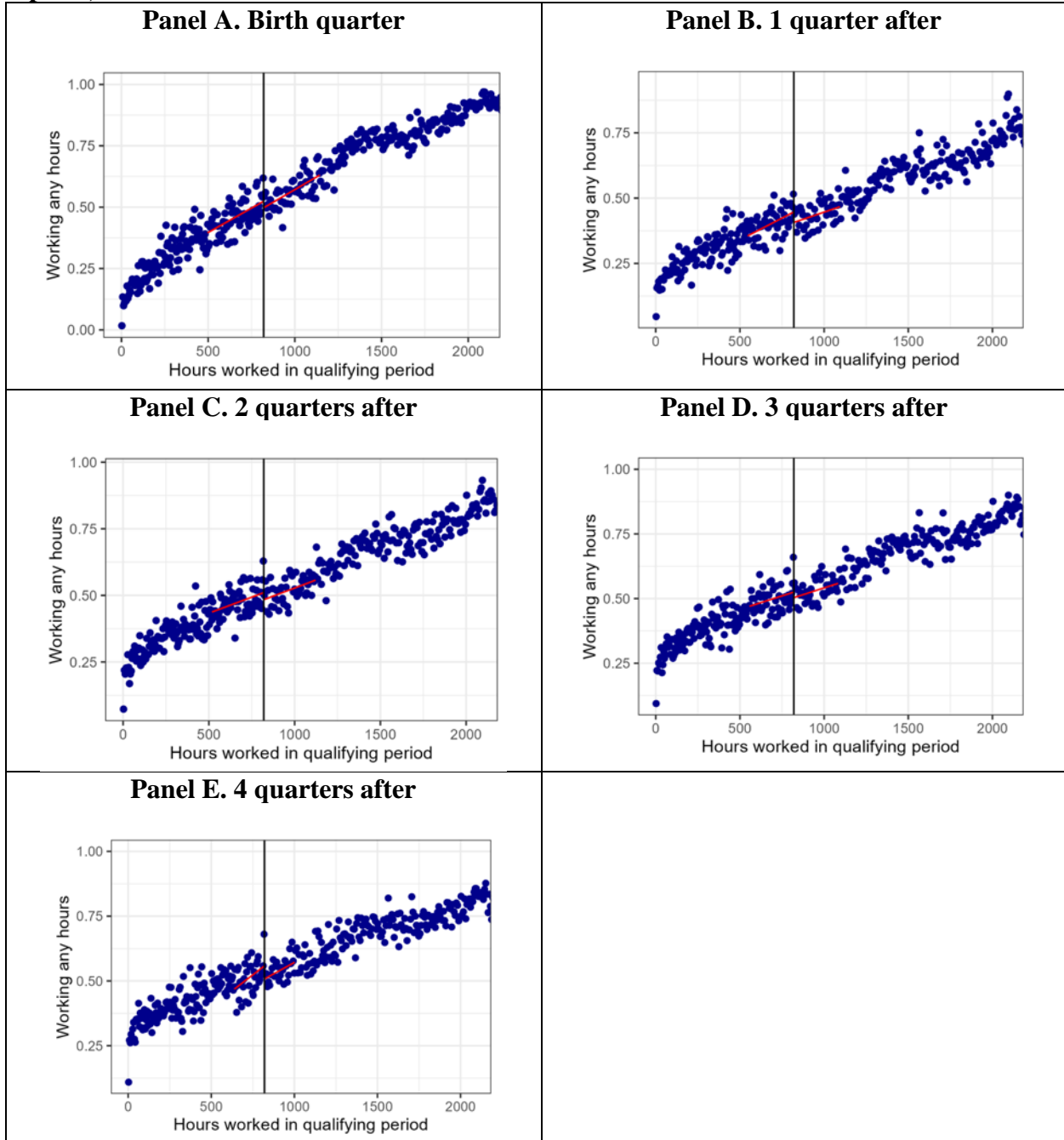
Figure 3.8. Employment status by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

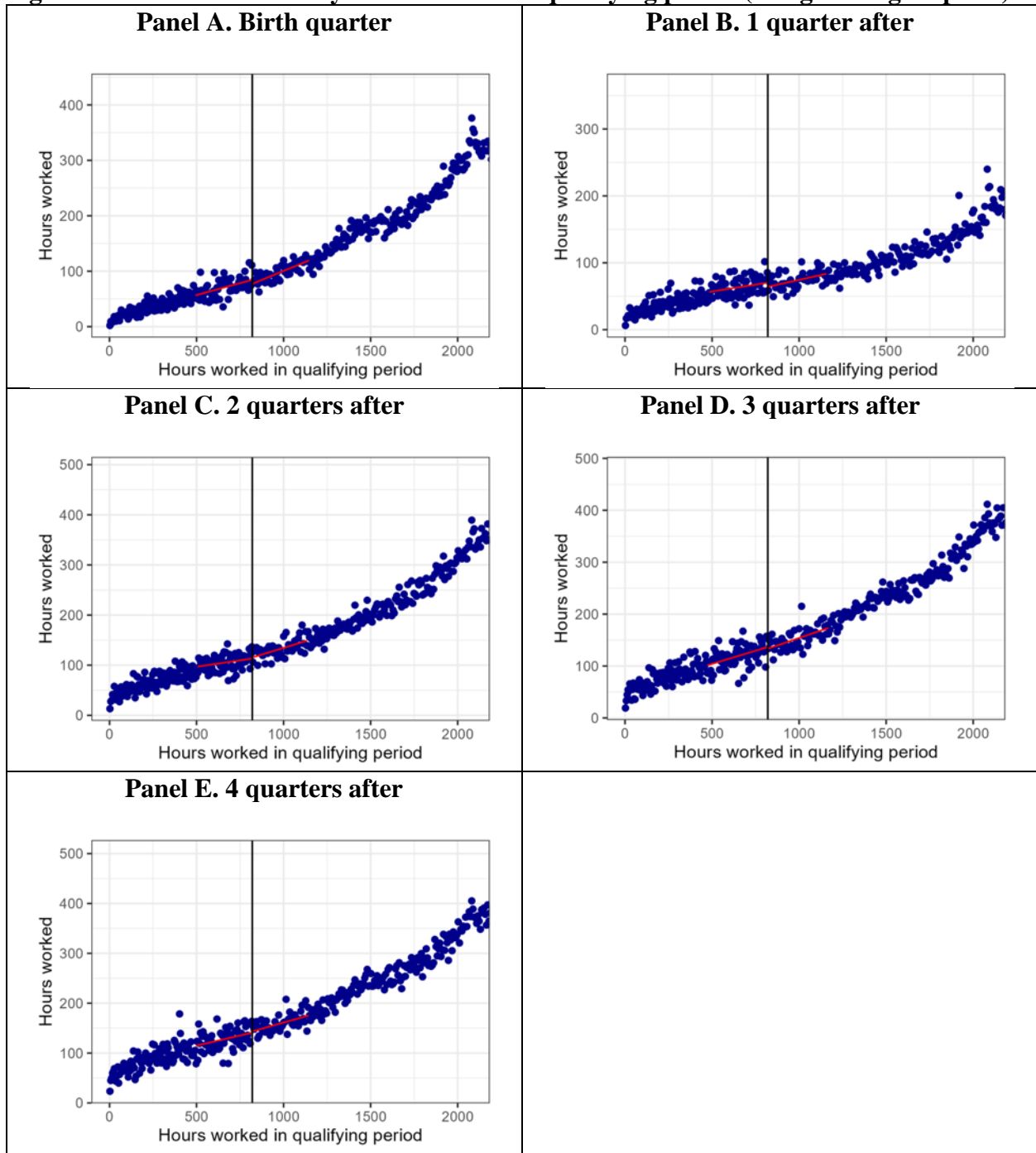
Figure 3.9. Employment status by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author’s analysis of data from WA-APCD and ESD.

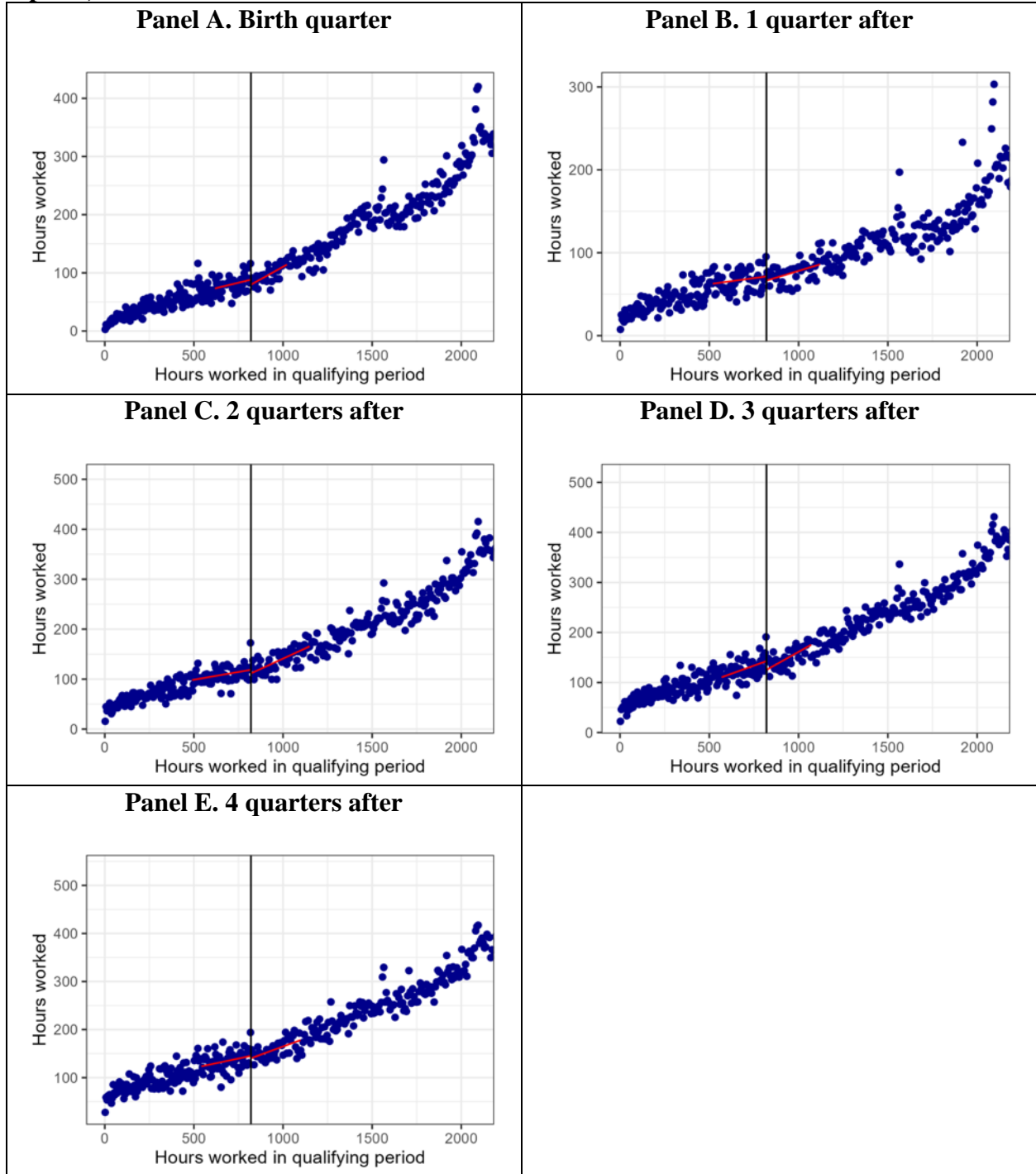
Figure 3.10. Hours worked by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

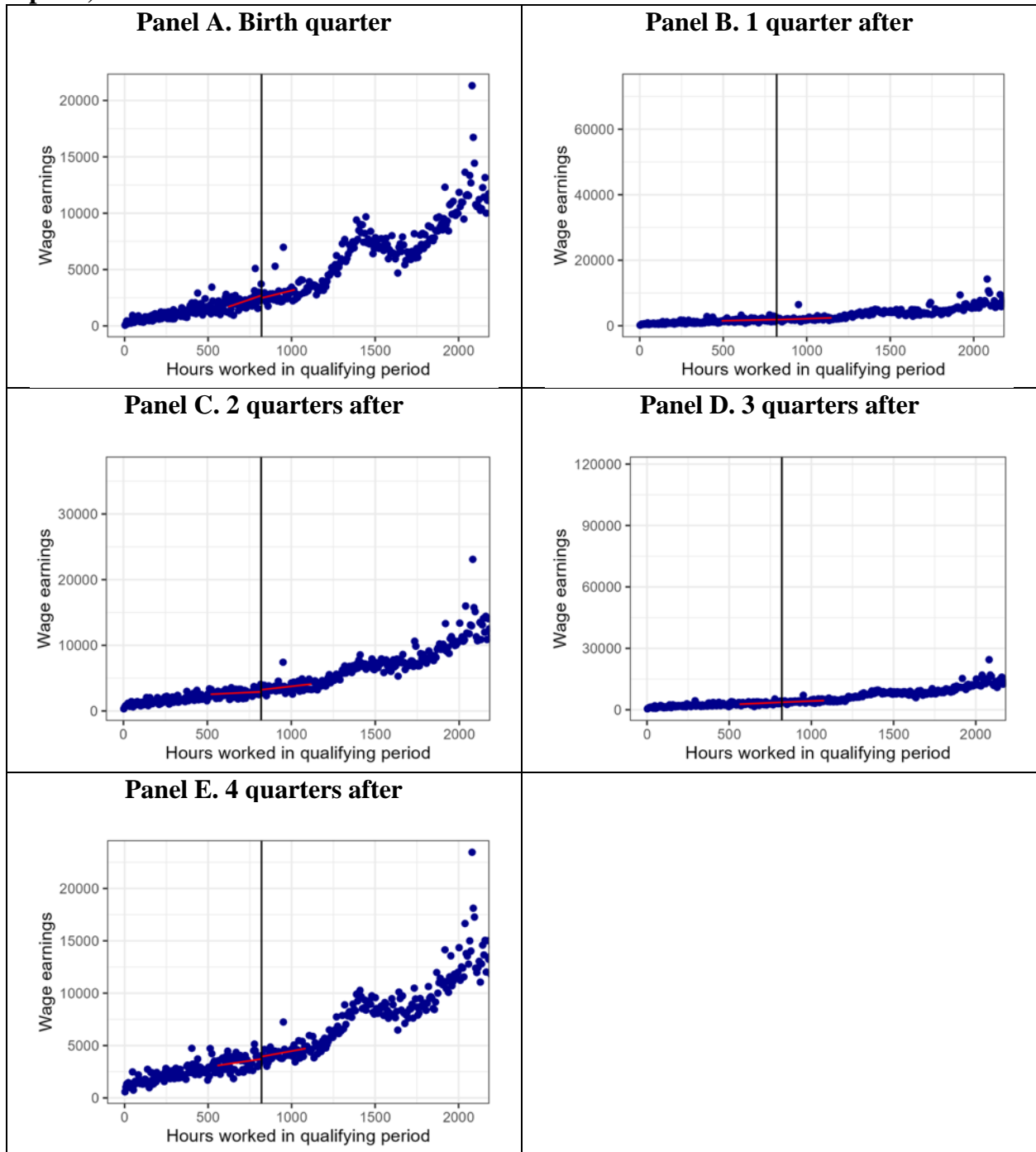
Figure 3.11. Hours worked by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

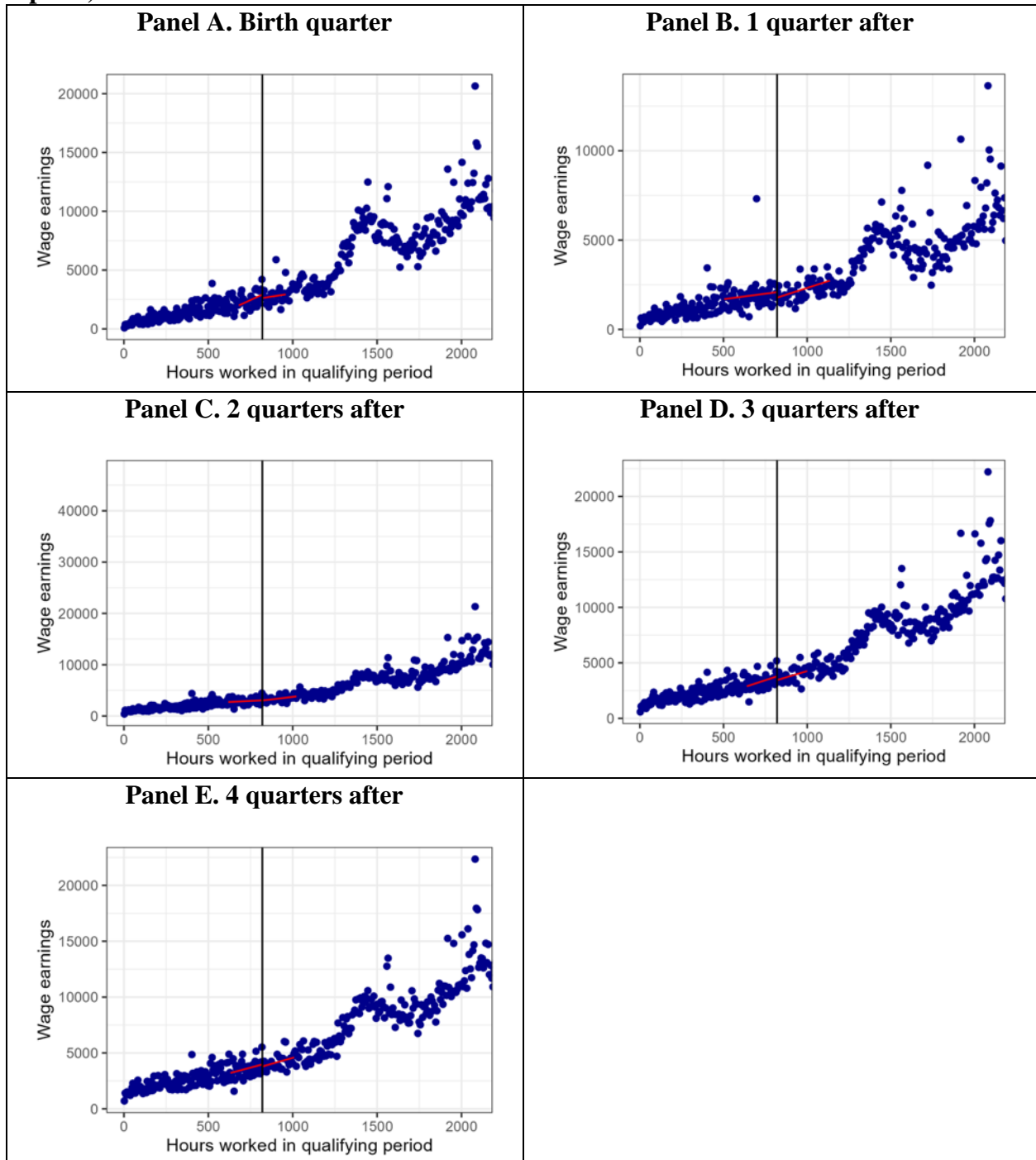
Figure 3.12. Earnings from work by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author’s analysis of data from WA-APCD and ESD.

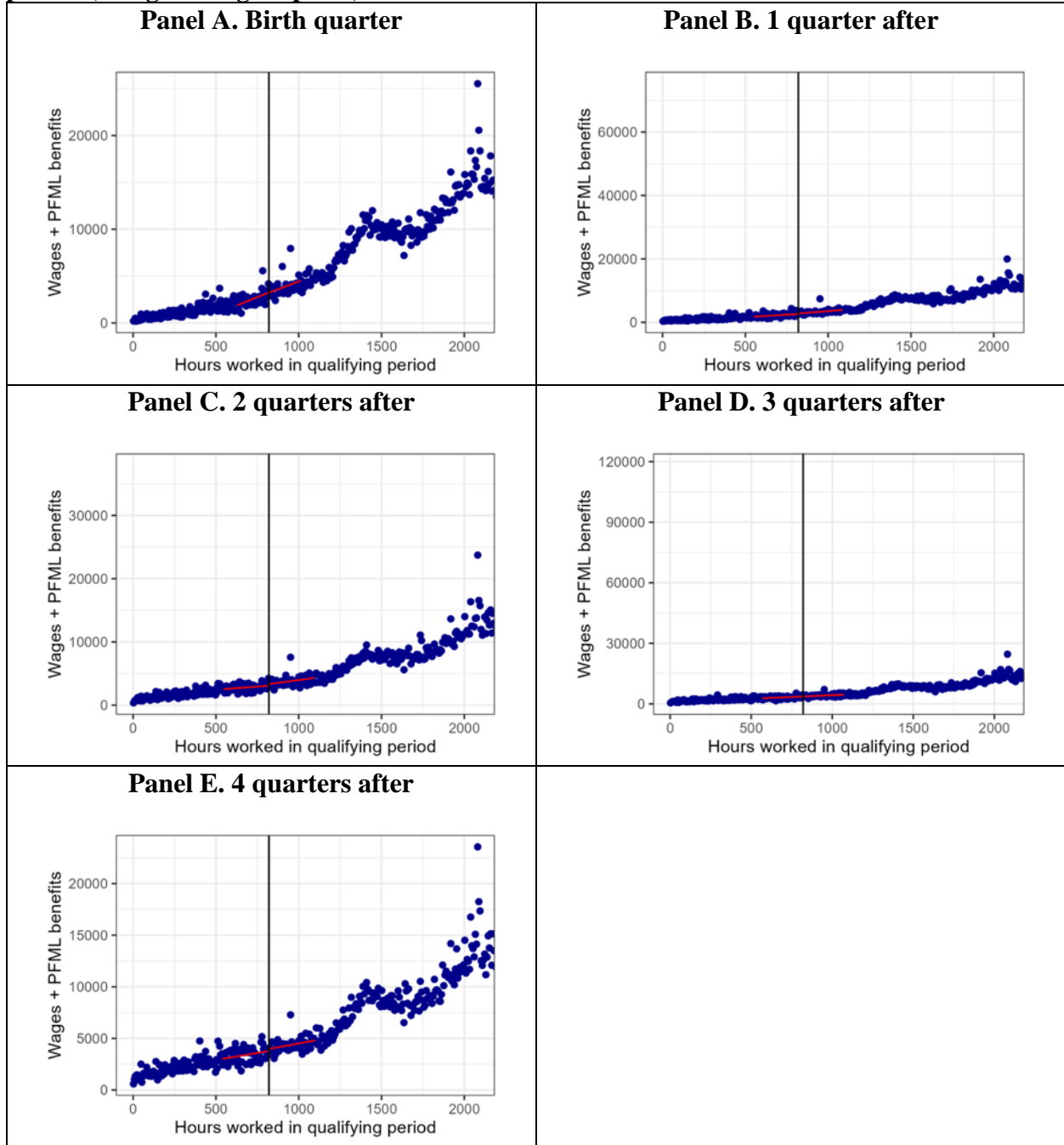
Figure 3.13. Earnings from work by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author’s analysis of data from WA-APCD and ESD.

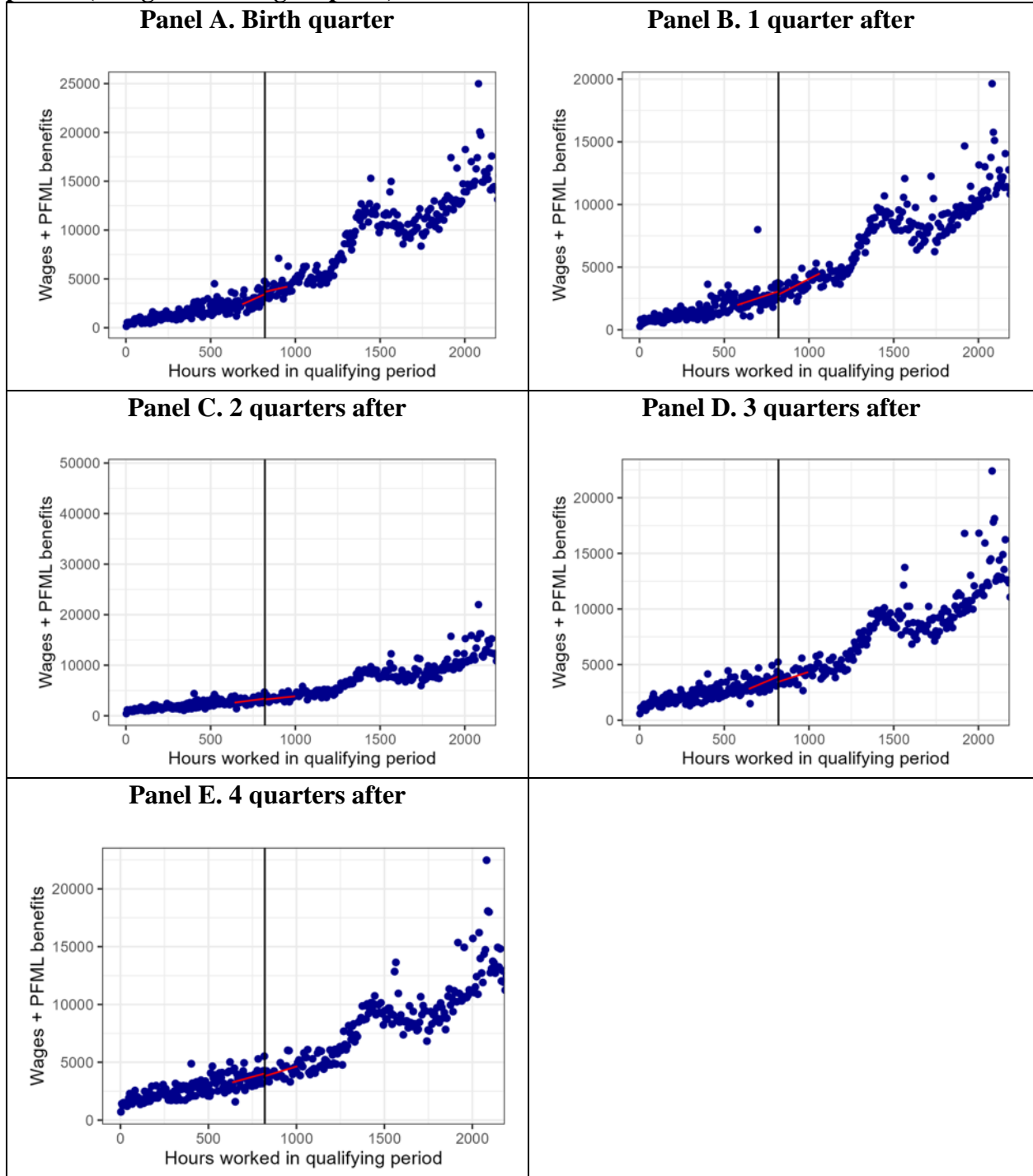
Figure 3.14. Earnings from work plus PFML payments by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author’s analysis of data from WA-APCD and ESD.

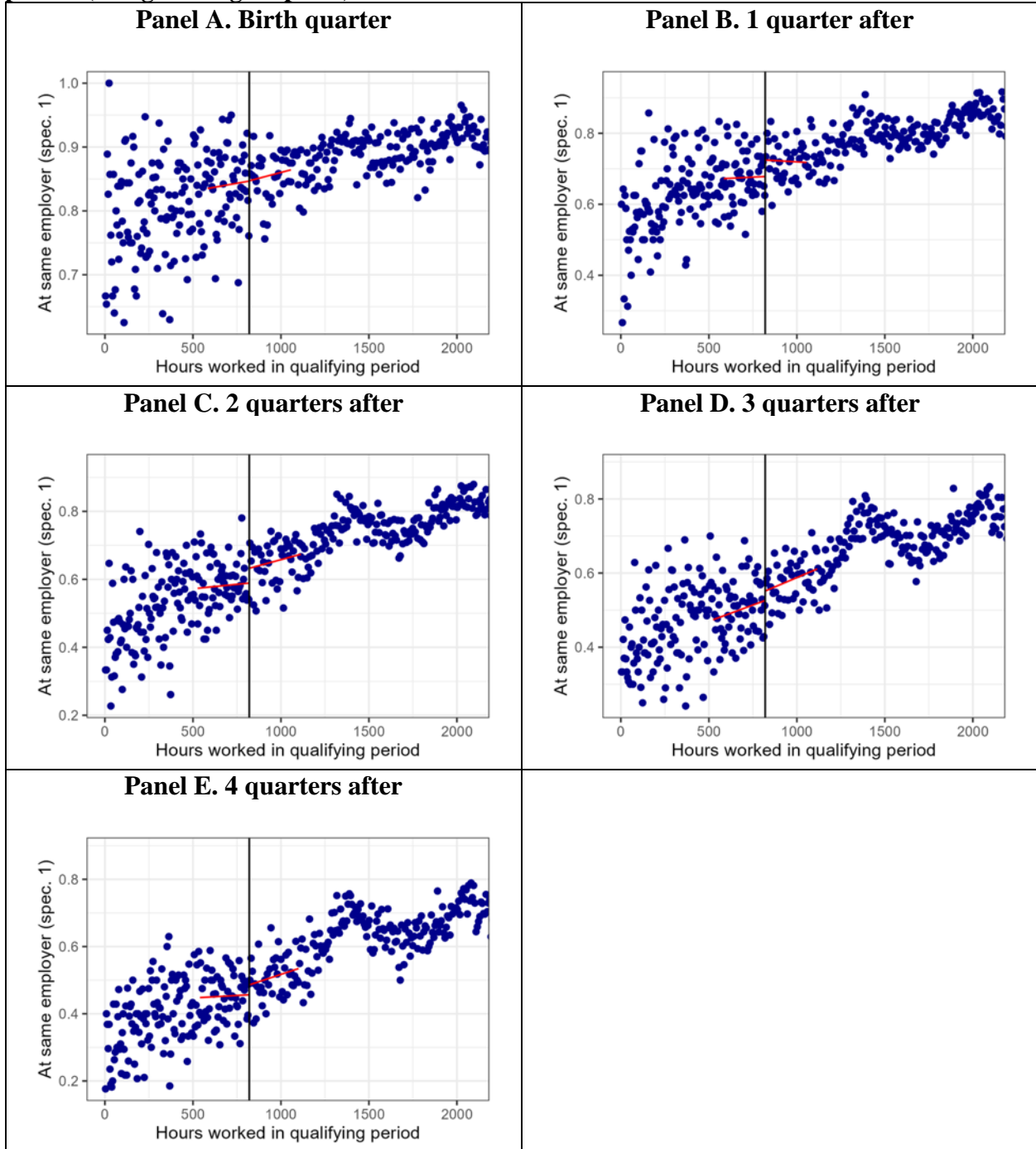
Figure 3.15. Earnings from work plus PFML payments by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

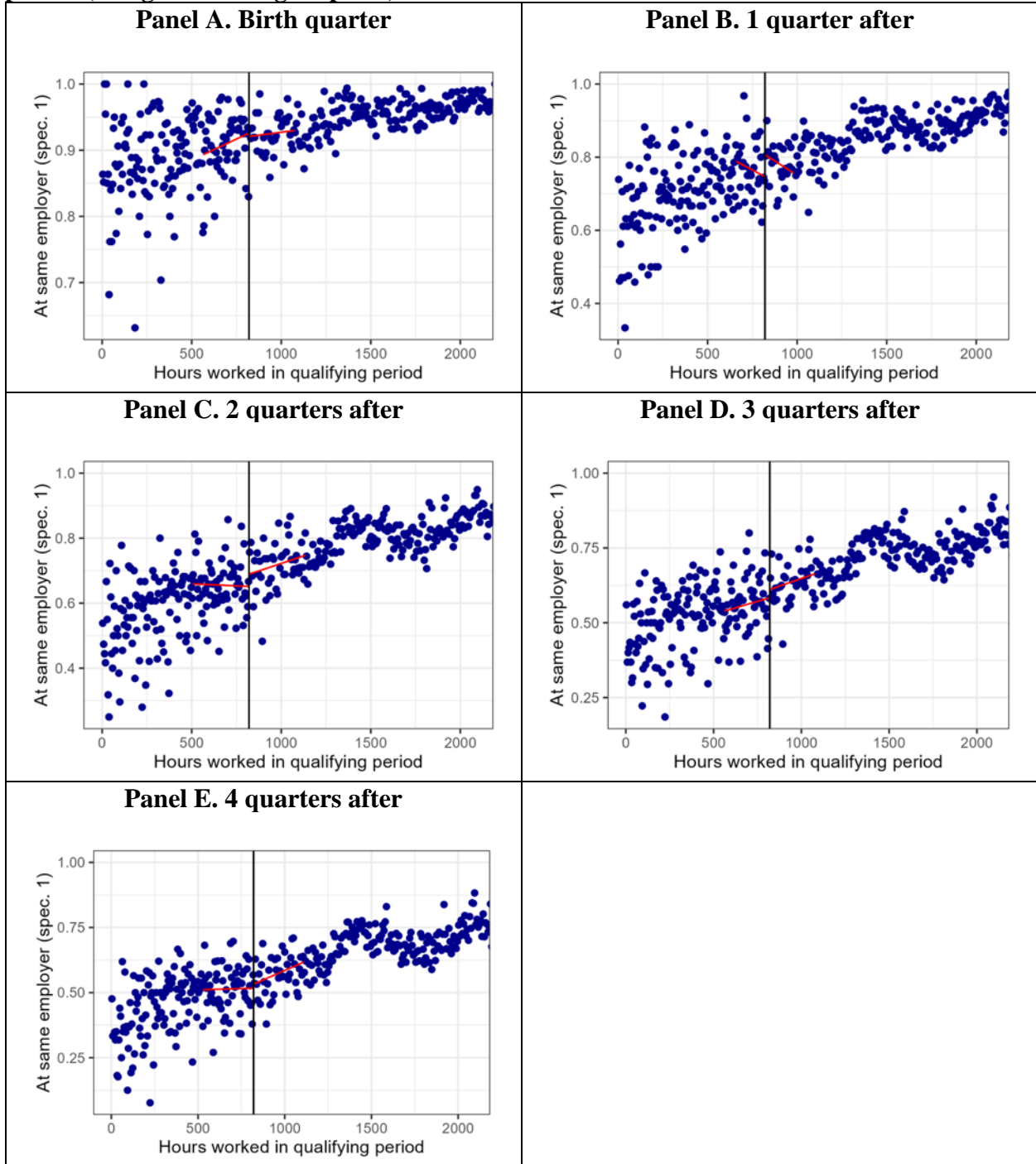
Figure 3.16. Worked for same employer (specification 1) by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

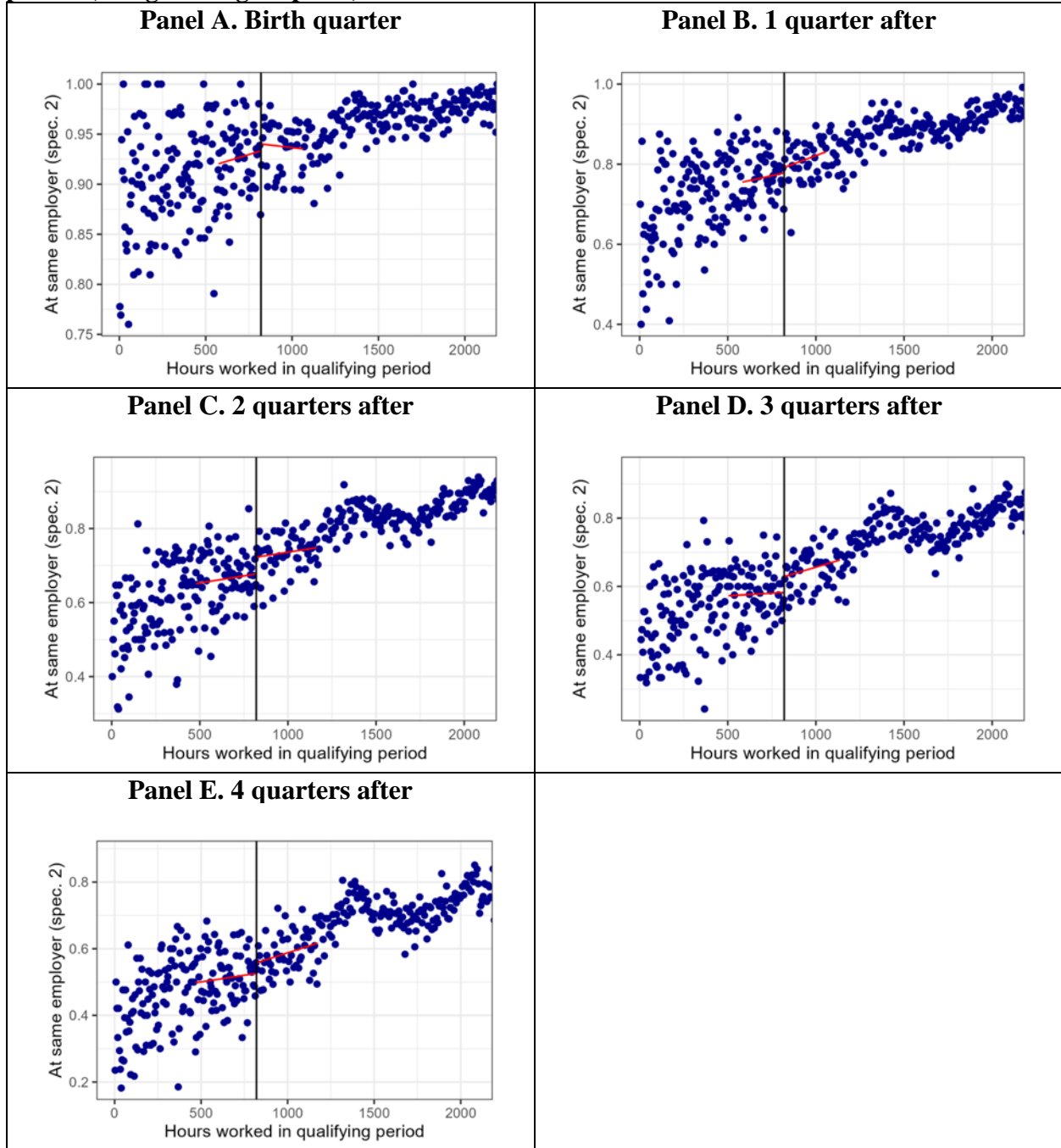
Figure 3.17. Worked for same employer (specification 1) by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

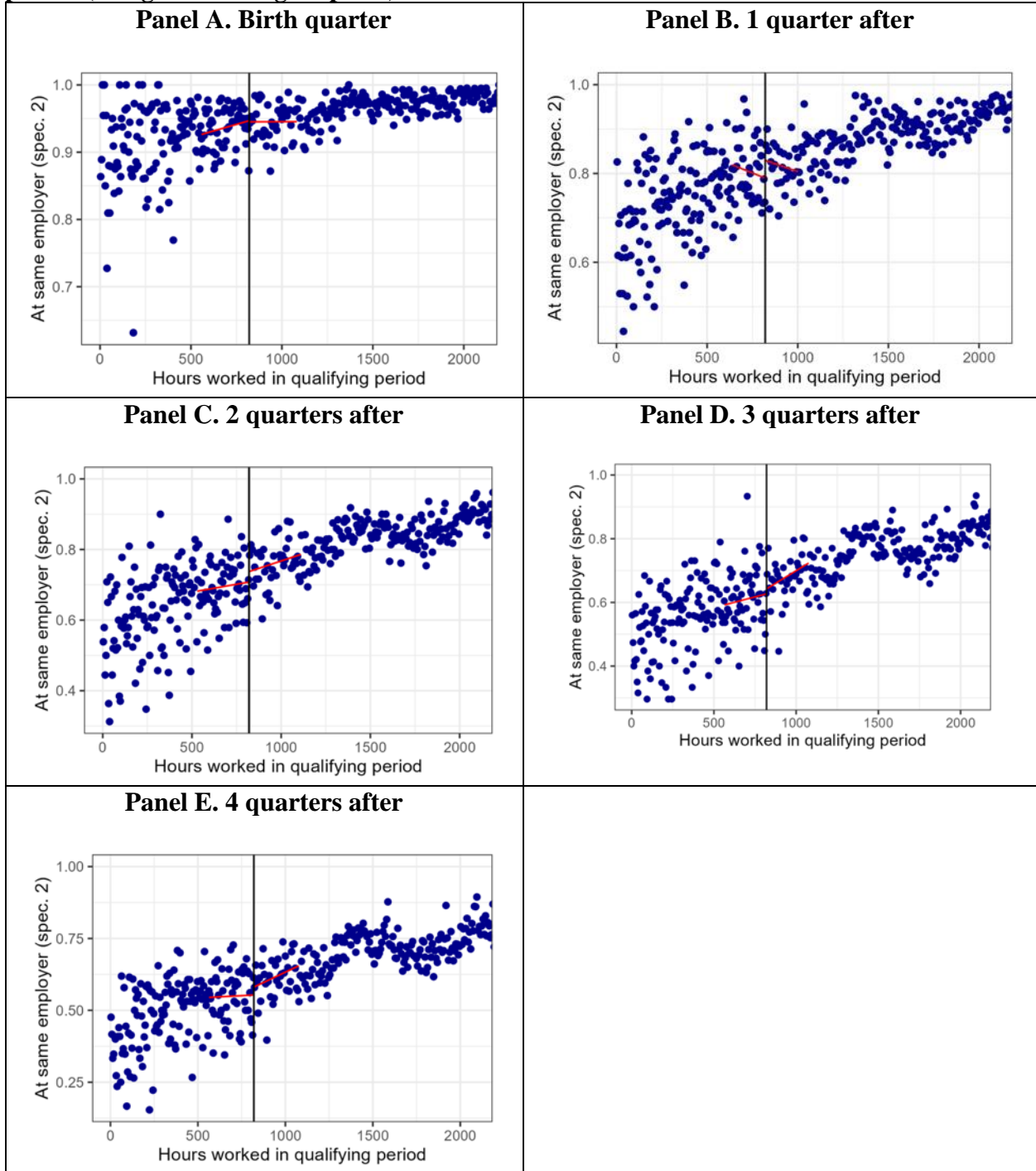
Figure 3.18. Worked for same employer (specification 2) by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

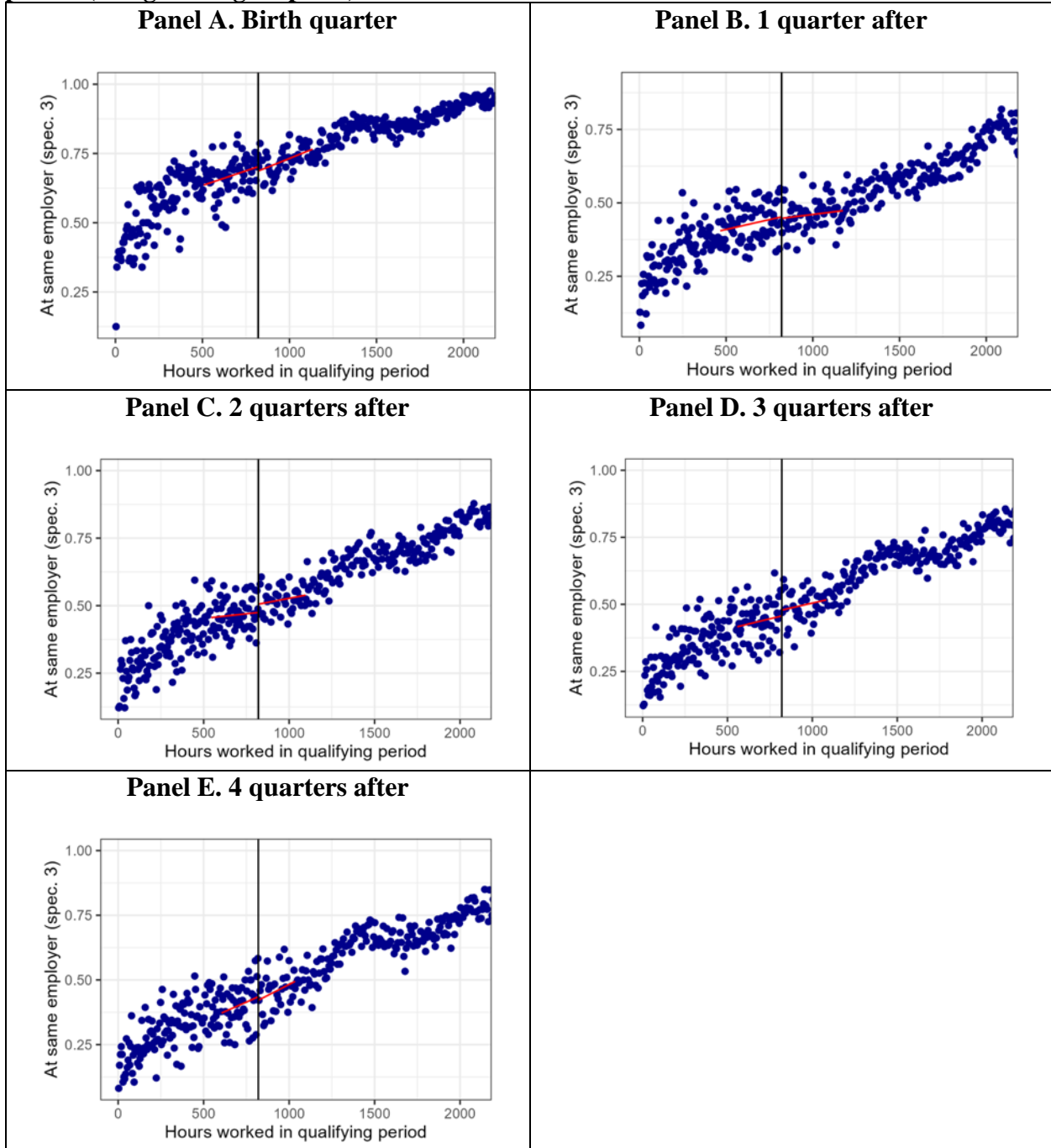
Figure 3.19. Worked for same employer (specification 2) by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

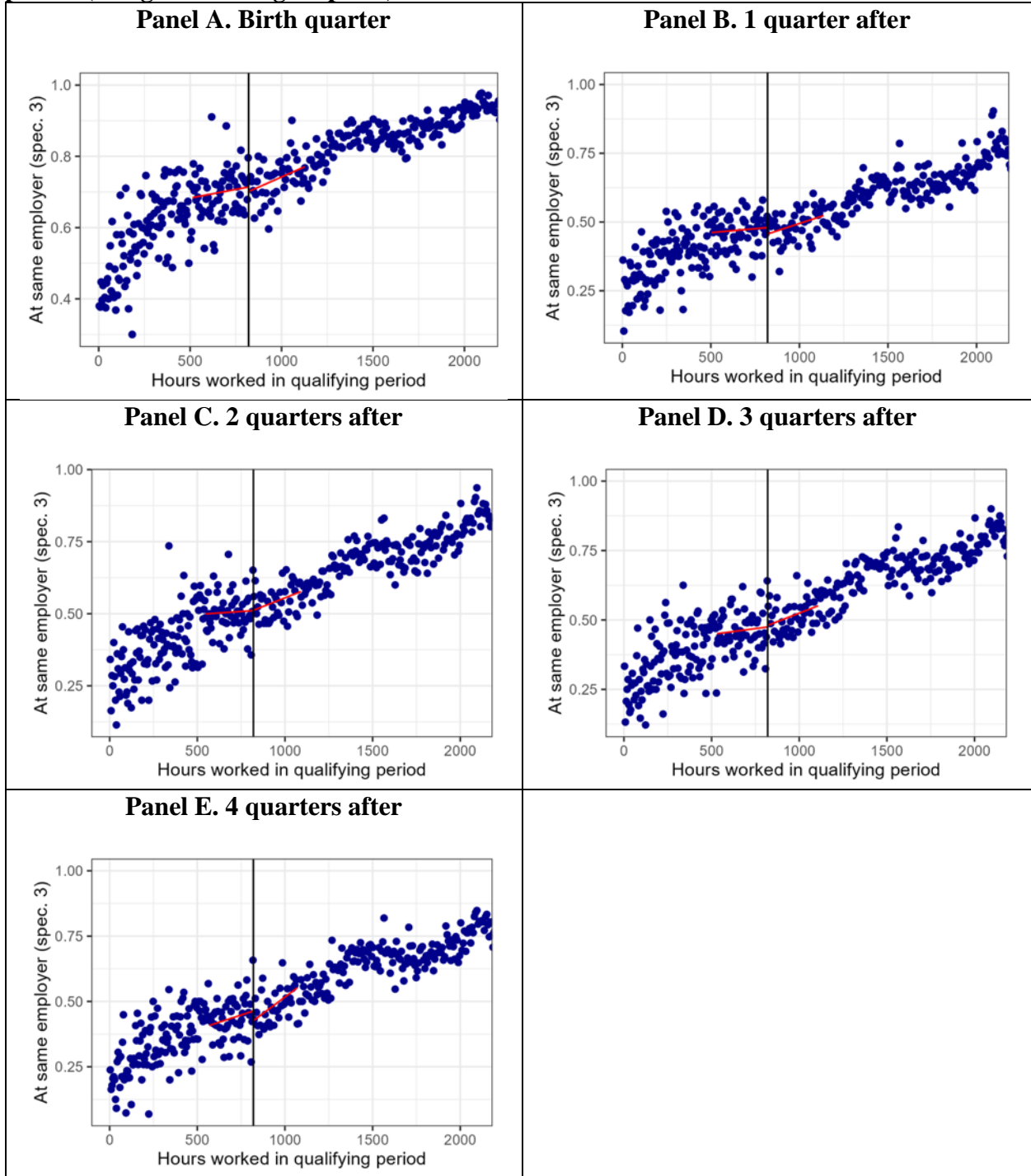
Figure 3.20. Worked for same employer (specification 3) by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

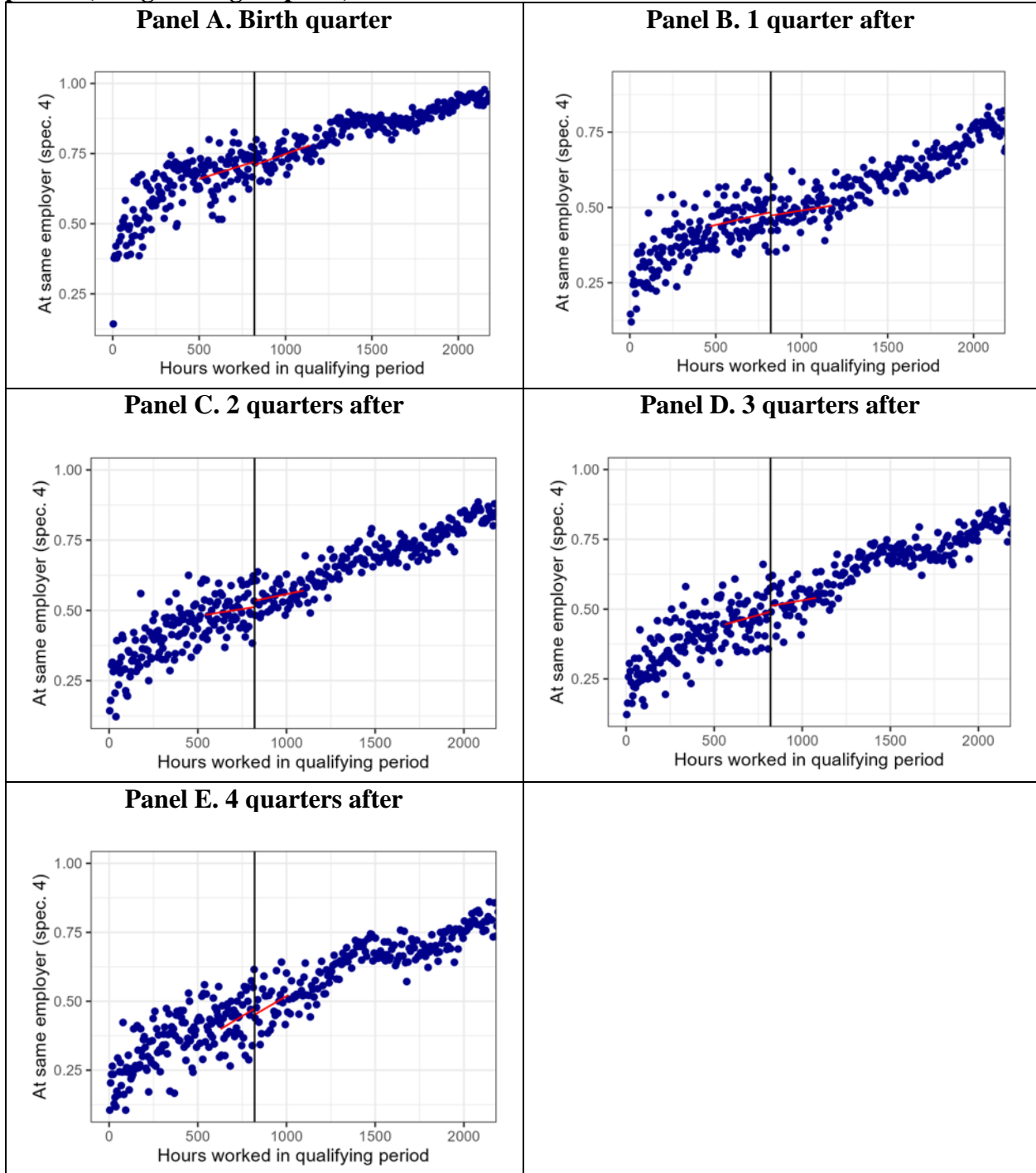
Figure 3.21. Worked for same employer (specification 3) by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

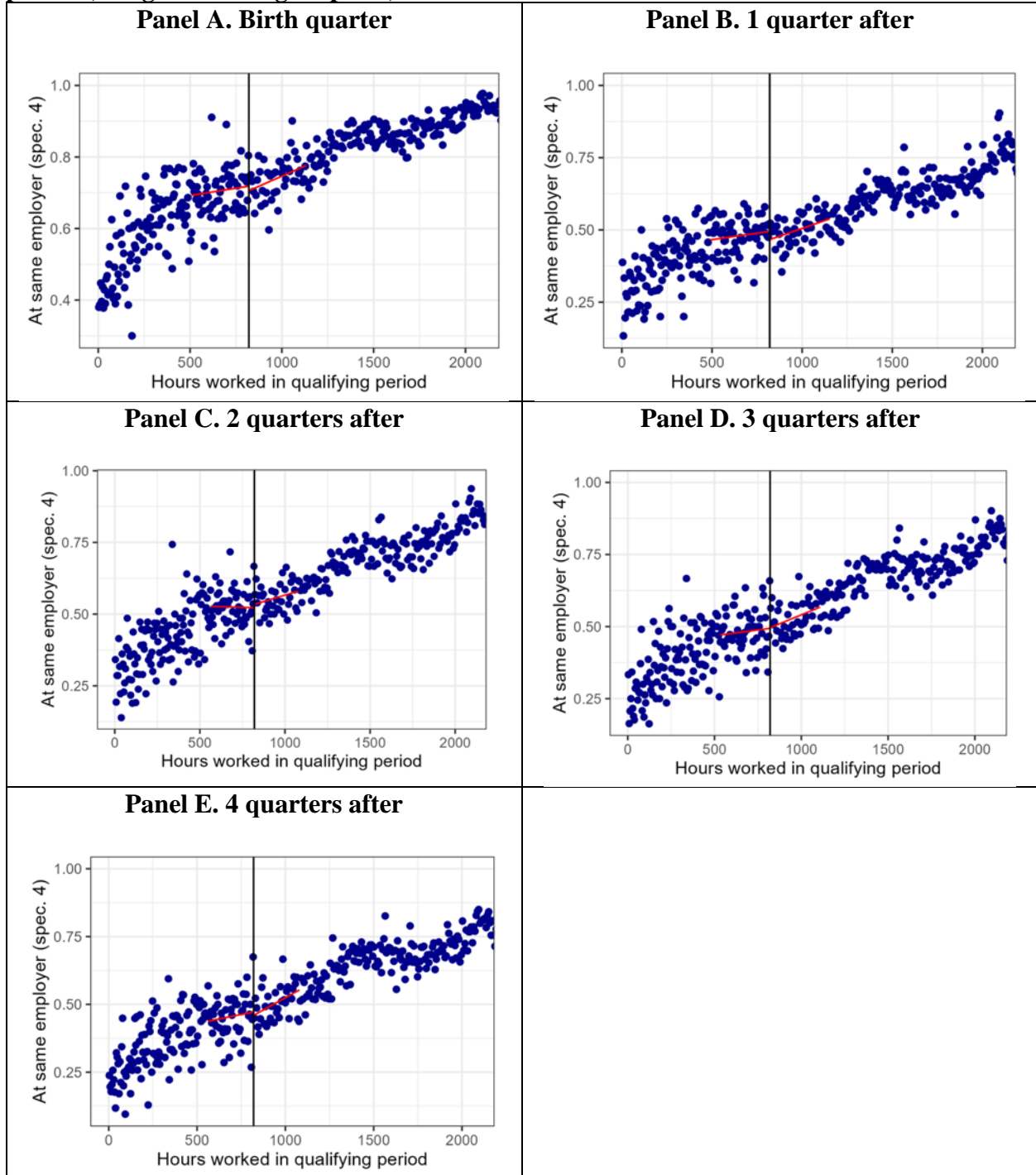
Figure 3.22. Worked for same employer (specification 4) by hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

Figure 3.23. Worked for same employer (specification 4) by hours worked in qualifying period (using PFML wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 11b and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.12. Estimates of the effect of threshold crossing on multiple-quarter employment outcomes (using UI wage reports)

OUTCOME	Reduced form					First stage					2SLS estimate				
	Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper				Lower	Upper
Employment status															
Birth quarter through 1 after	-0.024	0.018	0.173	-0.058	0.011	0.099***	0.016	0.000	0.068	0.131	-0.205	0.203	0.314	-0.603	0.193
Birth quarter through 2 after	0.005	0.021	0.792	-0.035	0.046	0.101***	0.015	0.000	0.071	0.131	-0.101	0.177	0.566	-0.447	0.245
Hours worked															
Birth quarter through 1 after	-13.656	7.069	0.053	-27.512	0.200	0.100***	0.016	0.000	0.069	0.130	-137.78	87.010	0.113	-308.315	32.756
Birth quarter through 2 after	-12.026	11.892	0.312	-35.333	11.281	0.099***	0.017	0.000	0.066	0.132	-101.721	143.577	0.479	-383.127	179.685
Wages from work															
Birth quarter through 1 after	-521.869	419.751	0.214	-1344.566	300.828	0.102***	0.015	0.000	0.072	0.131	-3671.784	4155.663	0.377	-11816.733	4473.165
Birth quarter through 2 after	-229.902	549.371	0.676	-1306.649	846.846	0.103***	0.015	0.000	0.074	0.131	-951.315	5440.460	0.861	-11614.421	9711.791
Earnings from work + PFML payments															
Birth quarter through 1 after	-369.701	575.381	0.521	-1497.428	758.026	0.101***	0.015	0.000	0.071	0.131	1151.944	4451.049	0.796	-7571.951	9875.839
Birth quarter through 2 after	-243.53	721.753	0.736	-1658.139	1171.079	0.103***	0.015	0.000	0.074	0.131	4268.759	5693.715	0.453	-6890.717	15428.236

Notes: Treatment status in the first stage and fuzzy model is represented by taking any hours of PFML in the quarter of birth and/or the quarter after. All coefficients are local linear regression estimates (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). All earnings and wage rate statistics are adjusted for inflation and reported in \$2023.

Sources: Author’s analysis of data from WA-APCD and ESD.

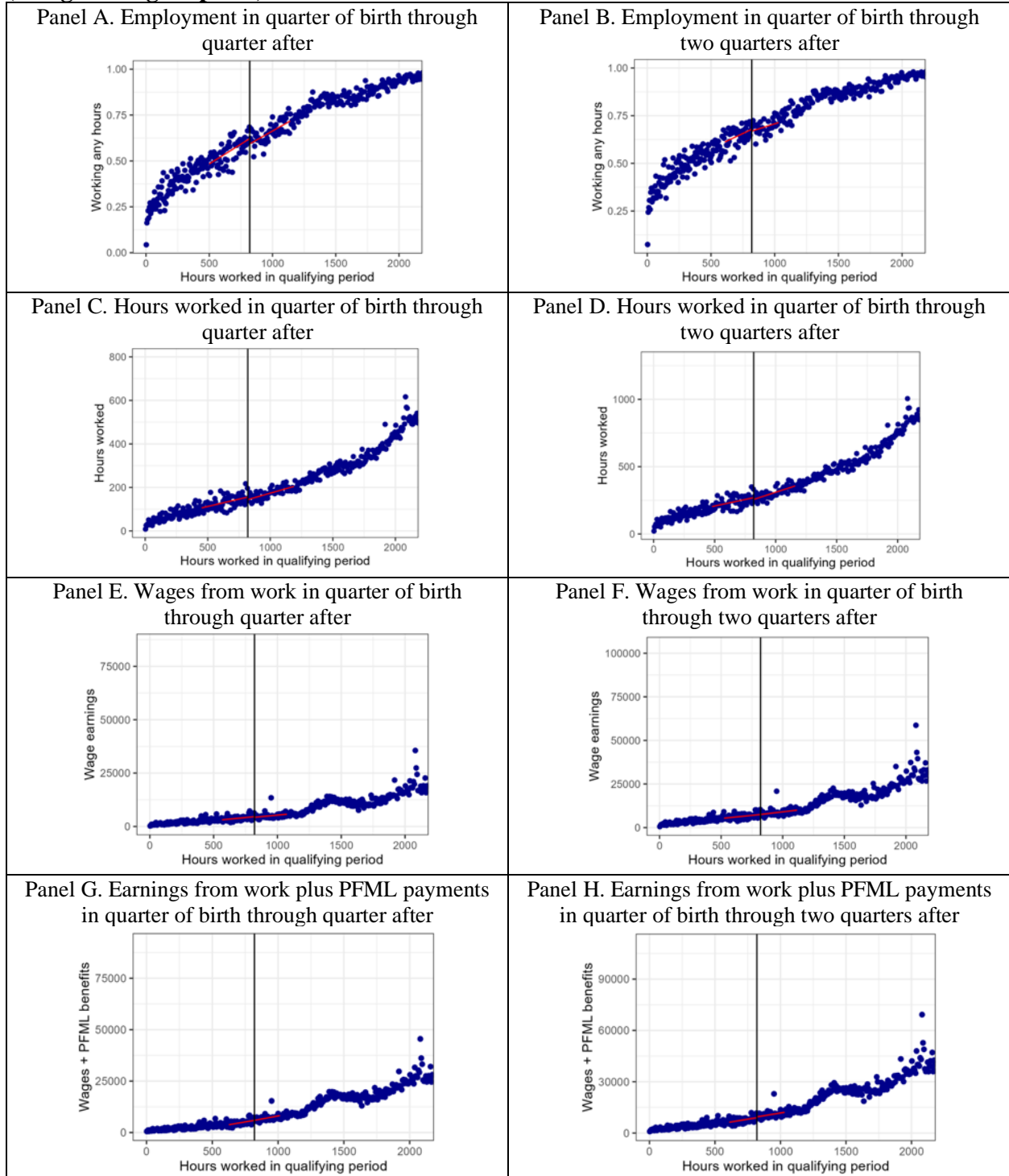
Table 3.13. Estimates of the effect of threshold crossing on multiple-quarter employment outcomes (using PFML wage reports)

OUTCOME	Reduced form					First stage					2SLS estimate				
	Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval		Coef.	Std. Error	P-value	95% confidence interval	
				Lower	Upper				Lower	Upper				Lower	Upper
Employment status															
Birth quarter through 1 after	-0.030	0.019	0.108	-0.066	0.007	0.134***	0.017	0.000	0.102	0.167	-0.222	0.148	0.134	-0.512	0.068
Birth quarter through 2 after	-0.036	0.019	0.054	-0.072	0.001	0.107***	0.021	0.000	0.065	0.149	-0.286	0.234	0.222	-0.745	0.173
Hours worked															
Birth quarter through 1 after	-12.155	8.591	0.157	-28.993	4.683	0.124***	0.018	0.000	0.088	0.160	-92.459	76.530	0.227	-242.456	57.538
Birth quarter through 2 after	-17.287	13.190	0.190	-43.138	8.565	0.123***	0.019	0.000	0.086	0.159	-123.747	123.514	0.316	-365.831	118.337
Wages from work															
Birth quarter through 1 after	-508.689	441.682	0.249	-1374.369	356.991	0.128***	0.018	0.000	0.094	0.162	-5296.773	3116.273	0.089	-11404.556	811.009
Birth quarter through 2 after	-707.457	657.677	0.282	-1996.481	581.567	0.121***	0.019	0.000	0.083	0.158	-5936.014	5093.428	0.244	-15918.950	4046.923
Earnings from work + PFML payments															
Birth quarter through 1 after	-65.606	480.767	0.891	-1007.892	876.680	0.131***	0.017	0.000	0.098	0.165	-1182.72	2945.587	0.688	-6955.964	4590.525
Birth quarter through 2 after	-261.99	688.909	0.704	-1612.226	1088.246	0.122***	0.019	0.000	0.086	0.159	-2416.037	4907.572	0.623	-12034.702	7202.628

Notes: Treatment status in the first stage and fuzzy model is represented by taking any hours of PFML in the quarter of birth and/or the quarter after. All coefficients are local linear regression estimates (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014). All earnings and wage rate statistics are adjusted for inflation and reported in \$2023.

Sources: Author's analysis of data from WA-APCD and ESD.

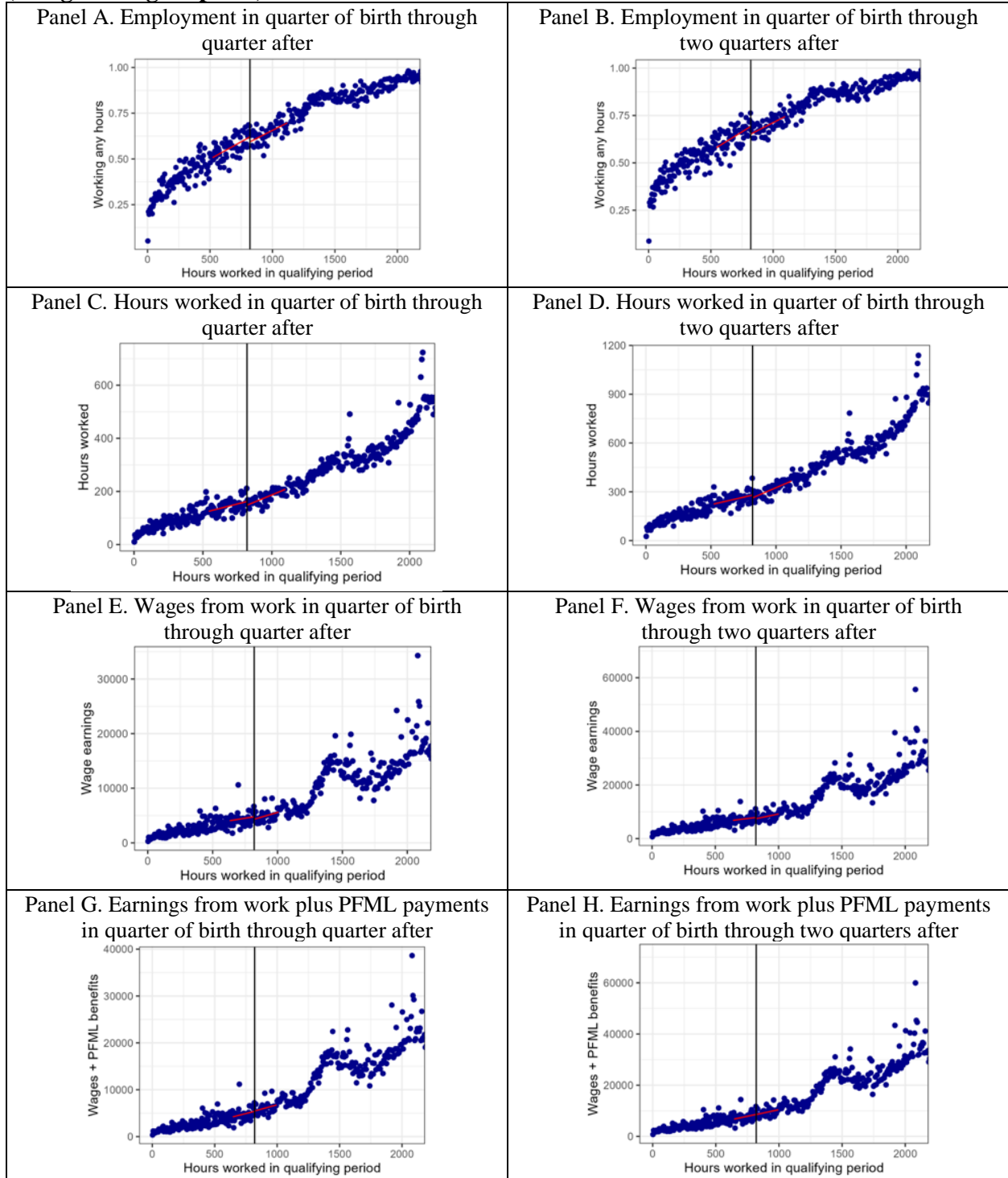
Figure 3.24. Multi-quarter employment outcomes across hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 12a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author’s analysis of data from WA-APCD and ESD.

Figure 3.25. Multi-quarter employment outcomes across hours worked in qualifying period (using UI wage reports)



Notes: Dots represent binned averages of the outcome variable across a 5-hour interval of hours worked in the qualifying period. Taking leave was defined as having any weeks with nonzero hours of PFML leave recorded in a given quarter. Red lines correspond to reduced-form estimates reported in Table 12a and are fit based on local linear regression (of order 1) with a MSE-optimal bandwidth estimated according to Calonico, Cattaneo, and Titiunik (2014).

Sources: Author's analysis of data from WA-APCD and ESD.

Table 3.14. Characteristics of mothers by selection into the bandwidth

	UI wage reports			PFML wage reports		
	Below BW	In BW	Above BW	Below BW	In BW	Above BW
Sample size						
Number of mothers	56239	12063	41725	52620	9248	37435
Race/ethnicity						
American Indian or Alaska Native, not Hispanic or Latina	0.03	0.02	0.02	0.03	0.02	0.02
Asian, not Hispanic or Latina	0.04	0.04	0.04	0.04	0.04	0.04
Black or African American, not Hispanic or Latina	0.09	0.10	0.09	0.09	0.10	0.09
Hispanic or Latina, any race	0.22	0.27	0.29	0.22	0.28	0.29
Multiracial or other, not Hispanic or Latina	0.04	0.03	0.03	0.04	0.03	0.03
Native Hawaiian or Pacific Islander, not Hispanic or Latina	0.05	0.05	0.05	0.05	0.05	0.05
White, not Hispanic or Latina	0.54	0.49	0.48	0.54	0.48	0.48
Age						
Share 10-17	0.02	0.01	0.00	0.02	0.00	0.00
Share 18-19	0.04	0.05	0.01	0.04	0.05	0.01
Share 20-24	0.19	0.28	0.18	0.20	0.27	0.17
Share 25-29	0.28	0.30	0.31	0.29	0.30	0.30
Share 30-34	0.28	0.23	0.31	0.27	0.24	0.31
Share 35-39	0.15	0.11	0.16	0.15	0.11	0.17
Share 40-44	0.04	0.02	0.03	0.03	0.03	0.04
Share 45 plus	0.00	0.00	0.00	0.00	0.00	0.00
Mean age	28.89	27.63	29.66	28.75	27.83	29.82
Region						
East (Ferry, Stevens, Pend Oreille, Lincoln, Spokane, Adams, Whitman, Garfield, Asotin)	0.12	0.13	0.12	0.12	0.13	0.12
King	0.20	0.21	0.24	0.20	0.21	0.25
North (Whatcom, Skagit, San Juan, Island)	0.05	0.06	0.05	0.05	0.06	0.05
North central (Okanogan, Chelan, Douglas, Grant)	0.04	0.05	0.05	0.04	0.05	0.05
Northwest (Clallam, Jefferson, Mason, Kitsap)	0.04	0.05	0.04	0.04	0.05	0.04
Out of state	0.12	0.02	0.02	0.12	0.01	0.02
Pierce	0.11	0.14	0.13	0.11	0.13	0.13
Snohomish	0.09	0.10	0.11	0.09	0.10	0.11
South central (Kittitas, Yakima, Benton, Franklin, Walla Walla, Columbia)	0.09	0.12	0.12	0.09	0.12	0.11
Southwest (Wahkiakum, Cowlitz, Clark, Skamania, Klickitat)	0.09	0.08	0.06	0.09	0.08	0.06
West (Grays Harbor, Pacific, Thurston, Lewis)	0.06	0.07	0.07	0.06	0.07	0.07

Table 3.14, cont. Characteristics of mothers by selection into the bandwidth (BW)

	UI wage reports			PFML wage reports		
	Below BW	In BW	Above BW	Below BW	In BW	Above BW
Employment rate (share with nonzero hours)						
4 before	0.13	0.83	0.98	0.15	0.80	0.96
3 before	0.13	0.83	0.99	0.15	0.82	0.99
2 before	0.12	0.78	0.97	0.14	0.78	0.96
1 before	0.11	0.66	0.92	0.13	0.66	0.91
Birth	0.09	0.51	0.83	0.10	0.51	0.82
1 after	0.10	0.42	0.66	0.12	0.42	0.66
2 after	0.14	0.50	0.75	0.16	0.50	0.74
3 after	0.16	0.52	0.75	0.18	0.52	0.74
4 after	0.18	0.53	0.74	0.20	0.53	0.74
Share working full time (390+ hours)						
4 before	0.00	0.09	0.69	0.00	0.10	0.68
3 before	0.00	0.07	0.70	0.00	0.07	0.69
2 before	0.00	0.06	0.64	0.00	0.07	0.65
1 before	0.01	0.10	0.60	0.01	0.12	0.60
Birth	0.01	0.04	0.25	0.01	0.05	0.28
1 after	0.01	0.04	0.12	0.01	0.04	0.15
2 after	0.02	0.10	0.35	0.03	0.11	0.37
3 after	0.03	0.13	0.43	0.04	0.14	0.44
4 after	0.04	0.14	0.43	0.05	0.15	0.44
Mean earnings (all mothers, including non-workers)						
4 before	293.86	4736.52	13666.45	345.64	4387.50	13434.20
3 before	292.17	4362.67	14221.28	346.17	4072.49	14126.08
2 before	255.78	4105.65	13757.01	317.86	4144.86	13722.03
1 before	411.45	4026.51	13152.14	508.35	4133.10	13084.15
Birth	321.52	2529.62	9092.58	421.97	2684.62	9356.90
1 after	392.21	1897.77	5509.75	481.35	2040.36	5731.19
2 after	689.49	3176.65	9486.01	826.80	3173.68	9501.21
3 after	889.40	3641.67	10577.32	1042.12	3627.65	10497.85
4 after	1017.49	3868.20	10683.01	1210.04	3923.90	10689.09
Mean earnings among working mothers						
4 before	2225.74	5676.20	13921.36	2344.07	5459.58	13936.79
3 before	2219.24	5249.04	14310.45	2361.97	4982.45	14316.54
2 before	2092.07	5250.34	14117.35	2309.58	5338.67	14231.45
1 before	3753.95	6081.36	14281.66	4006.81	6249.65	14379.39
Birth	3667.80	4969.83	10939.67	4132.56	5257.80	11400.72
1 after	3816.81	4572.15	8410.56	4028.71	4853.19	8711.52
2 after	4987.31	6403.74	12692.94	5249.33	6384.65	12782.21
3 after	5578.13	7005.17	14129.17	5783.18	7040.62	14116.92
4 after	5774.79	7302.36	14345.20	6062.30	7408.78	14481.77

Table 3.14, cont. Characteristics of mothers by selection into the bandwidth (BW)

	UI wage reports			PFML wage reports		
	Below BW	In BW	Above BW	Below BW	In BW	Above BW
Median earnings among working mothers						
4 before	1587.42	4698.84	11084.19	1669.16	4562.15	11040.79
3 before	1581.33	4416.20	11305.35	1640.62	4238.76	11232.70
2 before	1453.76	4211.30	11157.18	1565.27	4125.41	11182.69
1 before	2032.83	4721.65	11242.07	2205.91	4631.87	11308.91
Birth	1837.62	2979.31	7838.22	2026.50	3041.83	8234.16
1 after	2079.47	2803.08	5095.17	2151.47	2866.81	5283.08
2 after	3256.71	4775.69	9824.91	3297.89	4677.93	9916.07
3 after	3810.17	5451.37	11170.41	3869.47	5286.29	11214.45
4 after	4153.28	5808.71	11397.73	4194.56	5593.23	11542.16
Mean hours worked (all mothers, including non-workers)						
4 before	13.02	194.42	433.62	15.93	190.67	426.46
3 before	13.40	180.15	440.83	15.93	177.79	436.44
2 before	11.39	162.81	413.65	13.98	166.15	413.42
1 before	14.38	153.46	383.03	18.02	158.01	380.87
Birth	11.78	83.69	235.44	15.07	89.06	245.64
1 after	15.35	67.55	137.93	18.55	70.55	152.65
2 after	27.99	117.48	261.20	32.71	120.41	267.75
3 after	35.98	135.62	290.15	41.41	137.29	292.04
4 after	41.29	142.88	291.16	48.08	145.76	293.70
Mean hours worked among working mothers						
4 before	98.60	232.99	441.71	108.04	237.26	442.42
3 before	101.78	216.75	443.60	108.72	217.51	442.32
2 before	93.13	208.21	424.48	101.54	214.01	428.76
1 before	131.19	231.78	415.92	142.06	238.93	418.58
Birth	134.40	164.42	283.27	147.55	174.41	299.29
1 after	149.37	162.75	210.55	155.26	167.81	232.03
2 after	202.50	236.82	349.51	207.66	242.23	360.21
3 after	225.67	260.89	387.58	229.78	266.46	392.72
4 after	234.33	269.73	390.97	240.86	275.21	397.91
Median hours worked among working mothers						
4 before	80.00	231.00	462.00	86.00	234.00	465.00
3 before	80.00	215.00	463.00	83.00	213.00	464.00
2 before	73.00	202.00	450.00	79.00	208.00	454.00
1 before	96.00	219.00	445.00	107.00	223.00	449.00
Birth	84.00	126.00	272.00	94.00	138.00	296.00
1 after	99.00	118.00	164.00	102.00	126.00	187.00
2 after	158.00	208.00	374.00	162.00	214.00	389.00
3 after	189.00	241.00	421.00	193.00	245.00	430.00
4 after	203.00	251.00	424.00	209.00	256.00	433.00

Table 3.14., cont. Characteristics of mothers by selection into the bandwidth (BW)

	UI wage reports			PFML wage reports		
	Below BW	In BW	Above BW	Below BW	In BW	Above BW
Mean wage rate among working mothers						
4 before	34.74	37.12	32.99	38.79	27.21	32.82
3 before	31.70	33.60	34.90	44.42	31.86	36.10
2 before	39.25	30.91	35.56	48.03	27.96	34.72
1 before	41.57	36.52	36.04	52.65	30.04	37.61
Birth	45.30	42.96	61.35	60.32	34.45	60.35
1 after	50.27	59.17	93.99	80.34	50.79	78.62
2 after	55.19	40.24	51.45	49.98	31.90	47.27
3 after	37.54	33.21	47.04	54.24	30.04	45.77
4 after	41.42	31.91	44.94	46.28	37.04	43.45
Median wage rate among working mothers						
4 before	17.89	19.15	23.69	17.38	18.28	23.41
3 before	17.76	19.16	24.03	17.31	18.46	23.80
2 before	18.12	19.59	24.50	17.66	18.80	24.21
1 before	18.72	20.17	25.11	18.26	19.35	24.89
Birth	19.57	21.10	27.05	19.23	20.36	26.32
1 after	19.00	20.68	26.92	18.59	19.95	25.46
2 after	19.22	20.84	26.38	18.78	20.00	25.62
3 after	19.31	20.89	26.80	18.95	19.98	26.21
4 after	19.51	21.04	26.95	19.11	20.14	26.43
Share with any work hours with main employer from quarter before birth (of all working) (Spec. 1)						
Birth	0.91	0.93	0.97	0.92	0.94	0.97
1 after	0.71	0.79	0.91	0.74	0.81	0.91
2 after	0.61	0.70	0.85	0.64	0.73	0.86
3 after	0.53	0.61	0.79	0.55	0.65	0.80
4 after	0.47	0.55	0.73	0.49	0.58	0.74
Share with any work hours with main employer from quarter before birth (of all mothers) (Spec. 2)						
Birth	0.60	0.72	0.89	0.60	0.72	0.89
1 after	0.37	0.48	0.67	0.40	0.49	0.68
2 after	0.39	0.53	0.76	0.42	0.54	0.76
3 after	0.37	0.50	0.74	0.39	0.50	0.74
4 after	0.34	0.47	0.71	0.37	0.48	0.71
Share with same main employer from quarter before birth (of all working) (Spec. 3)						
Birth	0.80	0.85	0.90	0.89	0.92	0.96
1 after	0.62	0.70	0.82	0.70	0.77	0.89
2 after	0.52	0.62	0.78	0.59	0.68	0.83
3 after	0.46	0.54	0.72	0.51	0.60	0.77
4 after	0.40	0.48	0.67	0.46	0.54	0.71
Share with same main employer from quarter before birth (of all mothers) (Spec. 4)						
Birth	0.57	0.70	0.88	0.60	0.71	0.88
1 after	0.34	0.45	0.65	0.38	0.48	0.67
2 after	0.36	0.50	0.74	0.40	0.52	0.75
3 after	0.33	0.47	0.72	0.37	0.49	0.73
4 after	0.30	0.44	0.70	0.35	0.46	0.70

Notes: Since bandwidths are estimated empirically and are model-dependent, this analysis uses the average bandwidth across all models estimated with UI and PFML wage reports (258 for the UI data and 213 for the PFML data); therefore, mothers are in the bandwidth if their estimated hours worked in the qualifying period was 820 ± 258 or 820 ± 213 , respectively. All earnings and wage rate statistics are adjusted for inflation and reported in \$2023. Wage rate is calculated by dividing wages earned by hours worked for the primary job in each quarter, defined as the job for which a worker worked the most hours in that quarter.

Sources: Author's analysis of data from WA-APCD and ESD.

Appendix: Supplemental methodological information

Health insurance claims data

Appendix Table 3.1 lists all the diagnosis and procedure codes used to identify birth events in the All-Payer Claims Data.

Differences between Employment Security Department wage report data sources

Appendix Table 3.2 and Appendix Table 3.3 delve into the differences between the UI and PFML wage reports. Appendix Table 3.2 reports how the two data sources compare in measuring quarterly wage earnings, while Appendix Table 3.3 reports on the same discrepancies for quarterly hours worked. A few patterns are important to note here. First, between 78 and 86% of mothers had the same estimate of quarterly wages in a given quarter across both data sources, with a generally improving trend between 2019 and 2023 and the best matching in 2020 and early 2021. Exact match rates were slightly lower for quarterly hours measures in Appendix Table 3.3, hovering between 75 and 81% throughout the study period with a generally improving trend. While this rate of exact matches is relatively high given that these data are collected by different administrative agencies, there are key differences between the data sources that evolve over time. First, in the first year of data collection of the PFML wage reports (2019), there was a higher likelihood of the UI records reporting substantially higher wages and hours amounts than the PFML records. This aligns with context that the rollout of this data collection effort was gradual but improved over time. For example, in 2019 Q1, 12.8% of wages estimates and 11.1% of hours estimates were more than 10% higher in the UI data than in the PFML data, but these large discrepancies decrease as the study period goes on. However, there remain significant gaps; by 2022 and 2023, for example, approximately 5 to 6% of mothers have quarterly earnings in the UI data significantly higher than PFML data, and about 3 to 4% have significantly higher earnings reported in the PFML data in a given year.

Appendix tables and figures

Appendix Table 3.1. Diagnosis and procedure codes used to identify births in All-Payer Claims Data

Code Type	Code	Description
CPT	01960	Anesth vaginal delivery
CPT	01961	Anesth cs delivery
CPT	01967	Anesth/analg vag delivery
CPT	01968	Anes/analg cs deliver add-on
CPT	59400	Vaginal Delivery of Twins
CPT	59409	Vaginal & C-Section Delivery of Twins
CPT	59410	Vaginal delivery only (with or without episiotomy, and/or forceps), including postpartum care
CPT	59510	Routine obstetric care including antepartum care, cesarean delivery and postpartum care
CPT	59514	Cesarean delivery only
CPT	59515	Cesarean delivery only, including postpartum care
CPT	59612	VBAC Delivery of Twins
CPT	59614	Vaginal delivery only, after previous cesarean delivery (with or without episiotomy, and/or forceps) including postpartum care
CPT	59620	Cesarean delivery only, following attempted vaginal delivery after previous cesarean delivery
CPT	59622	Cesarean delivery only, following attempted vaginal delivery after previous cesarean delivery, including postpartum care
CPT	99464	Attendance at delivery
ICD-10-CM	O6010X0	Preterm labor w preterm delivery, unsp trimester, unsp
ICD-10-CM	O6010X0	Preterm labor with preterm delivery, unspecified trimester, not applicable or unspecified
ICD-10-CM	O6010X1	Preterm labor with preterm delivery, unsp trimester, fetus 1
ICD-10-CM	O6010X1	Preterm labor with preterm delivery, unspecified trimester, fetus 1
ICD-10-CM	O6010X2	Preterm labor with preterm delivery, unsp trimester, fetus 2
ICD-10-CM	O6010X2	Preterm labor with preterm delivery, unspecified trimester, fetus 2
ICD-10-CM	O6010X3	Preterm labor with preterm delivery, unsp trimester, fetus 3
ICD-10-CM	O6010X4	Preterm labor with preterm delivery, unsp trimester, fetus 4
ICD-10-CM	O6010X5	Preterm labor with preterm delivery, unsp trimester, fetus 5
ICD-10-CM	O6010X9	Preterm labor w preterm delivery, unsp trimester, oth fetus
ICD-10-CM	O6012X0	Preterm labor second tri w preterm delivery second tri, unsp
ICD-10-CM	O6012X1	Preterm labor second tri w preterm del second tri, fetus 1
ICD-10-CM	O6012X2	Preterm labor second tri w preterm del second tri, fetus 2
ICD-10-CM	O6012X3	Preterm labor second tri w preterm del second tri, fetus 3
ICD-10-CM	O6012X4	Preterm labor second tri w preterm del second tri, fetus 4
ICD-10-CM	O6012X5	Preterm labor second tri w preterm del second tri, fetus 5
ICD-10-CM	O6012X9	Preterm labor second tri w preterm delivery second tri, oth
ICD-10-CM	O6013X0	Preterm labor second tri w preterm delivery third tri, unsp
ICD-10-CM	O6013X1	Preterm labor second tri w preterm del third tri, fetus 1

ICD-10-CM	O6013X2	Preterm labor second tri w preterm del third tri, fetus 2
ICD-10-CM	O6013X3	Preterm labor second tri w preterm del third tri, fetus 3
ICD-10-CM	O6013X4	Preterm labor second tri w preterm del third tri, fetus 4
ICD-10-CM	O6013X5	Preterm labor second tri w preterm del third tri, fetus 5
ICD-10-CM	O6013X9	Preterm labor second tri w preterm delivery third tri, oth
ICD-10-CM	O6014X0	Preterm labor third tri w preterm delivery third tri, unsp
ICD-10-CM	O6014X1	Preterm labor third tri w preterm del third tri, fetus 1
ICD-10-CM	O6014X2	Preterm labor third tri w preterm del third tri, fetus 2
ICD-10-CM	O6014X3	Preterm labor third tri w preterm del third tri, fetus 3
ICD-10-CM	O6014X4	Preterm labor third tri w preterm del third tri, fetus 4
ICD-10-CM	O6014X5	Preterm labor third tri w preterm del third tri, fetus 5
ICD-10-CM	O6014X9	Preterm labor third tri w preterm delivery third tri, oth
ICD-10-CM	O6020X0	Term delivery w preterm labor, unsp trimester, unsp
ICD-10-CM	O6020X1	Term delivery with preterm labor, unsp trimester, fetus 1
ICD-10-CM	O6020X2	Term delivery with preterm labor, unsp trimester, fetus 2
ICD-10-CM	O6020X3	Term delivery with preterm labor, unsp trimester, fetus 3
ICD-10-CM	O6020X4	Term delivery with preterm labor, unsp trimester, fetus 4
ICD-10-CM	O6020X5	Term delivery with preterm labor, unsp trimester, fetus 5
ICD-10-CM	O6020X9	Term delivery with preterm labor, unsp trimester, oth fetus
ICD-10-CM	O6022X0	Term delivery w preterm labor, second trimester, unsp
ICD-10-CM	O6022X1	Term delivery with preterm labor, second trimester, fetus 1
ICD-10-CM	O6022X2	Term delivery with preterm labor, second trimester, fetus 2
ICD-10-CM	O6022X3	Term delivery with preterm labor, second trimester, fetus 3
ICD-10-CM	O6022X4	Term delivery with preterm labor, second trimester, fetus 4
ICD-10-CM	O6022X5	Term delivery with preterm labor, second trimester, fetus 5
ICD-10-CM	O6022X9	Term delivery w preterm labor, second trimester, oth fetus
ICD-10-CM	O6023X0	Term delivery w preterm labor, third trimester, unsp
ICD-10-CM	O6023X1	Term delivery with preterm labor, third trimester, fetus 1
ICD-10-CM	O6023X2	Term delivery with preterm labor, third trimester, fetus 2
ICD-10-CM	O6023X3	Term delivery with preterm labor, third trimester, fetus 3
ICD-10-CM	O6023X4	Term delivery with preterm labor, third trimester, fetus 4
ICD-10-CM	O6023X5	Term delivery with preterm labor, third trimester, fetus 5
ICD-10-CM	O6023X9	Term delivery with preterm labor, third trimester, oth fetus
ICD-10-CM	O632	Delayed delivery of second twin, triplet, etc.
ICD-10-CM	O700	First degree perineal laceration during delivery
ICD-10-CM	O701	Second degree perineal laceration during delivery
ICD-10-CM	O702	Third degree perineal laceration during delivery
ICD-10-CM	O7020	Third degree perineal laceration during delivery, unsp
ICD-10-CM	O7021	Third degree perineal laceration during delivery, IIIa
ICD-10-CM	O7022	Third degree perineal laceration during delivery, IIIb
ICD-10-CM	O7023	Third degree perineal laceration during delivery, IIIc
ICD-10-CM	O703	Fourth degree perineal laceration during delivery
ICD-10-CM	O704	Anal sphincter tear comp del, not assoc w third degree lac
ICD-10-CM	O709	Perineal laceration during delivery, unspecified

ICD-10-CM	O80	Encounter for full-term uncomplicated delivery
ICD-10-CM	O82	Encounter for cesarean delivery without indication
ICD-10-CM	Z370	Single live birth
ICD-10-CM	Z372	Twins, both liveborn
ICD-10-CM	Z373	Twins, one liveborn and one stillborn
ICD-10-CM	Z3750	Multiple births, unspecified, all liveborn
ICD-10-CM	Z3751	Triplets, all liveborn
ICD-10-CM	Z3752	Quadruplets, all liveborn
ICD-10-CM	Z3753	Quintuplets, all liveborn
ICD-10-CM	Z3754	Sextuplets, all liveborn
ICD-10-CM	Z3759	Other multiple births, all liveborn
ICD-10-CM	Z3760	Multiple births, unspecified, some liveborn
ICD-10-CM	Z3761	Triplets, some liveborn
ICD-10-CM	Z3762	Quadruplets, some liveborn
ICD-10-CM	Z3763	Quintuplets, some liveborn
ICD-10-CM	Z3764	Sextuplets, some liveborn
ICD-10-CM	Z3769	Other multiple births, some liveborn
ICD-10-CM	Z379	Outcome of delivery, unspecified
ICD-10-CM	Z3800	Single liveborn infant, delivered vaginally
ICD-10-CM	Z3801	Single liveborn infant, delivered by cesarean
ICD-10-CM	Z381	Single liveborn infant, born outside hospital
ICD-10-CM	Z382	Single liveborn infant, unspecified as to place of birth
ICD-10-CM	Z3830	Twin liveborn infant, delivered vaginally
ICD-10-CM	Z3831	Twin liveborn infant, delivered by cesarean
ICD-10-CM	Z384	Twin liveborn infant, born outside hospital
ICD-10-CM	Z385	Twin liveborn infant, unspecified as to place of birth
ICD-10-CM	Z3861	Triplet liveborn infant, delivered vaginally
ICD-10-CM	Z3862	Triplet liveborn infant, delivered by cesarean
ICD-10-CM	Z3863	Quadruplet liveborn infant, delivered vaginally
ICD-10-CM	Z3864	Quadruplet liveborn infant, delivered by cesarean
ICD-10-CM	Z3865	Quintuplet liveborn infant, delivered vaginally
ICD-10-CM	Z3866	Quintuplet liveborn infant, delivered by cesarean
ICD-10-CM	Z3868	Other multiple liveborn infant, delivered vaginally
ICD-10-CM	Z3869	Other multiple liveborn infant, delivered by cesarean
ICD-10-CM	Z387	Other multiple liveborn infant, born outside hospital
ICD-10-CM	Z388	Other multiple liveborn infant, unspecified as to place of birth
ICD-10-PCS	10D00Z0	Extraction of Products of Conception, Classical, Open Approach
ICD-10-PCS	10D00Z1	Extraction of Products of Conception, Low Cervical, Open Approach
ICD-10-PCS	10D00Z2	Extraction of Products of Conception, Extraperitoneal, Open Approach
ICD-10-PCS	10D07Z3	Extraction of Products of Conception, Low Forceps, Via Natural or Artificial Opening
ICD-10-PCS	10D07Z4	Extraction of Products of Conception, Mid Forceps, Via Natural or Artificial Opening

ICD-10-PCS	10D07Z5	Extraction of Products of Conception, High Forceps, Via Natural or Artificial Opening
ICD-10-PCS	10D07Z6	Extraction of Products of Conception, Vacuum, Via Natural or Artificial Opening
ICD-10-PCS	10D07Z7	Extraction of Products of Conception, Internal Version, Via Natural or Artificial Opening
ICD-10-PCS	10D07Z8	Extraction of Products of Conception, Other, Via Natural or Artificial Opening
ICD-10-PCS	10E0XZZ	Delivery of Products of Conception, External Approach

Appendix Table 3.2. Comparison of UI and PFML wage reports: Quarterly wages

		UI zero; PFML nonzero	UI >10% lower	UI 5- 10% lower	UI <5% lower	UI and PFML equal	UI <5% higher	UI 5- 10% higher	UI >10% higher	UI nonzero; PFML zero
2019 Q1	N	3668	2006	1501	5147	144329	3162	956	9434	14172
	%	2.0%	1.1%	0.8%	2.8%	78.3%	1.7%	0.5%	5.1%	7.7%
2019 Q2	N	3788	2878	1629	5107	145145	2923	921	8784	13200
	%	2.1%	1.6%	0.9%	2.8%	78.7%	1.6%	0.5%	4.8%	7.2%
2019 Q3	N	4028	2093	1278	6259	149360	3330	971	9817	7239
	%	2.2%	1.1%	0.7%	3.4%	81.0%	1.8%	0.5%	5.3%	3.9%
2019 Q4	N	4473	3508	2559	7225	147204	2930	968	8102	7406
	%	2.4%	1.9%	1.4%	3.9%	79.8%	1.6%	0.5%	4.4%	4.0%
2020 Q1	N	4303	2448	2588	7126	150035	3110	998	7175	6592
	%	2.3%	1.3%	1.4%	3.9%	81.4%	1.7%	0.5%	3.9%	3.6%
2020 Q2	N	4220	2057	1207	5551	158181	2601	658	4455	5445
	%	2.3%	1.1%	0.7%	3.0%	85.8%	1.4%	0.4%	2.4%	3.0%
2020 Q3	N	3855	1600	1254	5361	158017	2606	638	5955	5089
	%	2.1%	0.9%	0.7%	2.9%	85.7%	1.4%	0.3%	3.2%	2.8%
2020 Q4	N	4039	2274	1667	6761	155927	2125	676	5767	5139
	%	2.2%	1.2%	0.9%	3.7%	84.6%	1.2%	0.4%	3.1%	2.8%
2021 Q1	N	3924	2117	1655	6386	158142	2438	612	4756	4345
	%	2.1%	1.1%	0.9%	3.5%	85.8%	1.3%	0.3%	2.6%	2.4%
2021 Q2	N	3975	2158	2081	6567	156035	2764	625	5802	4368
	%	2.2%	1.2%	1.1%	3.6%	84.6%	1.5%	0.3%	3.1%	2.4%
2021 Q3	N	4050	1821	1458	6014	156479	2696	752	6606	4499
	%	2.2%	1.0%	0.8%	3.3%	84.9%	1.5%	0.4%	3.6%	2.4%
2021 Q4	N	4376	3305	2748	6804	152658	2701	756	6404	4623
	%	2.4%	1.8%	1.5%	3.7%	82.8%	1.5%	0.4%	3.5%	2.5%
2022 Q1	N	4098	3555	2675	6373	153871	2808	685	5844	4466
	%	2.2%	1.9%	1.5%	3.5%	83.5%	1.5%	0.4%	3.2%	2.4%
2022 Q2	N	4406	2609	2451	6731	154478	2593	687	6040	4380
	%	2.4%	1.4%	1.3%	3.7%	83.8%	1.4%	0.4%	3.3%	2.4%
2022 Q3	N	5908	3191	1474	7380	152367	2853	684	6384	4134
	%	3.2%	1.7%	0.8%	4.0%	82.6%	1.5%	0.4%	3.5%	2.2%
2022 Q4	N	4444	2972	2787	7440	149966	3383	1051	6980	5352
	%	2.4%	1.6%	1.5%	4.0%	81.3%	1.8%	0.6%	3.8%	2.9%
2023 Q1	N	4716	2568	2769	7744	153376	2446	639	5889	4228
	%	2.6%	1.4%	1.5%	4.2%	83.2%	1.3%	0.3%	3.2%	2.3%
2023 Q2	N	4850	2113	2481	8108	152164	2302	662	6405	5290
	%	2.6%	1.1%	1.3%	4.4%	82.5%	1.2%	0.4%	3.5%	2.9%

Notes: Comparisons are estimated for all mothers with a birth in the APCD data between 2019 and 2023.

Sources: Author's analysis of data from WA-APCD and ESD.

Appendix Table 3.3. Comparison of UI and PFML wage reports: Quarterly hours

		UI zero; PFML nonzero	UI >10% lower	UI 5- 10% lower	UI <5% lower	UI and PFML equal	UI <5% higher	UI 5- 10% higher	UI >10% higher	UI nonzero; PFML zero
2019 Q1	N	3668	4604	2430	8476	137892	5767	1163	6203	14172
	%	2.0%	2.5%	1.3%	4.6%	74.8%	3.1%	0.6%	3.4%	7.7%
2019 Q2	N	3788	4786	2423	8763	139000	5864	1024	5527	13200
	%	2.1%	2.6%	1.3%	4.8%	75.4%	3.2%	0.6%	3.0%	7.2%
2019 Q3	N	4028	4331	2219	9616	144139	6021	1204	5578	7239
	%	2.2%	2.3%	1.2%	5.2%	78.2%	3.3%	0.7%	3.0%	3.9%
2019 Q4	N	4473	5188	3200	11281	140139	5921	1446	5321	7406
	%	2.4%	2.8%	1.7%	6.1%	76.0%	3.2%	0.8%	2.9%	4.0%
2020 Q1	N	4303	5132	3676	12021	142444	4871	1041	4295	6592
	%	2.3%	2.8%	2.0%	6.5%	77.3%	2.6%	0.6%	2.3%	3.6%
2020 Q2	N	4220	4352	2058	9774	149215	4903	868	3540	5445
	%	2.3%	2.4%	1.1%	5.3%	80.9%	2.7%	0.5%	1.9%	3.0%
2020 Q3	N	3855	4967	2462	9150	149810	4827	772	3443	5089
	%	2.1%	2.7%	1.3%	5.0%	81.3%	2.6%	0.4%	1.9%	2.8%
2020 Q4	N	4039	5021	2854	10889	147430	4549	957	3497	5139
	%	2.2%	2.7%	1.5%	5.9%	80.0%	2.5%	0.5%	1.9%	2.8%
2021 Q1	N	3924	4915	2996	11707	148447	4448	738	2855	4345
	%	2.1%	2.7%	1.6%	6.3%	80.5%	2.4%	0.4%	1.5%	2.4%
2021 Q2	N	3975	5232	3164	11714	147128	4734	772	3288	4368
	%	2.2%	2.8%	1.7%	6.4%	79.8%	2.6%	0.4%	1.8%	2.4%
2021 Q3	N	4050	5539	2881	10787	147500	4841	797	3481	4499
	%	2.2%	3.0%	1.6%	5.9%	80.0%	2.6%	0.4%	1.9%	2.4%
2021 Q4	N	4376	6389	3713	11854	144878	4182	935	3425	4623
	%	2.4%	3.5%	2.0%	6.4%	78.6%	2.3%	0.5%	1.9%	2.5%
2022 Q1	N	4098	6143	4160	11146	146827	3879	635	3021	4466
	%	2.2%	3.3%	2.3%	6.0%	79.6%	2.1%	0.3%	1.6%	2.4%
2022 Q2	N	4406	5481	3762	11006	147372	4293	773	2902	4380
	%	2.4%	3.0%	2.0%	6.0%	79.9%	2.3%	0.4%	1.6%	2.4%
2022 Q3	N	5908	5958	2725	9963	146917	4444	864	3462	4134
	%	3.2%	3.2%	1.5%	5.4%	79.7%	2.4%	0.5%	1.9%	2.2%
2022 Q4	N	4444	5797	4018	10506	145114	5267	878	2999	5352
	%	2.4%	3.1%	2.2%	5.7%	78.7%	2.9%	0.5%	1.6%	2.9%
2023 Q1	N	4716	4871	4232	11134	148085	3762	752	2595	4228
	%	2.6%	2.6%	2.3%	6.0%	80.3%	2.0%	0.4%	1.4%	2.3%
2023 Q2	N	4850	4367	3622	11802	146968	3960	785	2731	5290
	%	2.6%	2.4%	2.0%	6.4%	79.7%	2.1%	0.4%	1.5%	2.9%

Notes: Comparisons are estimated for all mothers with a birth in the APCD data between 2019 and 2023.

Sources: Author's analysis of data from WA-APCD and ESD.

Conclusion

These three studies explored multiple facets of household economic conditions during the time around the birth of a child. The analysis documented that parents experience a significant amount of economic volatility in the perinatal period. Furthermore, these experiences disproportionately affect economically vulnerable parents and families. This dissertation also discussed two policy responses with the potential to buffer families from this economic volatility: means-tested public assistance programs and paid leave programs. Results suggested that while these programs had the potential to help families around the time of a birth, they did not fully protect families from economic instability. I also presented evidence that features of these programs can exacerbate and/or perpetuate inequality.

Chapter 1 descriptively documented trends in employment, earnings, and income at both the parent and household level in the two-year period around a birth. Using birth certificate records merged to employment and means-tested program records, I described the economic circumstances of the universe of parents listed on birth certificates in Washington State between 2010 and 2016. First, I described individual parents' employment trajectories in the quarters around a birth. I showed that parents—in particular, mothers—experience significant employment and earnings volatility when a child is born. Next, I analyzed earnings and income at the household level, including tracking trends in use of SNAP, TANF, and child care subsidies in the quarters around a birth. I showed that even after accounting for the income of both parents listed on a birth certificate, household income around a birth is very volatile – especially for single-mother households. Households increasingly use safety net programs in the quarters around a birth, and safety net program income does buffer perinatal earnings volatility to some degree. However, substantial volatility remains even after accounting for these programs.

Chapter 2 explored how the earnings histories documented in Chapter 1 intersect with policy rules to shape eligibility for paid leave policies. While the states that have passed paid family and medical leave policies in recent years are often discussed together (Bipartisan Policy Center, 2022), these state policies differ substantially. This paper discussed one dimension of this variation: the fact that each state policy has very different rules for who can qualify to be eligible for paid leave. Using microdata on parents of newborns in Washington State, I simulated whether each parent would have been eligible to take paid leave under each of 10 different state policies. This allowed me to show that states vary dramatically in terms of both overall rates of eligibility for paid leave and disparities in eligibility across subgroups. I demonstrated that policies that are less restrictive and allow more parents to access paid leave also significantly narrow disparities in who is eligible. I found that policies with more stringent employment requirements disproportionately exclude mothers (versus fathers); mothers working in low-wage jobs; mothers with lower educational attainment; and Black, Indigenous, and Latina mothers from qualifying for paid leave.

Chapter 3 focused on one specific state's paid leave policy in more detail. As the first causal evaluation of Washington State's Paid Family and Medical Leave program, this paper assessed use of the policy and estimated its effect on employment outcomes among mothers of newborns. I demonstrated how health insurance claims data could be merged to employment and paid leave program records to both estimate policy take-up rates and study the causal effect of the policy on employment. I found that a majority of eligible Washington mothers who gave birth between 2020 and 2022 used PFML at some point during the perinatal period. Take-up increased between 2020 and 2022 as the policy rolled out, especially for medical leave. Analysis of policy take-up by mother characteristics revealed some important disparities. For example,

results suggested that eligible Native Hawaiian/Pacific Islander and American Indian/Alaska Native mothers were less likely to take up paid bonding and medical leave than mothers identifying with other racial and ethnic groups. I also showed that mothers in more urban areas are more likely to take up both types of leave. Furthermore, there are sharp disparities by wage rate, such that mothers in lower-wage jobs are significantly less likely to take up leave. Next, regression discontinuity analyses of the average local treatment effect of PFML eligibility on mothers around the eligibility threshold found mixed results. There was some evidence that eligibility for PFML has small negative effects on employment status and intensity in the quarters immediately following a birth. However, I also found that this mostly does not translate into significant reductions in total earnings (including wages plus PFML benefits), suggesting that mothers who are eligible for the program, on average, are able to spend more paid time off with their children without experiencing a reduction in income. Finally, I showed relatively consistent evidence that PFML eligibility is associated with an increase in continuity of work with the same employer.

Taken together, these results offer contributions to the research literatures on earnings volatility, household economic security, and paid leave. First, by showing the extent of earnings volatility around the time of a birth, particularly for working mothers, Chapter 1 demonstrated that research on earnings and income volatility needs to directly address the perinatal period. Chapter 2 demonstrated that research on state paid leave policies needs to address differences in policy designs across states. In future causal studies of the effects of these policies that examine multiple states, differences in eligibility requirements, as well as other features of policy design not covered by this analysis, may lead to different treatment effect sizes and different policy implications across states. These findings suggest that more work needs to be done to understand

the implications of these differences in policy design, pointing to a future paid leave research agenda that pays more close attention to specifics of these policies. These findings also contribute to the literature on policy design and inequality by describing another case of employment-based eligibility requirements disproportionately excluding potential policy users along racial and socioeconomic lines. Chapter 3 contributes to the literature on state paid leave programs, bringing a new causal inference method that has rarely been applied in prior research and examining a new policy context. Given that many states have sharp eligibility thresholds, it would be valuable to apply a regression discontinuity design to additional state contexts.

The use of administrative data in this dissertation also moves forward the research literature on these topics. The administrative microdata enables a focus on inequalities and heterogeneous experiences, including among smaller groups that often cannot be studied using survey data. Chapters 1 and 2, for example, demonstrated how birth certificate records merged to state Unemployment Insurance wage reports and public assistance program data can describe in detail the economic conditions of families with children, including understanding these conditions for small subgroups of interest. Chapter 2 showed how these records could be used to simulate the effects of different policy decisions. These efforts could be replicated with administrative data in other states, and also used to track trends within a given state over time. Chapter 3 revealed the promise of merging health insurance claims data to employment and paid leave program records. Critically, this merge allowed the identification of a population of potential users of Washington's PFML program, including estimation of eligibility for the program based on employment history. This allowed estimates of policy take-up at the individual level, enabling the estimation of take-up rates for small subgroups and over time. The merging of these records also points to the potential for future work on the intersections of employment,

health, and policy. For example, these records could be used to better understand the economic conditions of workers with chronic medical conditions and their use of paid medical leave.

These results also have policy relevance. First, the work contributes new understanding of how common economic volatility is among families around the time of a birth – and which parents and families are particularly affected. This information has important implications for policymakers looking to promote families’ economic security and reduce disparities in experiences of poverty and hardship. Second, the project shows detailed estimates of the generosity and equity of different state paid leave policies. Paid leave policies differ significantly across states, and few researchers have looked into the implications of these differences for policy beneficiaries. Findings on the effects of different state policy designs are critically important to policy discussions, especially as new states continue to adopt paid leave policies and if, down the road, a policy were to be considered at the federal level that incorporates knowledge from state-level experiences with these types of programs. Third, understanding the effects of Paid Family and Medical Leave in Washington, as well as who is accessing the program, will help state policymakers understand both how the program has been successful and areas for improvement. Overall, these findings suggest that while paid family and medical leave policies have the potential to support families around the time of a birth, decisionmakers hoping to promote equitable use of these policies need to be attentive to inequalities that can emerge in both eligibility and take-up.

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