



Essays in Health Economics

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Essays in Health Economics

Abstract

This dissertation consists of three chapters that relate to the following broad areas in health economics: care provision for vulnerable populations, challenges in efficient insurance market functioning and the value of continuity of care.

Chapter 1: The Impact of Federally Qualified Health Centers on Youth Outcomes.

Health events that occur in youth such as adolescent pregnancy often have an enormous impact on adult outcomes. Adolescents are generally well-covered by health insurance but may not have access to care for other reasons. Using the large and staggered geographic expansion of Federally Qualified Health Centers (FQHCs) in the last two decades, this paper studies the impact of these community-based providers on teen pregnancy rates and high school graduation rates. Openings are associated with a 10 percent drop in the teen birth rates in an area. Declines are larger in counties with more than one opening and among low-income populations. I find no statistically significant effect on educational attainment overall but a 17 percent decline in the proportion of women who did not complete high school in areas where FQHC openings had the largest effects on the teen birth rate. These findings highlight the potential of community-based institutions to impact opportunities for youth.

Chapter 2: Physician Handoffs and Patient Mortality

Transitions of patient care, or handoffs, have primarily been studied and associated with adverse events and errors among physician trainees. The relationship between handoffs and patient outcomes among physicians who have completed training is unknown, however, even though similar concerns apply outside the trainee setting. Using a 20% random sample of

Medicare fee-for-service beneficiaries hospitalized during 2008-2012 and treated by a hospitalist, we analyzed whether patient 30-day mortality varied according to date of admission relative to the treating physician's last working day. Admission towards the end of a physician's shift block is predictive of a higher likelihood of handoff among otherwise similar patients, thus providing a setting for quasi-experimental analysis. We find that handoffs are associated with a 1.2 percentage point increase in 30-day mortality, with larger effects among high risk patients. This suggests a need for systematic measurement and evaluation of handoff processes within individual hospitals.

Chapter 3: The Extremely Under and Overcompensated in Individual Health Insurance Markets

This study seeks to investigate and describe the characteristics of individuals grossly underpaid and overpaid post risk adjustment and test the potential for adverse selection in the individual health insurance market. Using the 2016 HHS-HCC Risk Adjustment model software, we modeled risk-adjustment payments and analyzed residuals (the difference between payments and spending). Potential for supply-side and demand-side selection were explored through the measurement of the persistence of residuals and the correlation of individual expected spending and spending residuals, respectively. We found that the residual distribution is right-tailed but has a significant left tail as well and high spending variance HCCs are represented in both groups. Extreme residuals were highly persistent; the persistently underpaid spend disproportionately on specialty drugs while the persistently overpaid were frequently coded with transplant HCCs. The strong persistence of extreme residuals points to the potential for selection. Attention to the grossly over and underpaid individuals may lead to directions for improvement in plan payment systems. In addition, the role of specialty drugs in contributing to the persistence of residuals is worthy of more discussion.

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Chapter 1: The Impact of Federally Qualified Health Centers on Youth Outcomes

1. Introduction

About 80% of teen pregnancies are unwanted (1,2). While U.S. teen pregnancy rates have experienced large declines since the 90s, they remain substantially higher than other industrialized nations'. For instance, the U.S. teen pregnancy rate is about 50% greater than the rate in England, more than twice the rate in France and about seven times that of Switzerland (3). Adolescent pregnancy may have a large impact on adult educational attainment and economic outcomes. Only about half of teenage mothers complete high school (4). Early pregnancy impacts not only the mother's opportunities but that of her child and subsequent children (5). Moreover, adolescents have higher pregnancy complication rates and incidence of low birth weight babies (6). Conversely, access to contraception has been found to affect the timing of birth and marriage and increase career investments and earnings (7).

In this paper, I study the impact of federally qualified health center (FQHC) openings on teen birth rates and educational attainment. Adolescent youth are a population that are traditionally well covered (through private insurance and the Children's Health Insurance Program, or CHIP) but may not have access to care (8). Only 5% of children under 19 are uninsured (9), however, about 40% of children are on CHIP and experience challenges in finding a doctor who accepts their insurance and in obtaining appointments and access to specialty care (10, 11). In addition, children may face significant provider shortages where they live especially in the rural South and Midwest (12). These structural barriers highlight the importance of research into what improves access, conditional on coverage.

Subsidized by federal section 330 grants, FQHCs have to locate in federally designated medically underserved areas (MUAs). They provide primary and preventive care and accept patients regardless of ability to pay. From the start of program, FQHCs have also been required to provide family

planning services (13). Many receive Title X funding which requires that they provide a broad range of contraceptive and screening services and follow special confidentiality protections (14, 15).¹ In the last two decades, there has been a large expansion in FQHC delivery sites from 731 in 2000 to 14,194 in 2019. Despite their prevalence, there is a lack of evidence on the causal effects of FQHCs on access and outcomes.²

I study the effects of FQHC openings using event study and difference-in-difference methods. I define the treatment group as counties that experienced an opening during my study period and the control group as counties where an FQHC opens in the future. My identification strategy assumes that the timing of an opening is uncorrelated with factors that could themselves influence teen health and education measures. I find no differential trends in the pre period between the treatment and control group for my outcome measures and both groups trend similarly with respect to other economic and insurance coverage measures, providing evidence in support of this assumption.

FQHC openings have a large impact on youth outcomes. The first FQHC opening in a county is associated with a 10% decrease in teen birth rates three to five years post an FQHC opening. A sensitivity analysis using counties where no FQHCs opened as the control group shows very similar results. These effects are also comparable with estimates from a recent working paper which finds a 20% decline in county level birth rates among young teens and a 5% decline among older teens as a result of a school-based health center (SBHC) opening (17).³

¹ By law, FQHCs may not perform abortions.

² Most studies are observational, confined to particular geographic area or health center types or focus on the program introduction in the 70s (16;17;18;19;20;21;22;23;24). Finally, studies of FQHCs have been limited to studying health centers (rather than centers as well as their associated delivery sites) due the unavailability of validated Health Center Uniform Data System (UDS) information on delivery sites (25).

³ FQHCs are the largest sponsor of SBHCs representing over 40% of SBHCs. Not all SBHCs provide family planning services however, by statute all FQHCs are required to do so. A large proportion of FQHCs also collaborate with other entities such as schools to provide adolescent family planning services (26).

I study heterogeneity of effects by treatment intensity and observe a larger decline (12%) for FQHCs that also receive Title X funding which is associated with better onsite availability of all types of long acting reversible contraceptives (LARCs), greater levels of collaboration with other entities and more staff training compared to clinics that are not Title X recipients. I also find greater declines in counties where more than one FQHC opened (13%).

FQHC openings may have larger relative effects among low income populations who are more likely have experienced provider shortages and other challenges in access. On the other hand, teen pregnancy is a complex issue and low-income youth may be inelastic to these interventions if other drivers of risky behavior are not addressed (27;28;29;30). I find large declines in teen pregnancy among youth enrolled in Medicaid, suggesting some returns to increased access and outreach.

I then leverage rich health insurance claims data for girls enrolled in Medicaid to identify the mechanisms behind this sharp decrease in birth rates. I find large increases in long-acting reversible contraception (LARC) use; a 47% increase in Intrauterine device (IUD) use three to five years post the FQHC opening. The uptake in IUD use can explain roughly 15-20% of the observed decline in pregnancy rates. Compared with shorter-term, user-dependent contraceptive methods (such as the oral contraceptives) LARCs have much lower failure rates; less than 0.1% compared to 8% and 15% for oral contraceptives and condoms respectively (31). The divergence in effectiveness may be larger among adolescent populations. In 2012, the American College of Obstetricians and Gynecologists released guidelines advising that sexually active adolescents at high risk of unintended pregnancy be encouraged to consider LARCs as a contraceptive option (32). The recent decade has seen a substantial rise in LARC use (from 0.4% in 2005 to 7.1% in 2013) among low income adolescent users of Title X services (33). My results indicate that FQHC expansion may have played an important role in facilitating this provision.

Together, these results have two implications. First, health insurance coverage alone does not achieve optimal levels of contraceptive access among teens; supply-side policies in context of insurance result in substantial increases in contraceptive use and declines in pregnancy. Second, while teen pregnancy is often a marker of a low economic opportunity (34) where access to contraception is not the primary limiting factor, there are marginal pregnancies which are avoided via better access to contraception.

Overall teen birth rates have declined substantially (about 60%) over the last three decades, primarily due to the increased rates of contraceptive use among teens (35). My event-study estimates imply that FQHC openings can conservatively explain about 18% of the decline in teen birth rates between 2007 and 2017 in the counties that experienced an opening.

I then turn to the effects of FQHC openings on male and female high school graduation rates. For girls, the fertility reduction from FQHC openings could lead to higher graduation (7;36). For both boys and girls, access to better health care treatment via FQHCs, including treatment for mental health conditions such as depression, could have an independent effect on graduation rates. Overall, I find no evidence of an effect of FQHC openings on graduation rates. However, if I focus on counties with the highest eventual FQHC penetration, I find a 17% decrease in the proportion of 18-29 year old females who did not complete high school. High school completion among males in the same areas is not affected, suggesting that the fertility reduction is the most likely channel by which dropout rates are reduced.

This paper contributes to a large body of literature on the impacts of contraceptive access. The bulk of this research is focused on the “contraception revolution” of the 1960s and the introduction of the Pill; this work finds large and persistent reductions in fertility rates. For young unmarried women, legal access to the Pill delayed timing of marriage and of births and had broader positive impacts on

both men and women's education levels, career investments and lifetime wage earnings. Importantly, prevented teen pregnancies impact not only the mother, but also the outcomes of her children in the future (7;37;38;39;40;41;42). Populations with greater access to oral contraceptives were more likely to enroll and complete college, and women were more likely to work and to pursue nontraditional professions. About thirty percent of the convergence in the gender wage gap in the 1990s has been attributed to the opportunities afforded by access to oral contraceptives (43).

A related literature studies the impacts of abortion legalization in the 70s and finds a reduction in adverse outcomes for cohorts born in the post period potentially suggesting that the marginal child not born was more likely to be economically disadvantaged (44). However, since these policies may also impact the pregnancy rate (45), it is difficult to infer parallel effects from policies targeting contraception provision.⁴

While this older literature which focused primary on the contraceptive revolution finds large fertility and economic effects in response to increased access to contraceptives, recent work has been limited and tentative. In particular, some studies suggest that there may be a limit to how much contraceptive provision can affect youth outcomes today; some teenage mothers may already be on a 'low economic trajectory' (34) possibly indicating less responsiveness to family planning services and less economic benefits to avoided pregnancy.

Recent empirical work includes Lovenheim et al., 2016 (17) which studies that impact of SBHC openings on teen outcomes, finding a significant decline in county-level teen fertility rates. Conversely, Buckles and Hungerman, 2016 find that distribution of condoms in schools in the 90s (intended to

⁴ Birth cohorts after abortion legalization may be composed of both marginal children not born and more births from marginal pregnancies and it is difficult to disentangle the contribution of each mechanism to the improvement in cohort outcomes.

prevent the transmission of HIV) led to increased sexual activity and was associated with a 10% increase in teen birth rates (46), indicating that the impact of contraception provision may be heterogenous (47) and may vary by type of contraceptive. Long-acting reversible contraceptives (LARCs) may be particularly effective in reducing teen fertility. Title X clinics providing greater access to LARCs achieved larger decreases in teen child bearing than those that did not (48).

Understanding the potential and limitations of family planning interventions targeting adolescent pregnancy is an important policy concern. First, to what extent should state and federal funds be focused on these interventions relative to investing more broadly in economic policies targeting youth? Second, which interventions are most effective in achieving lower pregnancy rates? Recent work indicates there may be heterogenous effects depending on the type of intervention (17;46;48).

The rest of this paper is organized as follows: Section 2 introduces the institutional background. Section 3 describes the data. Section 4 presents the empirical strategy. Section 5 shows the main results and sensitivity analyses and Section 6 concludes.

2. Background

2.1 Federally Qualified Health Centers

2.1.1 History and Scope

FQHCs are community-based organizations that receive federal funding under Section 330 of the Public Health Service Act to provide comprehensive primary and preventive care regardless of ability to pay or insurance status. They provide care on a sliding fee scale and are located in federally designated medically underserved area. They are also eligible for enhanced payments under Medicare and Medicaid (49).

Launched under the Economic Opportunity Act of 1964 (50), FQHCs have expanded in number steadily over time in large part due to bipartisan support and early studies showing evidence of their effectiveness. In recent years, expansion in the number of FQHCs has been supported by the large financial federal investments in the 2000s; specifically \$2 billion dollars under the American Recovery and Reinvestment Act (ARRA) and the \$11 billion Community Health Center fund under the 2010 Affordable Care Act (ACA) (51;52). FQHCs may have multiple delivery sites; the recent expansion in FQHCs has often been through existing centers opening up new sites in other medically underserved areas (25).

Today FQHCs serve more than 1 in 12 U.S. residents and almost 1 in 6 Medicaid enrollees in more than 14,000 delivery sites (53;54). In 2016, about half of their patient population was covered by Medicaid and almost a quarter were uninsured (55). 70% of patients were under 100% of the Federal Poverty Line (FPL) and more than half were Black or Hispanic. Finally, FQHCs are also an important provider of care for children and teens; a third of FQHC patients on average are under eighteen (55). FQHCs' largest source of revenue is Medicaid (44% of revenue) followed by federal grants (18%) (51). Many centers also received other source of state and federal funding such as Title X grants (15).

2.1.2 Family Planning Services

Since health centers were established, voluntary family planning has been a required service (13) and in 2016 almost one third of low-income women of child bearing age relied on a health center for reproductive health services (15). These services encompass contraceptive provision, family planning consultations and often collaboration with other entities such as schools. In terms of number of delivery sites, FQHCs are the largest provider of publicly funded family planning services, representing over half the share of all health settings (including health departments, hospitals and planned parenthood clinics) that offer publicly funded family planning programs (56).

The last decade has seen an increase in both in access and the types of family planning services available at FQHCs. A 2018 survey found that two thirds of centers offered access to initial contraceptive visits on a same-day and walk in bases and a rapidly growing proportion offered LARCs on-site. For instance, the share of FQHCs that offered contraceptive implants on site grew from 36% in 2011 to 63% in 2017, as did the share that provided Intrauterine devices or IUDs (from 56% in 2011 to 64% in 2017) (15). Among FQHCs that also that receive Title X funding, a larger share offered LARCs on-site (e.g 89% for the implant) and were more likely to offer the full range of contraceptive methods (15). LARC methods have a large potential to impact unintended pregnancy as they are more effective than commonly used contraceptive methods (48).⁵

FQHCs have also made efforts to tailor their services to effectively serve the adolescent population. Two thirds of recently surveyed centers reported that staff members received training in adolescent family planning and most centers reported maintaining special confidentiality restrictions for minors. In addition, more than half collaborate with other entities to engage in family planning outreach to adolescents including school-based education and treatment (26). Clinics which received Title X funding were particularly well equipped for effective adolescent family planning service provision.

The importance of these targeted and non-clinical dimensions of contraceptive provision, such as outreach, education, confidentiality protections and drop-in centers, has been illustrated by the experience of recent state and local initiatives targeting teen pregnancy. As part of a federal effort to develop the empirical evidence base for pregnancy prevention approaches, the Office of Adolescent Health commissioned the evaluation of several teen pregnancy prevention initiatives. While they varied in content and setting, almost all programs involved regular group-based education and outreach as an

⁵ More than third of unplanned pregnancies are to women using contraception (48).

important and often primary component. The results of the evaluation show measurable impacts on several of the targeted outcomes and highlight the effectiveness of some forms of adolescent outreach (57;58).

2.2 Teen Pregnancy Rates in the U.S

Over the past 25 years there has been a large decline in teen births, falling from 61.8 births per 1000 girls between 15 and 19 years in 1991 to 18.8 in 2017 (59;60). Nonetheless, the U.S teen pregnancy rate remains much higher than other industrialized nations' and is at least 45% higher than most other countries with comparable GDP per capita (3).

80% of teenage pregnancies are unplanned (1;2). In 2013, about 60% ended in a live birth, 15% ended in miscarriage and 25% ended in abortion (61). There are also substantial racial and geographic disparities in teen birth rates (62). Estimates from 2013 show that 8% of White, 16% of Black and 17% of Hispanic teenage women will give birth by their 20th birthday (63). Geographic variation exists both across and within states (62); states with the highest teen pregnancy rates tend to be clustered in the South. Massachusetts has the lowest teen birth rate (0.81% of teens) while Arkansas has the highest (3.3%) (64).

Teen pregnancy is among one of the primary reasons for high school dropout; nearly a third of teenage drop outs report pregnancy or parenthood as the key reason (36) and only 53% of teenage mothers complete high school compared to 90% of women who did not give birth as teens (4). Moreover, children of teenage mothers are more likely to have lower educational attainment, drop out of high school, and face unemployment as a young adult (5). Thus reducing teenage pregnancy rates may have potential 'multiplier effects'. The economic impacts of reducing pregnancy may be more pronounced in recent years as the premium on higher levels of educational attainment has risen (65).

3 Data

This paper relies on several sources of data described below.

3.1 FQHC Openings

I use the 2018 provider of services (POS) file from the Centers for Medicare and Medicaid Services (CMS) to identify FQHCs. These are publicly available files which describe health care facilities certified to serve Medicare patients. A provider type category code identifies FQHC sites. The data includes location zip code, a unique Medicare provider number and the date at which FQHC began participating in Medicare or Medicaid. Newly certified FQHCs appear in the POS when they apply for Medicare and Medicaid payment. I define the opening year as the year in which the provider is first approved to provide Medicare and/or Medicaid services (obtained from the participation date in the POS file).

I construct a county-level file that includes the year of the first health center opening in that county as well as the number of health centers that eventually opened in that county. Most of my results are identified off openings after 2007 since my panel data sources containing information on teen reproductive outcomes begin in 2007. Between 2007 and 2018, 687 counties experienced a first opening. Figure 1.1 shows the locations of FQHCs over time. They appear to be mostly located in coastal areas, the East and the South.

Figure 1.1: FQHC Locations in 2000, 2008 and 2015



Notes: These figures show the zips in which at least one FQHC was open in 2000, 2008 and 2016 in the top, middle and bottom maps respectively. FQHC location information and open dates were obtained from the 2018 Provider of Service File.

I obtain characteristics of the counties where FQHCs opened and those whether they did not from the Integrated Public Use Microdata Series (IPUMS USA). This contains yearly harmonized U.S

census micro data. I obtain information about employment, income, health insurance coverage and demographic characteristics of the individuals in every county and aggregate to the county level using sample weights. Many counties in the IPUMS data are not identified due to confidentiality restrictions and hence the summary statistics in Table 1.1 are limited to counties for which I have descriptive information.

Table 1.1: Summary Statistics of Late and Early Openings

County Characteristics (2008)	Late Openings (N=29)		Early Openings (N=70)		Difference
	Mean	Std Dev	Mean	Std Dev	
% Male	49.20	0.68	48.97	0.88	-0.231
% 0-12 years old	16.55	2.56	16.77	2.60	0.212
% 13-19 years old	9.83	1.55	9.85	1.37	0.017
% 20 to 50 years old	41.71	4.76	42.22	4.59	0.514
% > 50 years old	31.91	7.31	31.17	5.77	-0.743
% White	83.90	9.42	80.65	12.36	-3.245
% Black	8.47	8.55	11.22	11.65	2.749
% Asian	3.01	2.18	3.21	2.90	0.199
% Other	0.00	0.00	0.00	0.01	0.001
% Any health ins	87.72	4.75	86.75	4.51	-0.966
% Any private ins	71.32	9.52	69.93	8.74	-1.398
% Any public ins	28.41	8.85	28.32	7.20	-0.087
% Medicaid	14.19	5.35	14.70	4.67	0.507
% Less than HS	9.37	3.71	9.74	4.63	0.375
% HS graduate	37.61	6.84	36.65	7.83	-0.963
% College or more	53.02	9.22	53.61	10.52	0.588
% Employed	47.10	5.46	47.37	4.85	0.268
% Income <= \$30k	44.92	8.21	45.50	8.08	0.581
% Income \$30k-\$60k	32.63	3.73	32.11	3.90	-0.517
% Income > \$60k	22.45	8.11	22.39	8.72	-0.064

* p<0.10, ** p<0.05, *** p<0.001. Notes: This table presents summary statistics for counties where the first FQHC opening was during or before 2012 (Early Openings) and those where the first FQHC opening was post 2012. Counties where the first FQHC opening was before 2007 are dropped. The last column presents the results of a t test between counties that experienced early versus late openings. Significant differences at the 1%, 5% and 10% level are marked with stars. This analysis is limited to counties that are identified in the IPUMs data. IPUMs data does not include the universe of U.S counties due to confidentiality restrictions. Summary statistics are calculated as of 2008, the earliest year in the study period where IPUMs data are available for the county characteristics displayed

I identify FQHCs that also received Title X funds using the HHS Directory of Title X grantees (66). FQHCs from the POS file are matched to the Title X grantee list by address since provider number is not available in the directory. This matching is not perfect; FQHCs whose zipcodes are not represented in the Title X directory are marked as a non-Title X recipients while the remainder of FQHCs are matched as closely as possible via street address. Under this algorithm, FQHCs defined as

non-Title X recipients are almost certainly so, however there may be small subset of FQHCs marked as Title X recipients that are not.

3.2 Teen Birth and Pregnancy Rates

I obtain data on teen birth rates from three sources. The first is the Centers of Disease Control (CDC) National Vital Statistics System (NVSS) publicly available natality data from 2007 to 2017. These are based on birth certificate data received from states. I obtain yearly data at the county level; specifically, I obtain the count of live births to teenage mothers (women between 13 to 19 years of age) at the county level from 2007 to 2017. The CDC definition of live births does not include miscarriages. The advantages of this data is that it is national and not limited to a subset of the population. In addition, it is based on birth certificate information and hence is more reliable than estimates based on surveys. One of the main limitations is that counties with fewer than 100,000 individuals are suppressed for confidentiality reasons. Hence my analysis based on CDC data is limited to large counties.

I obtain the denominator; the number of teens in each county year from the American Community Survey (ACS). The ACS is a survey-based dataset that provides yearly information on population characteristics, employment, educational attainment, health insurance information among a range of other indicators. Birth rates are county-year level counts of live births to teens divided by the number of teens in the county year as determined by the ACS.

As a secondary source of information on teen pregnancies and birth rates I use the 2007-2012 Medicaid MAX data files which include the enrolment file and inpatient and outpatient claims data. Since FQHCs primarily serve Medicaid enrollees and the uninsured, potential impacts may be larger among this population. I restrict to beneficiaries who are not enrolled in a managed care plan since I do

not observe claims data for this group. This restriction, though necessary, is not trivial; about two thirds of Medicaid beneficiaries today are enrolled in a Medicaid Managed Care (MMC) plan.

A young woman is defined as having given birth during the year if she ever has an ICD-9 diagnosis code for delivery, complications related to delivery or immediate post-partum care. Birth is an indicator variable and does not take on different values if a woman had multiple births in the year. Pregnancy is defined as having birth indicator on or having ICD-9 code indicating pregnancy or complications related to pregnancy.

I may not observe all pregnancies; by definition I observe all pregnancies that end in an observable birth, however, I may not observe all pregnancies that end in miscarriage or abortion. This data limitation is not problematic as long as the likelihood of observing pregnancies that end in abortion or miscarriage does not change after an FQHC opening. This may not be the case however; FQHC providers may refer women to pre-natal care and hence increase the likelihood of observing pregnancy in the claims data. To the extent that this is true, this would tend to bias to the null any decreases in pregnancy I observe as a result of an opening. I aggregate these teen birth and pregnancy counts to the county-year level.

I do not use the number of teen enrollees as the denominator, since enrolment may be endogenous to these outcomes. For instance, eligible teens who may have otherwise not enrolled in Medicaid, may enroll once they are pregnant. In 2016, 10% of the uninsured population were CHIP eligible children.⁽⁶⁷⁾ I use predicted teen Medicaid enrolment to proxy for actual enrolment based on data from the control group and from the pre-opening period of the treatment group. (Described further in the next sections)

3.3 Contraception Use

I use information from 2007 to 2017 Medicaid claims data to track the use of different types of contraceptives following an FQHC opening. Using the diagnoses and procedure code-based definitions developed by the Department of Health and Human Services (HHS) (63), I identify individuals who have obtained an implant or an IUD. HHS also publishes a comprehensive list of NDCs representing oral contraceptives which I use to identify teen enrollees who had any fills for birth control medication during the year. I use the same denominator as for the birth and pregnancy rate analysis; a measure of predicted Medicaid enrolment.

3.4 High School Completion Rates

I construct male and female high school graduation rates using 2007 to 2017 data from the American Community Survey (ACS). High school non-completion is defined as individuals for whom the highest level of education attained was less than high school. The denominator is the number of females or males between 18 and 29 years of age in the county year also obtained from the ACS. Like the CDC NVSS data, the ACS also suppresses counties that have small populations.

Any effects on graduation rates may appear more clearly in the long-term since teenagers have to age into the 18 to 29 year old age group. For this reason, I use a longer time period of openings from the POS file, 1997-2018 in order to better observe any long-term effects. I collapse the data to two-year buckets, where the male and female drop-out rate is the weighted average of the drop-out rates across the two years.

4 Empirical Strategy

I study the effects of health center openings using an event study framework with time and county fixed effects. The event is defined as the first health center opening in a county. The study period begins in

2007 and ends in the last year for which I have information from each of my panel data sources.

Counties where an opening occurred before 2007 are dropped from the analyses.

Counties where an FQHC opened are likely different from those with no FQHCs; in particular, they may not be medically underserved. For this reason, I use counties with 'late openings' as a control group for relatively earlier openings in my study period. Specifically, I define counties that experienced a first opening between 2007 and 2012 as my treatment openings and counties that had an opening post 2012 as my control. Hence, my results are identified off the timing rather than the occurrence of an opening; the identifying assumption in this case is that the timing of openings are uncorrelated with factors that could affect the outcomes of study. In particular, if there were no FQHC opening, teen birth outcomes would have trended similarly in counties currently experiencing an opening compared to counties that have an opening in the future.

There are reasons to challenge this assumption; for instance, health center openings may occur as part of a local push to improve outcomes and may be part of range of new policies and institutions. I provide some qualitative and empirical evidence to support this assumption. Qualitatively, FQHCs are for the most part non-profit institutions that apply for FQHC designation to benefit from federal support and enhanced payment under Medicare and Medicaid. As such, the FQHC designation decision is more a private (non-profit) rather than a governmental one. Second, to the extent that the timing of openings is non-random it appears to be linked to large expansions in funding or coverage for instance, the largest increase in FQHC openings occurred in 2014 during Medicaid expansions – that are not correlated with nuances in local area conditions.

To empirically determine the appropriateness of this empirical strategy, I run placebo analysis using measures of insurance coverage, employment and income as dependent variables in an event study comparing the economic and coverage trends of counties that experienced a first opening between 2007

and 2012 to those whose first opening was post 2012. If these measures change differentially in treatment counties pre-opening then the timing of openings is predictable. Even if the timing is not predictable, an opening that appeared to lead to a large change in these measures is problematic for identification as there may be confounding contemporaneous changes at play. In section 5, I show that treatment and control counties trend similarly both before and after the FQHC opening suggesting that the timing of openings may be uncorrelated with area level trends that may themselves affect youth outcomes. When studying the impact on female high school graduation rates, I use male high school graduation rates as a placebo. A reduction in teen birth rates might be expected to have a larger impact on females' educational attainment compared to males'.

4.1 Empirical Model

My empirical strategy is a stacked difference-in-difference used by Deshpande, 2019 (68) and others (69;70). For each cohort of openings between 2007 and 2012, I use a control group of counties that opened more than five years later. For instance, for counties whose first FQHC opening was in 2007, I use counties that opened between 2013 and 2018 as the control group and for the 2008 treatment cohort I use counties with first openings in 2014 through 2018 as the control. I create this dataset for each cohort and append them. Since the control counties are required to have opened more than five years later, I do not have county-years that appear both in the treatment and control group.⁶ Event-study years that are more than five years post opening are dropped.⁷

My empirical strategy is outlined below.

⁶ This strategy does not require treatment and control counties to be mutually exclusive. Contexts in which the treatment group does span the control group would just necessitate the inclusion of a treatment dummy in equation (1)

⁷ since at six years post an opening in the treatment group there will be some counties in the control group that experience an opening

$$Y_{it} = a_i + \sum_{\tau} D_{t\tau} + \sum_{\tau} \beta_{\tau} [D_{t\tau} \times Treated_i] + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

Y_{it} is the outcome (e.g. teen birth rates or female high school graduation rates) for county i in year t . The γ_i are county fixed effects, and δ_t are year fixed effects. The $D_{t\tau}$ are indicators equal to 1 if year t is τ years after or before the first opening at the county level and 0 otherwise. The coefficients of interest are β_{τ} ; this describes how outcomes diverge with relation to the control group and pre and post the FQHC opening. If the treatment and control groups are trending similarly pre-opening we expect β_{τ} to be close to 0 for all event years pre the opening. I run pooled versions of this analysis with two periods: the short-term (0-2 years post opening) and the long-term (more than 2 years post opening). Standard errors are clustered at the county level.

I use the stacking approach where I have panel data of sufficient length; in particular the CDC data which spans eleven years (2007 to 2017) allows for this empirical approach. For the Medicaid claims based analyses, where I have fewer years of claims data (2007 to 2012) I use a standard control group set up; counties that opened past 2012 are the control for all treatment openings and I estimate the following model:

$$Y_{it} = a_i + \sum_{\tau} \beta_{\tau} [D_{t\tau} \times Treated_i] + \gamma_i + \delta_t + \varepsilon_{it} \quad (2)$$

As sensitivity, I compare counties where an FQHC opened to counties where an FQHC never opened. To do this, I estimate (2) where the control group is counties that never opened.

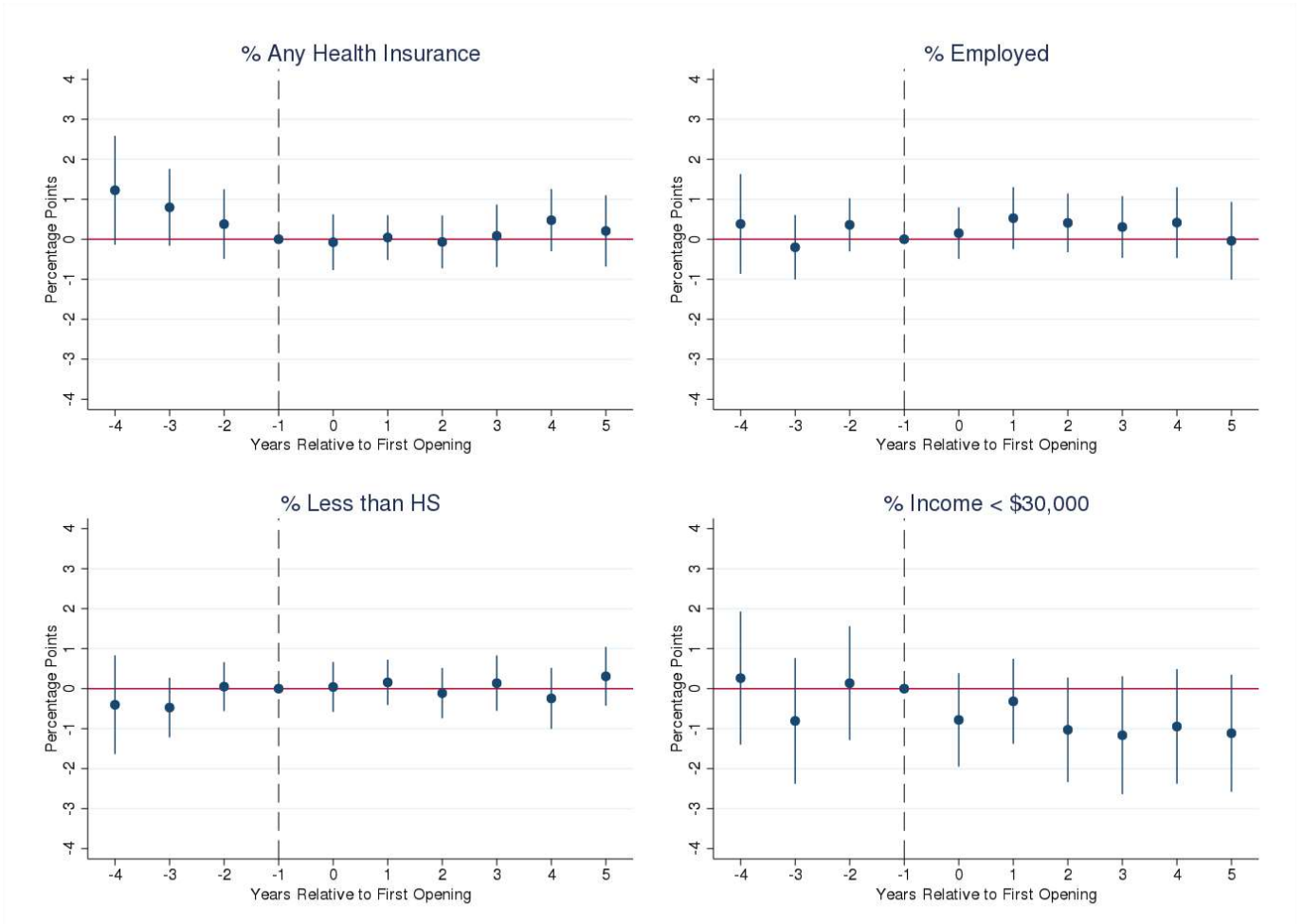
5 Results

Table 1 shows summary statistics and a t-test of the differences between counties with early openings compared to those with late openings. The former are counties where the first FQHC opened before or during 2012 and the second group are those whether the first FQHC opened after 2012. The counties represented in Table 1 are limited to those represented in the IPUMS data. There are a total of

687 counties that experienced a first opening between 2007 and 2018. Of these, 675 are represented in the Medicaid data, but much fewer are represented in the IPUMs/ACS and CDC data due to confidentiality restrictions. Table 1.1 presents the proportion of the county population in each race category, age group, income group, and health insurance type among other characteristics in 2008, which is the earliest year during the 2007-2018 study period for which the full set of demographic, health insurance, economic and education data are available. The two groups appear similar, with almost all the differences less than 1 percentage point and none of the differences significant.

It may be the case the two groups are similar in 2008, but trend differently. In particular, the timing of an opening may be correlated with factors affecting youth outcomes. To test this, I run my event study specification with various economic and coverage measures as the dependent variable. (Figure 1.2) The treatment group is counties where the first opening was before or during 2012, and the control group are counties where the first opening was later. The dependent variables are: the fraction of the county population with any health insurance coverage, the fraction that are employed and the fraction that did not graduate high school and finally the fraction with incomes below \$30,000. While FHQCs may be expected to impact some of these measures for instance they may enroll individuals in Medicaid or they may prevent pregnancies which may then affect educational and economic outcomes these effects are likely to be concentrated in a subset of the population or materialize in the long-term.

Figure 1.2: Placebo Analysis: Effects of Openings on Economics Measures



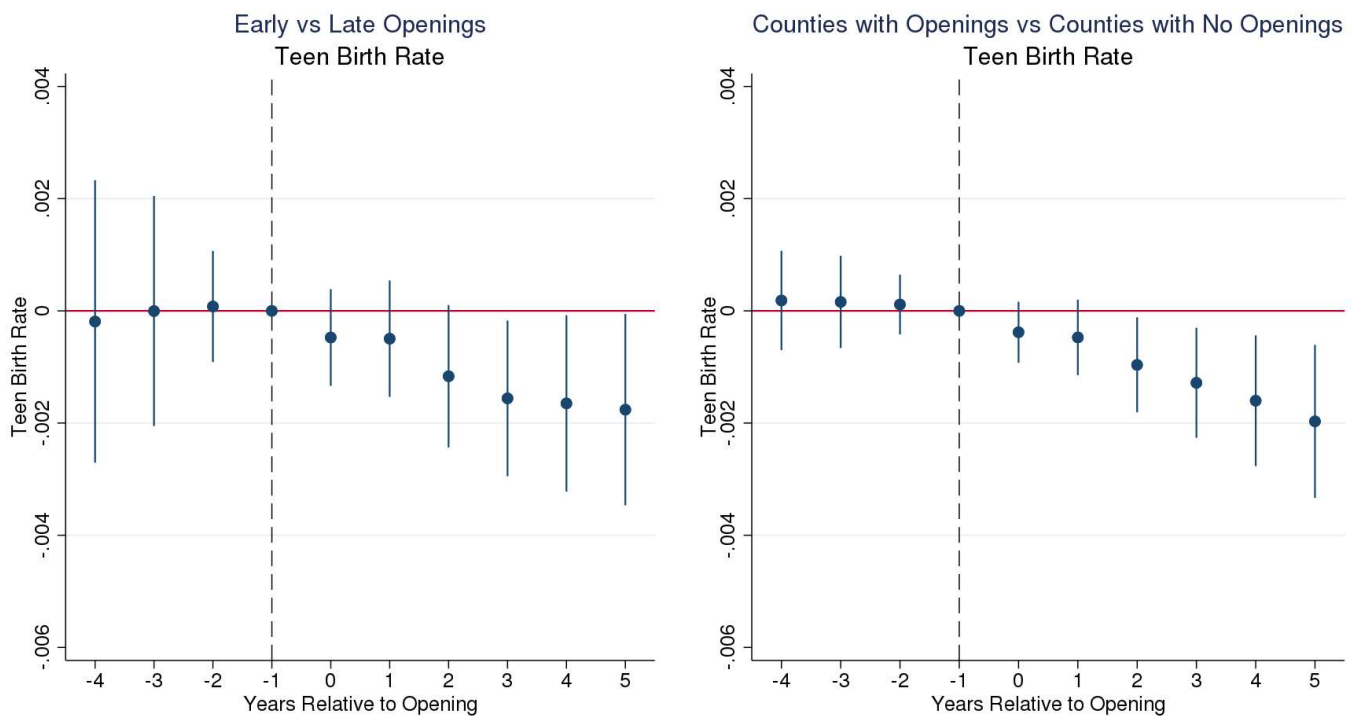
Notes: These figures plot estimates of the effect of openings on various placebo economic measures: i) the proportion of the county population with any health insurance coverage, ii) the proportion that are employed, iii) the proportion that did not graduate high school and iv) the proportion of that has incomes less than \$30,000. The left-out category is the year preceding the opening year.

Figure 1.2 shows relatively flat pre and post trends, implying that counties with early early openings are not trending differently to the control group before the opening of an FQHC with respect to these selected economic variables. In addition, the timing of openings do not coincide with an observable change in economic and policy conditions. Together, these provide suggestive evidence that the timing of FQHC openings is likely uncorrelated with other factors that may influence teen birth and pregnancy rates. I use counties that opened relatively later as the primary control group in the rest of the analyses.

5.1 Impacts on Overall Teen Birth Rates

I start by looking at overall teen birth rates (obtained from the CDC data based on birth certificates) and find that a health center opening is associated with clear declines in teen birth rates. The left panel in Figure 3 plots the event-study interaction coefficients from model (1). Since the control group experiences openings six or more years after the treatment group, event years that are after five years post the treatment group's FQHC opening are dropped. The effects on birth rates increase over time; representing a 0.18 percentage point and a 10% decline in birth rates three to five years post opening (Left panel of Figure 1.3, and Table 1.2, Column 4).

Figure 1.3: Effect of Openings on Teen Birth Rates using two Control Groups



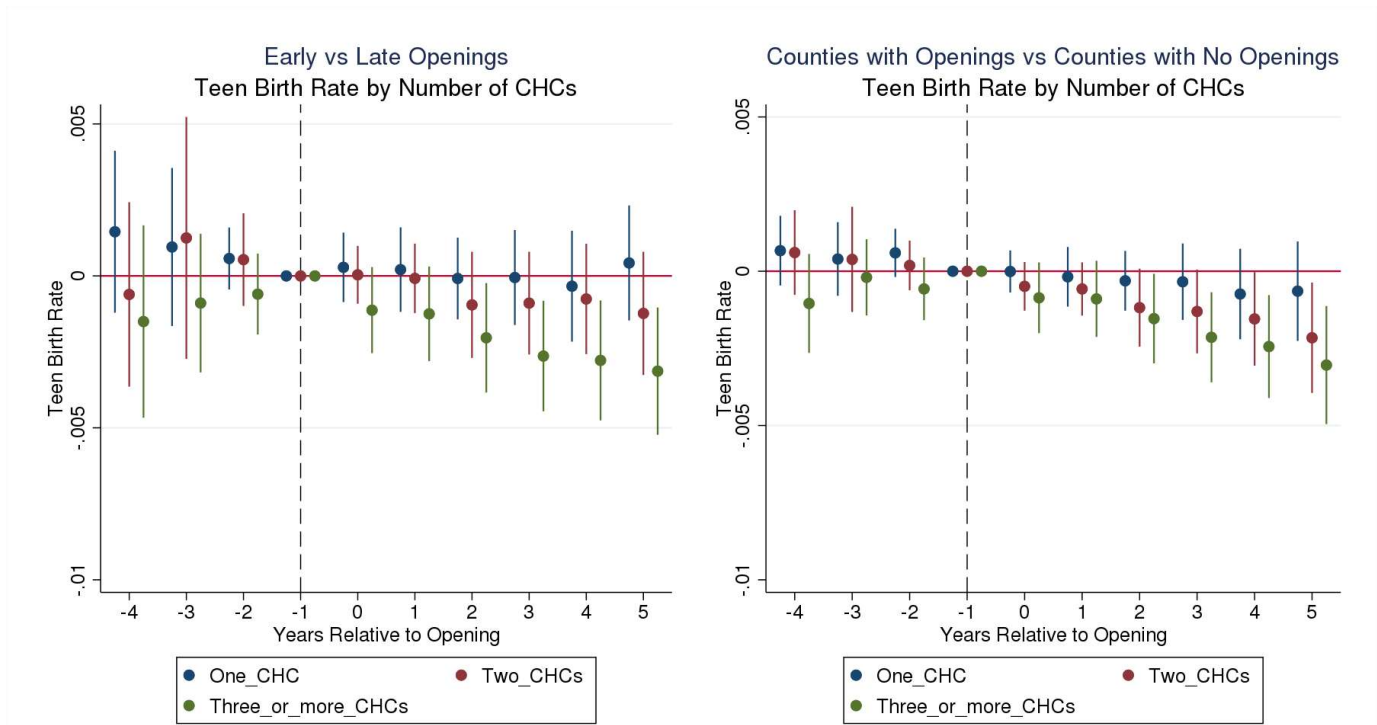
Notes: These figures plot estimates of the effect of openings on birth rates among women between 13-19 years of age for two control groups based on data from the CDC. The figure on the left compares counties whose first opening was early in the study period to counties where FQHCs opened later while the figure on the right compares counties where an FQHC opened

to those where an FQHC never opened. Specifically, the figure on the left plots β_t from equation (1), which is a regression of teen birth rates on calendar year and county fixed effects and event study years. The treatment group are the set of counties whose first opening occurred between 2007 and 2012 and the control group are counties whose first opening was at least five years later. The figure on the right plots β_t from equation (2) which is a regression of teen birth rates on county and calendar year fixed effects. For the latter specification, event-years -4 through 5 are plotted for easier comparison between figures. The left-out category is the year preceding the opening year.

As sensitivity, I run my analyses using counties where no FQHC opened as the control group (rather than counties where an FQHC opened later). The right panel in Figure 1.3, plots the β_t from model (2). Despite the fact that counties with FQHCs are likely different to those with none, the two groups have similar trends in teen birth rates prior to the FQHC opening. As with the main results, there is a monotonic decline in birth rates reaching statistical significance three years after the opening onward. The effect sizes are remarkably similar across both control groups (late openings and no openings) both showing a decline of about 0.2 percentage points five years post opening.

The impact on teen birth rates is heterogenous by intensity of treatment, as proxied for by FQHC penetration and receipt of Title X funds. Compared to counties with only one opening during the study period, counties that experienced subsequent health center openings experienced larger declines in teen birth rates and the largest decreases were among counties with three or more openings in total. (Figure 1.4). In counties with at least one subsequent opening, teen birth rates declined by 12% to 13% 3+ years post the first opening, relative to counties with late openings and counties with no openings respectively. (Table 1.2). In fact, the impacts on teen birth rates are concentrated in counties that had at least one other opening and are not significantly different from zero in counties that only have one opening, even several years after the opening. These findings imply that there may be more than an additive effect of a second FQHC opening; potentially there is greater awareness of FQHC services after a subsequent opening. In addition, FQHC delivery sites that open near an existing site are often part of the same center (i.e. they are owned by the same organization). There may be a critical size in terms of staffing and infrastructure that allows for better family planning service provision.

Figure 1.4: Effect of Openings on Teen Birth Rates by Number of FQHCs in the County



Notes: These figures plot estimates of the effect of openings on birth rates among women between 13-19 years of age for two control groups based on data from the CDC for each of three groups : i) counties where only one FQHC opened, ii) counties where two FQHCs opened and iii) counties where three or more FQHCs opened, between 2007 and 2017. The figure on the left compares counties whose first opening was early in the study period to counties where FQHCs opened later while the figure on the right compares counties where an FQHC opened to those where an FQHC never opened. Specifically the the figure on the left plots the three sets of $\beta\tau$ from equation (1), which is a regression of teen birth rates on calendar year and county fixed effects and event study years. The treatment group are the set of counties whose first opening occurred between 2007 and 2012 and the control group are counties whose first opening was at least five years later. The figure on the right plots the three sets of $\beta\tau$ from equation (2) which is a regression of teen birth rates on county and calendar year fixed effects. For the latter specification, event-years -4 through 5 are plotted for easier comparison between figures. The left-out category is the year preceding the opening year.

Table 1.2: Pooled Results for Teen Birth Rates CDC

	CDC: Openings vs No Openings			CDC: Early vs Late Openings		
	(1) All	(2) 1 FQHC	(3) > 1 FQHCs	(4) All	(5) 1 FQHC	(6) > 1 FQHCs
0-2 years	-0.0003 (0.00)	-0.0005 (0.00)	-0.0004 (0.00)	-0.0007 (0.00)	-0.0004 (0.00)	-0.0009 (0.00)
3+ years	-0.0014** (0.00)	-0.0009 (0.00)	-0.0020** (0.00)	-0.0018* (0.00)	-0.0006 (0.00)	-0.0023** (0.00)

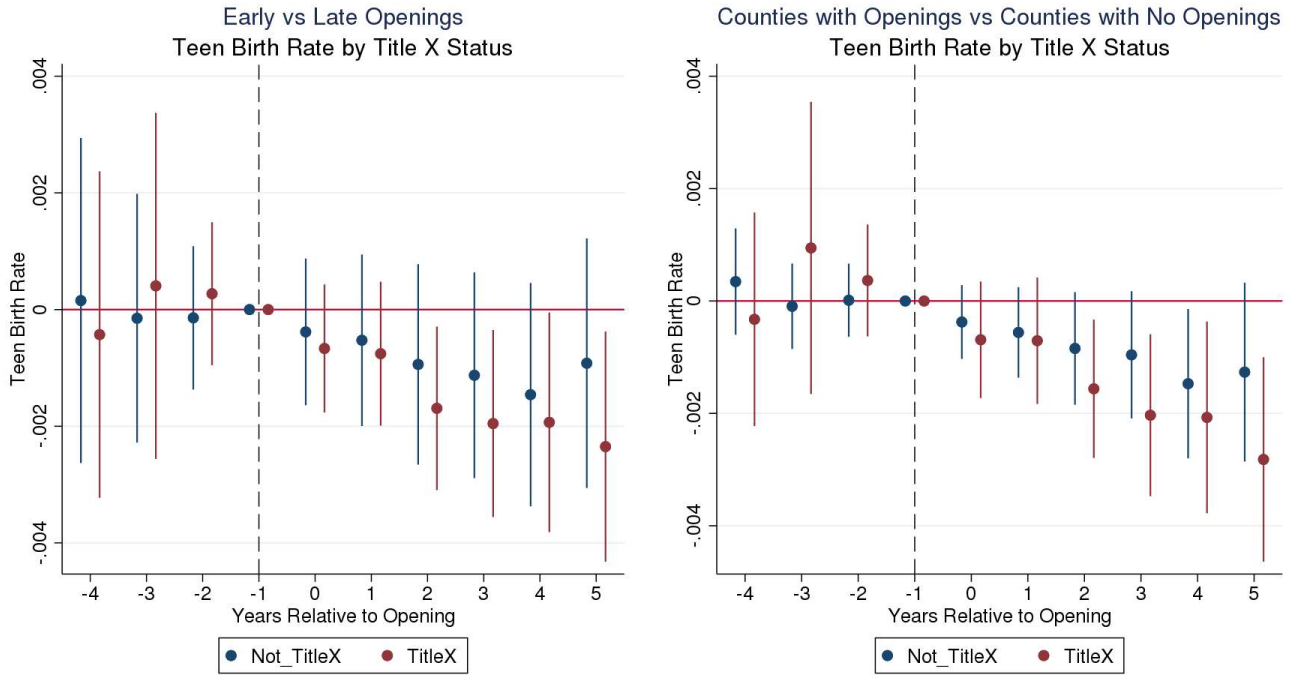
Constant	0.0191*** (0.00)	0.0168*** (0.00)	0.0196*** (0.00)	0.0192*** (0.00)	0.0186*** (0.00)	0.0182*** (0.00)
Treated pre-opening mean	0.016	0.014	0.017	0.018	0.017	0.018
Observations	1647.0	851.0	1192.0	1380.0	883.0	1135.0

* p<0.10, ** p<0.05, *** p<0.001

Notes: The first set of columns presents estimates from the pooled regression comparing counties where an FQHC opened between 2007 and 2012 to counties where an FQHC opened at least five years later. The second set of columns presents estimates from the pooled regression comparing counties where an FQHC opened to those where an FQHC never opened. The first row represents estimates from the interaction of the treated dummy with a short-term post dummy (which equals 1 for in the opening year and up to two years post the opening year and is zero otherwise). The second row represents the interaction of the treated dummy with a long-term post dummy which equals 1 for calendar years that are at least three years post opening and is zero otherwise. The second and fifth column is restricted to counties where only one FHQC opened during the study period (2007-2012) and the third and sixth column is restricted to counties where at least one other FQHC opened after the first FHQC opening. The "Treated pre-opening mean" is the mean teen birth rate for the event years pre the first FQHC opening

Receipt of Title X funding is a strong predictor of LARC availability onsite, well trained staff, the presence of a drop-in center and collaborations with other entities for family planning service provision (15). A quarter of FQHCs receive Title X funding (in addition to Section 330 funding and enhanced Medicare and Medicaid payments) and must adhere to detailed family planning requirements. Compared to other FQHCs, Title X funded health centers are much more likely to offer all seven of the most effective contraceptive methods onsite. Title-X funded clinics are also more likely to incorporate evidence-based best practice methods relating to screening, counseling and contraception initiation (15). In line with this, these clinics are able to achieve larger improvements in teen outcomes. First FQHC openings that receive Title X funds achieve a 12% reduction in teen birth rates 3-5 years post opening (Figure 1.5).

Figure 1.5: Effect of Openings on Teen Birth Rates by receipt of Title X Funds



Notes: This figure plots estimates of the effect of openings on birth rates among women between 13-19 years of age for two control groups based on data from the CDC for : i) counties where the opening FQHC received Title X funds ii) counties where the opening FQHC did not receive Title X funds. The figure on the left compares counties whose first opening was early in the study period to counties where FQHCs opened later while the figure on the right compares counties where an FQHC opened to those where an FQHC never opened. Specifically the figure on the left plots the two sets of $\beta\tau$ from equation (1), which is a regression of teen birth rates on calendar year and county fixed effects and event study years. The treatment group are the set of counties whose first opening occurred between 2007 and 2012 and the control group are counties whose first opening was at least five years later. The figure on the right plots the two sets of $\beta\tau$ from equation (2) which is a regression of teen birth rates on county and calendar year fixed effects. For the latter specification, event-years -4 through 5 are plotted for easier comparison between figures. The left-out category is the year preceding the opening year.

5.2 Impacts on Teen Birth Rates in Medicaid

The Medicaid population is potentially more likely to be impacted by FQHC services. First, teen birth rates are higher among low-income populations (71). Second, Medicaid enrollees may face significant barriers to health care access; either because providers are unwilling to accept their insurance or because there are health care professionals shortages where they live (10;11;12)

By statute, FQHCs may only locate in federally designated medically underserved areas and are required to provide services to all patients regardless of ability to pay. In addition, Medicaid is

required to cover services furnished by FQHCs (72), which potentially reduces the risk of claims denial relative to other providers who see Medicaid patients.⁸

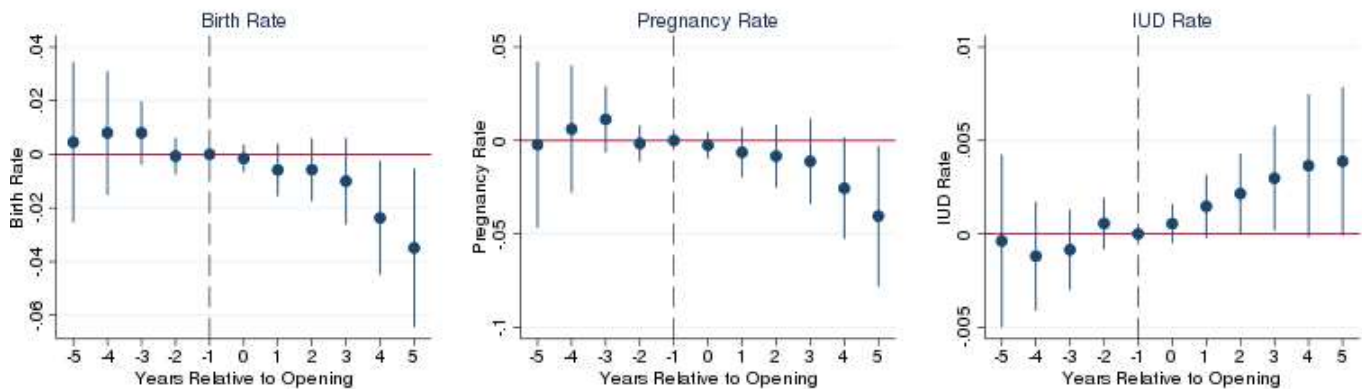
I use 2007 through 2012 county level teen birth and pregnancy rates among Medicaid beneficiaries based on claims data to evaluate the impact of FQHC openings among this population. The control group is defined as counties that experienced a first opening post 2012 while treatment counties experience first FQHC openings before or during 2012. The teen birth rate among this population is very high; 8.7% of teen enrollees per year. However, they are in line with estimates among other at risk groups. In 2009, teen birth rates were above 6% in several southern states and above 7% among all Hispanic teens. (34). Medicaid eligible teens have arguably higher risk of pregnancy and birth, (71). Finally, the endogeneity of enrollment in Medicaid to pregnancy (that is, pregnancy may induce teens who otherwise may not have enrolled to enroll in Medicaid) could contribute to elevated teen birth rates among teen Medicaid enrollees.

The probability of Medicaid enrolment could change as a result of an FQHC opening. First, as mentioned, if enrollment is endogenous to pregnancy, a change in the teen pregnancy rate may lead to a change in the teen enrolment rate. Second, FQHCs may help to enroll eligible teens into Medicaid. For this reason, I use an alternate measure as the denominator for the Medicaid teen and pregnancy rates. This is a predicted enrolment measure which uses control group data and pre-opening treatment group data to proxy for enrolment. In particular, I regress Medicaid teen enrolment on county and state by year dummies and use the predictions from this model as the denominator for the Medicaid teen birth and pregnancy rates.

⁸ Denial rates have been linked to provider willingness to see Medicaid patients. Reducing or eliminating this risk may lead to greater health care access among Medicaid populations. (73)

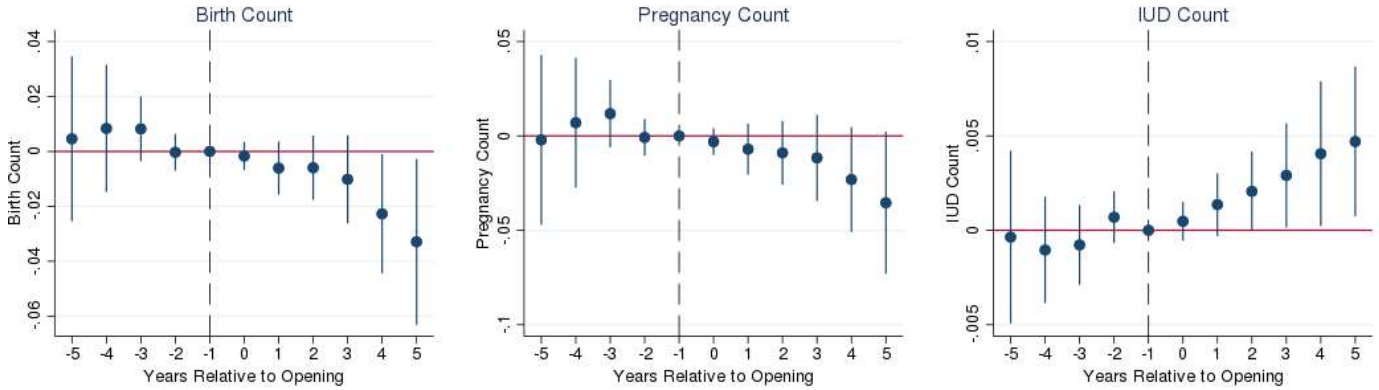
Figure 1.6 plots the event-study coefficients from model (2) for the Medicaid population. While the standard errors are large, there is suggestive evidence that health center openings are associated with monotonic declines in teen birth and pregnancy rates. As with the overall results, counties that experience more than one FQHC opening experience greater declines in teen pregnancy and birth rates in the Medicaid population, both in absolute and relative terms. Teen pregnancy rates decline by about 20% in counties with more than one opening. I also estimate a version of the event study using the county level counts of teen births and pregnancies (Figure 1.7) and controlling for the actual number female teen Medicaid enrollees. The results are very similar to those described.

Figure 1.6: Effect of Openings on Teen Pregnancy, Birth rates and Take up of Contraceptives



Notes: These figures plot estimates of the effect of openings on pregnancy and birth rates and take up of contraceptives among females in Medicaid between 13-19 years of age. Specifically the figures plot $\beta\tau$ from equation (2) which is a regression of teen birth rates on event study years with county and state by year fixed effects. Pregnancy and birth are defined using ICD 9 diagnoses codes from the inpatient and outpatient claims data. Intrauterine Device (IUD) and birth control use is identified using HHS developed definitions of contraceptive use. The denominator is predicted medicaid enrollment. The left-out category is the year preceding the opening year.

Figure 1.7: Effect of Openings on Teen Pregnancy, Birth Counts and Take up of Contraceptive



Notes: These figures plot estimates of the effect of openings on pregnancy, birth counts and contraceptive use among females in Medicaid between 13-19 years of age. Specifically the figures plot $\beta\tau$ from equation (2) which is a regression of teen birth rates on event study years with county and state by year fixed effects and in addition controls for the actual number of Medicaid female teen enrollees in the county-year. Pregnancy and birth are defined using ICD 9 diagnoses codes from the inpatient and outpatient claims data. The left-out category is the year preceding the opening year.

Table 1.3: Pooled Results for Teen Birth Rates Medicaid

	Birth Rate		Pregnancy Rate		IUD Rate		Rx Rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	> 1 FQHCs	All	> 1 FQHCs	All	> 1 FQHCs	All	> 1 FQHCs
0-2 years	-0.0035 (0.01)	-0.0193** (0.01)	-0.0046 (0.01)	-0.0258** (0.01)	0.0011 (0.00)	0.0042** (0.00)	0.0073* (0.00)	0.0052 (0.01)
3+ years	-0.0151 (0.01)	-0.0406** (0.02)	-0.0163 (0.01)	-0.0535** (0.02)	0.0033* (0.00)	0.0062** (0.00)	0.0054 (0.01)	0.0018 (0.01)
Constant	0.0803*** (0.00)	0.0903*** (0.00)	0.1445*** (0.00)	0.1607*** (0.00)	0.0079*** (0.00)	0.0082*** (0.00)	0.1235*** (0.00)	0.1330** (0.00)
Treat pre-opening mean	0.087	0.144	0.151	0.245	0.006	0.009	0.116	0.181
Observations	3120.0	2274.0	3120.0	2274.0	3120.0	2274.0	3120.0	2274.0

* p<0.10, ** p<0.05, *** p<0.001

Notes: This table shows the results from the pooled regressions on Medicaid data comparing counties where the first FQHC during or before 2012 to those where the first FQHC opening was post 2012 (the control group). Columns 1,3,5 and 7 shows estimates among all counties represented in Medicaid that have non-zero teenage enrollees. Columns 2, 4, 6 and 8 restrict to counties where more than one FQHC opened during the study period (between 2007 and 2012). The birth and pregnancy counts were defined based on ICD 9 diagnoses codes in the inpatient and outpatient claims data. Use of IUDs was captured using ICD 9 diagnosis and procedure codes in the outpatient file as per the HHS definition. Birth control medication claims were captured using the drug component of the claims files. The 'Rx Rate' represents extensive margin use of birth control, i.e, the proportion of female teens who had any birth control fills during the year. The "Treated pre-opening mean" is the mean teen birth rate for the event years pre the first FQHC opening.

5.3 Mechanisms

A recent large scale survey finds that decline in teen pregnancy rates between 2003 and 2010 is largely due to greater contraceptive use rather than teens delaying sex (35). FQHCs may have contributed to the decline in a number of ways; through the provision of traditional or modern contraceptives, as well as outreach and education. The provision of translation and transport services, outreach and education and confidentiality protections for minors may also contribute to increasing health care and contraceptive access among youth. This section explores this question further by studying the extent to which use of birth control medication and of LARCs (including intrauterine devices and implants) changes after an FQHC opens in a county.

I follow the HHS definitions for these categories of contraception (74). I find no effects on the use of implant but substantial increases in intrauterine device (IUD) use and a suggestive increase in the proportion of female teens who had any birth control fills in the years post opening (Figure 1.6, Table 1.3). IUD use increases by 47% 3-5 years post opening with larger and more significant increases in counties with multiple FQHCs at 69% (Table 1.3). The increase in IUD use can account for roughly 15-20% of the observed decline in birth rates among the Medicaid population. The CDC has documented a substantial rise in LARC use (from 0.4% in 2005 to 7.1% in 2013) among low income adolescent users of Title X services (33). FQHCs and non-FQHC Title X providers have likely played a large role in driving these recent trends.

In counties with more than one FQHCs these effects are larger in absolute terms and similar in relative terms. A version of the specification using county level claim counts for IUD and birth control

medication and controlling for the actual number female teen Medicaid enrollees also shows similar results⁹ (Figure 1.7).

5.4 High School Graduation Rates

Teen pregnancy has been cited as one of the primary reasons for high school drop-out. Therefore, a decrease in teen fertility rate might be expected to translate into higher graduation rates. On the other hand, given the large secular declines in teen pregnancy, it is possible that teenagers likely to become pregnant today experience different treatment effects to contraception provision compared to estimates based on the contraception revolution literature. Perhaps they may have dropped out anyway, or they dropped out first and then became pregnant.

I find no statistically significant effect on the overall proportion of men and women between 18 and 29 years of age who did not complete high school. However, when I focus on counties where other FQHCs opened after the initial opening I find an increase in high school completion rates among young women. This is perhaps not surprising given that the largest decreases in teen birth rates occur in counties that experienced subsequent openings. There is no contemporaneous effect on male completion rates in these counties (those with more than one FQHC), potentially indicating prevented pregnancy as the primary mechanism for the change among women. Figure 1.8 shows the effects of FQHC openings on the proportion of females between 18-29 years of age who did not complete high school for counties where one, two and more than two FQHCs opened. In particular, it plots estimates from the interaction terms of model (2).¹⁰

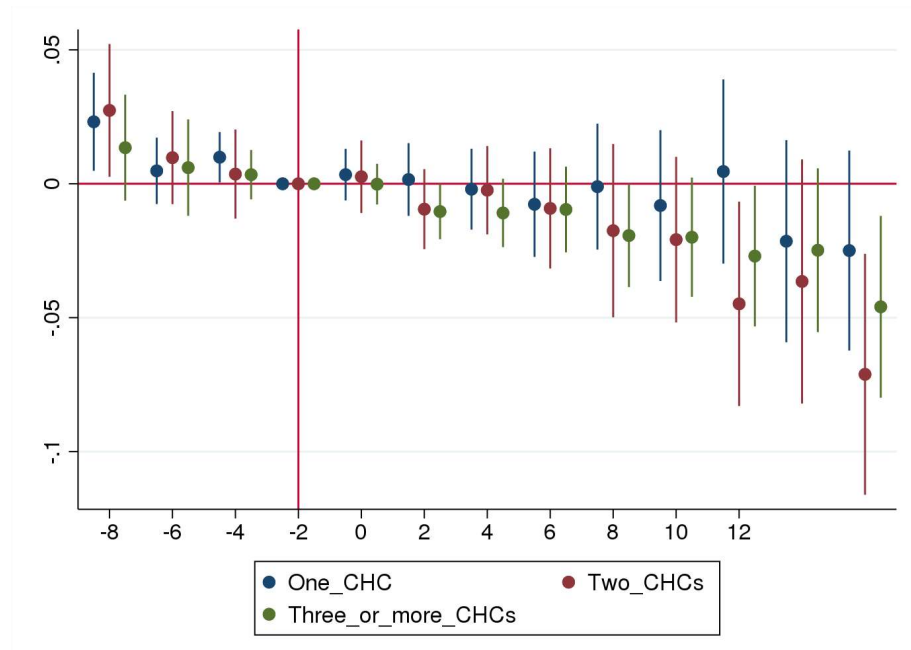
⁹This sensitivity analysis aims to ascertain that the results in the main specification are not very sensitive to the denominator which is predicted teen Medicaid enrollment.

¹⁰ Empirical approach (1) is not ideal for this analysis because in approach (1) each cohort is constrained to a post period of the same length. Hence, requiring a long post period reduces the amount of identifying variation, by restricting the number of cohorts used to those at the start of the study period

Effects on graduation may only materialize in the long terms since it takes five years for a cohort of teens to age into the 18-29 year old age bucket and also FQHC treatment effects on birth rates are small in the short term but increase over time. For this reason, this analysis includes openings pre-2007 (from 1997 onwards) and collapses event-years to two-year buckets to capture potential long-term effects.

The event study plots are noisy but indicate that female drop-out rates decline after an opening and decline more in counties with more FQHCs (Figure 1.8). Table 1.4 shows the post period interactions for this event study, for all counties and for the set of counties where more than one FQHC opened. Between eight to sixteen years after an opening, there is 17%-28% decline in the proportion of women between 18 and 29 years of age who have not graduated high school and no statistically significant change in the proportion of 18-29 year old males who did not graduate high school in these counties.

Figure 1.8: Effect of Openings on Female High School Drop-out Rates



Notes: This figure plots estimates of the effect of openings on Female High School drop-out rates, where the treatment

group is all counties where the first FQHC opening is between 2000 and 2014 and the control group are counties where the first FQHC Opening was post 2014. Specifically the figures plot β_τ from equation (2) which is a regression of drop-out rates on event study years with county and state by year fixed effects. This figure present results for three groups; i) counties where only one FQHC opened during the study period, ii) counties where one one other FQHC opened and iii) counties where at least two other FQHCs opened post the first opening. Data is collapsed into two year buckets and the left-out category is 2 years before the first opening.

Table 1.4: Effect of Openings on Male and Female High School Drop-out Rates

	Female Drop-out Rate		Male Drop-out Rate	
	(1) All	(2) > 1 FQHCs	(3) All	(4) > 1 FQHCs
0-2 years	0.0004 (0.00)	0.0019 (0.00)	-0.0019 (0.00)	0.0011 (0.00)
2-4 years	-0.0059 (0.00)	-0.0087* (0.01)	-0.0099* (0.01)	-0.0059 (0.01)
4-6 years	-0.0075 (0.01)	-0.0101 (0.01)	-0.0125* (0.01)	-0.0056 (0.01)
6-8 years	-0.0098 (0.01)	-0.0109 (0.01)	-0.0135 (0.01)	-0.0057 (0.01)
8-10 years	-0.0146 (0.01)	-0.0208** (0.01)	-0.0161 (0.01)	-0.0111 (0.01)
10-12 years	-0.0184 (0.01)	-0.0238* (0.01)	-0.0164 (0.01)	-0.0083 (0.01)
12-14 years	-0.0244* (0.01)	-0.0353** (0.01)	-0.0227 (0.02)	-0.0186 (0.02)
14-16 years	-0.0267* (0.02)	-0.0339** (0.02)	-0.0245 (0.02)	-0.0149 (0.02)
Constant	0.1165*** (0.00)	0.1232*** (0.01)	0.1588*** (0.01)	0.1593*** (0.01)
Treated pre-opening mean	0.112	0.121	0.156	0.166
Observations	1666.0	1147.0	1666.0	1147.0

* p<0.10, ** p<0.05, *** p<0.001

Notes: The first set of columns presents estimates from post period interactions of the event-study comparing counties where the treatment group is all counties where the first FQHC opening is between 2000 and 2014 and the control group are counties where the first FQHC Opening was post 2014. Specifically the figures plot β_τ from equation (2) which is a regression of drop-out rates on county and state by year fixed effects. Data is collapsed into two year buckets and the left-out category is 2 years before the first opening.

6 Discussion

The location of an individual’s childhood years has large causal effects on future outcomes, as highlighted by recent literature (75;76). In fact place can account for at least half of the variation in

intergenerational mobility across counties. Neighborhoods predictive of greater mobility share common observable features such as better schools and less concentrated poverty, however many place predictors are less well understood and are not captured by location rents. (75;76). Institutions such as FQHCs that impact childhood environment may play a substantial role in driving adult outcomes.

In this paper, I study the effect of a first FQHC opening on teen birth rates and educational attainment. I find that openings lead to a 10% decline in teen birth rates with larger effects among low income populations, in counties where other FQHCs subsequently opened and for Title X funded centers. Contraceptive provision by FQHCs to low-income adolescents appear in Medicaid claims data and show an increase in the years after the opening particularly for LARC methods. The declines in teen births translate into gains in education; in counties where teen births decreased the most there is a reduction in the proportion of young women who did not complete high school. There is no change in this proportion among young men.

The last three decades have seen large declines in teen birth rates and recent survey data attribute this change largely to an increase in contraceptive use. Between 2007 and 2017, teen birth rates declined by 1.13 percentage points in counties that experienced an opening between 2007 and 2012. Given that FQHC openings lead to a 0.2 percentage point reduction in the teen birth rate three to five years post opening, a rough back of the envelope calculation implies that FQHC openings between 2007 and 2012 accounted for 18% of the decline in teen birth rates in these counties. This proportion is likely conservative because it does not account for the continued and increasing effects on teen birth rates beyond five years post opening, i.e. openings in 2007 are likely to have achieved greater than a 0.2 percentage point decline by 2017.

These results have several implications for policy. First, they shed light on some of the institutional drivers of the declines in teen birth rates in the U.S. over the last two decades. Second, they

highlight that coverage alone does not guarantee access. While almost all adolescents are insured, only 25% of sexually active students in 2013 reported that either they or their partner had used any of the following forms of contraception; birth control pills, an IUD, an implant, a patch or birth control ring, before last sexual intercourse (77).¹¹ Health centers with same day consultations, easy access to contraceptives and confidentiality protections for minors may facilitate more frequent use of contraceptives. Third, the heterogeneity of effects by number of FQHCs imply there may be a multiplier effects to safety providers co-locating; perhaps due to capacity constraints or in cases where the providers are part of the same organization, due to size and infrastructure requirements for effective service provision.

Differential declines and large disparities in teen birth rates by race and state are also a persistent concern, especially given potential inter-generational impacts. Gaining a deeper understanding of the factors behind low rates of contraceptive use and the characteristics of marginal teens affected by greater access is a natural avenue for future work.

¹¹ Although reported condom use is higher at about 60%.

Chapter 2: Physician handoffs and patient mortality

Monica Farid and Professor Anupam B. Jena

1. Introduction

Transitions of patient care, or handoffs, have been associated with greater adverse events, preventable medical errors, and costs (78;79;80;81;82;83;84). Although handoffs occur in a number of medical settings, their impact has primarily been studied and associated with adverse events and errors with trainees. (82;84) Interventions to improve the safety and efficacy of handoffs, (85;86;87;88) including a large multi-center study which implemented and analyzed the effects of patient safety training and a structured handoff tool (89) have similarly focused on resident physicians.

Handoffs are ubiquitous in the clinical practice that occurs once physicians complete their residency training and yet limited large-scale data exists on the relationship between physician handoffs and patient outcomes outside the trainee setting (90). The absence of empirical evidence on this relationship is particularly important since the structured emphasis on safe handoffs that routinely occurs in residency programs may infrequently carry forward once physicians enter independent practice, though the same safety considerations remain.

An important setting where handoffs commonly occur is inpatient care provided by hospitalist physicians (91). Hospitalists – usually, general internists who specialize in hospital-based care – provide the majority of inpatient general medical care in the U.S. and typically work contiguous days in which handoff of patients to another physician occurs at the end of a scheduled block. Using data on Medicare beneficiaries hospitalized with a general medical condition and treated by a hospitalist physician during 2008-2012, we analyzed the relationship between physician handoffs and patient mortality by comparing outcomes of patients admitted at the beginning versus the end of a scheduled

work block, at which point a handoff to another physician would be more likely. Based on prior studies and the way in which patients are typically assigned to hospitalist physicians (92;93;94;95), we hypothesized that patients treated by a given hospitalist at the beginning versus the end of a scheduled work block would otherwise be similar on both observable and unobservable characteristics that are correlated with mortality, a quasi-experimental analysis.

2. Methods

Study Sample and Data Sources

We identified all acute care hospitalizations of a 20% random sample of Medicare fee-for-service beneficiaries aged ≥ 65 years during 2008-2012 using the Medicare Provider Analysis and Review (MedPAR) files linked by beneficiary ID to the 20% Medicare Carrier files. We supplemented these data with annual Beneficiary Summary Files, which include demographics and chronic illness diagnoses. We focused on hospitalizations that involved a general medical, rather than surgical, condition (as defined by the presence of a medical diagnosis related group [MS-DRG] on admission) and in which care was provided by a hospitalist.

We first used established methods to assign an attending physician to each hospitalization based on the physician National Provider Identifier (NPI) in the Carrier File that accounted for the most Part B spending (evaluation and management (E&M) services, tests, procedures) during that hospitalization (92;94;95;96). We then identified those hospitalizations for which the attending physician was a hospitalist, using a validated approach to define hospitalists: general internists with at least five evaluation-and-management billings in a given year who filed at least 90% of their total Evaluation and Management (E&M) billings in an inpatient setting. This claims-based approach has been previously validated by calling physicians to confirm that they were hospitalists (sensitivity, 84%; specificity, 97%;

positive predictive value, 89%) (97). We restricted hospitalizations to those that were 14 days or less to reduce the possibility of multiple handoffs occurring during a given hospitalization due to the hospitalization spanning scheduled work blocks of multiple hospitalist physicians.

Study Outcomes

The primary outcome was 30-day mortality, defined as death within 30 days of hospital admission. Secondary outcomes included 60-day, 180-day and 1-year mortality, chosen to evaluate whether any potential short-term effect of handoffs on patient mortality was simply to hasten deaths that would otherwise have occurred in the subsequent several months.

Identification of handoffs

A simple comparison of mortality rates between patients with and without handoffs would be confounded by the fact that patients with longer length of stay, often due to underlying disease severity that is correlated with mortality, are more likely to experience handoffs. We addressed this issue by analyzing whether patient mortality varied according to date of admission relative to the assigned hospitalist's last working day in a given shift block, hypothesizing that otherwise similar patients admitted towards the end of a physician's shift block would be more likely to be handed off to another physician compared to patients admitted earlier in the shift block.

For each hospitalist in our data, we used the Carrier File to identify their last day of work in a possible shift block by isolating those inpatient E&M visits in which no inpatient billing was observed by that provider in the Carrier File in the subsequent 7 consecutive days (in a sensitivity analysis this threshold was lowered to 5 days, see Supplementary Appendix). The calendar dates of these E&M visits were assumed to reflect the last day of a possible shift block for each hospitalist. For each hospitalization, we then defined a distance measure that was equal to the difference between the patient

admission date and the last working date of the admitting hospitalist for their presumed shift block. For instance, if a patient was admitted May 16, 2010 and the admitting physician filed inpatient E&M claims on May 16 and 17 but not May 18 onwards, the distance measure would be 2 days, reflective of when a patient was admitted relative to the hospitalist's last working day in a given shift block (in this example, May 17). Given that the average length of stay of patients in the study population was 3.6 days, a patient admitted on May 16 would, on average, be substantially more likely to be handed off to a second physician than an otherwise similar patient admitted by that same hospitalist on May 10.

Patient Covariates

Covariates included patient sex, age, ethnicity/race, indicators for 11 chronic conditions obtained from the Medicare Chronic Condition Data Warehouse, and admission Diagnosis Related Group (DRG); indicator variables for day of week of admission, included to allow for the possibility that the day of week a patient was admitted may be correlated with mortality (98); indicator variables for calendar year to account for secular trends in patient mortality; and hospital fixed effects, or hospital-specific indicator variables, included to account for time-invariant hospital factors that may be correlated with patient mortality (our analysis therefore compared mortality rates of patients admitted at the beginning versus the end of hospitalists' scheduled work blocks within the same hospital).

Statistical Analysis

We began by plotting the probability of physician handoff as a function of the date of patient admission relative to the last working day of the admitting hospitalist in their respective shift block, hypothesizing that patients admitted just prior to the hospitalist's last day would be substantially more likely to experience handoff compared to patients admitted earlier in the shift block.

We then compared characteristics of patients who were admitted near the end of a hospitalist's shift block (specifically, days -1/-2, the 2 days prior to day 0, the last working day) versus early in the block (specifically, six or seven days prior, days -6/-7) to assess for whether significant clinical differences existed in the types of patients who would be more likely to be handed off to another clinician (i.e., those patients admitted just before the shift block ended). In addition to comparing patient demographics and comorbidities, we also compared the probability distributions of admission DRG between both groups (an approach used in prior studies) in order to assess whether reason for hospitalization differed between patients admitted towards the beginning versus the end of a hospitalist shift block (99;100).

We next estimated the relationship between a patient's date of admission relative to a hospitalist's last working day in a shift block and mortality risk. We estimated a hospitalization-level multivariable linear regression model in which the dependent outcome was 30-day mortality and the key independent variables were a set of relative date indicators (i.e., indicator variables for day -1, day -2, etc., until day -7), with other covariates described above. We plotted adjusted 30-day mortality rates according to the date a patient was admitted relative to a hospitalist's last working day. We estimated linear models due to a failure of logistic regressions to converge with indicator variables for over 500 DRGs and 4,500 hospitals (in a sensitivity we estimated logistic models excluding hospital fixed effects).

To facilitate interpretation in both the overall analysis and in sub-group analyses, we also estimated a hospitalization-level multivariable linear regression model in which the outcome variable was 30-day mortality (secondary outcomes included 60-day, 180-day and 365-day mortality) and the key independent variable was a binary indicator for whether a patient was admitted in the two days prior to the admitting hospitalist's last working day in a shift block (i.e., days -1/-2) versus the six or seven

days prior (days -6/-7), with other covariates described above, and model interactions described below. The model was first estimated for the sample overall and then in two sub-group analyses: (1) patients in the top versus bottom quartile of predicted mortality risk, as estimated by a multivariable linear probability model of 30-day mortality as a function of patient demographics, DRG, and comorbidity indicators, an analysis conducted to assess whether any adverse effect of handoffs was larger for patients with greater mortality risk; (2) according to teaching hospital status (identified from the 2015 American Hospital Association Annual Survey), an analysis conducted to determine whether the relationship between physician handoffs and patient mortality varied according to whether trainees were involved in care and therefore in handoffs, as might occur in resident services of teaching hospitals. A formal test of interactions was performed in these sub-group analyses.

Analysis were performed in SAS and Stata (v. 14). The 95% confidence interval around reported estimates reflects 0.025 in each tail or $P \leq 0.05$. The study was approved by the institutional review board at Harvard Medical School.

3. Results

Overall, 153,974 hospitalizations were analyzed (Table 2.1). The probability of handoff was highest for patients admitted the day prior to a hospitalist's last day in a shift block (day -1) and was lowest for patients admitted 7 days prior (day - 7) (Figure 2.1). On average, 66.0% of admissions that occurred one day prior to a hospitalist's last day in a shift block resulted in handoff compared to 43.6% of admissions that occurred 2 days prior, 10.7% of admissions that occurred 6 days prior, and 7.4% of admissions that occurred 7 days prior.

A total of 44,627 hospitalizations occurred in the 2 days prior to the admitting hospitalist's last working day in a shift block (days -1/-2) and 38,296 occurred in the 6 or 7 days prior (days -6/-7).

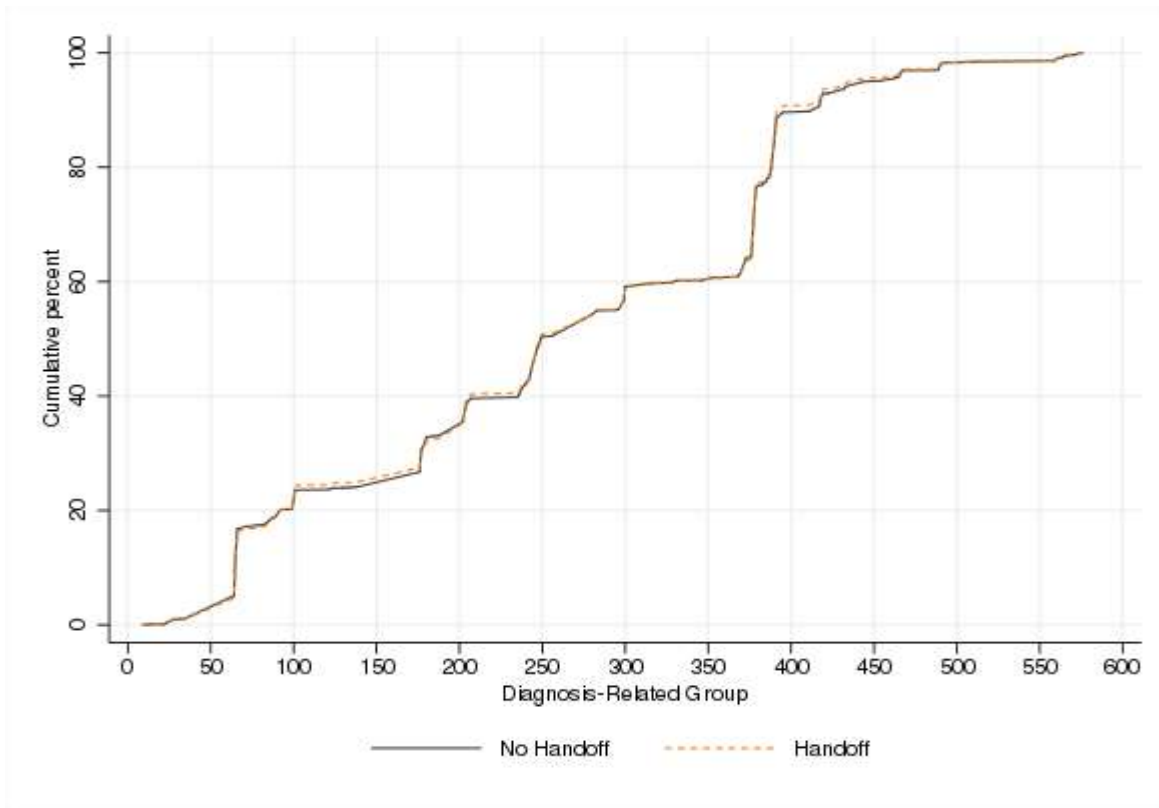
Statistically significant differences in patient characteristics between these groups were small in magnitude and of unclear clinical significance. For example, patients who were admitted in the 2 days prior to a hospitalist’s last working day were, on average, slightly younger (75.3 vs 76.0 years) and had fewer chronic conditions (5.8 vs 6.1 chronic conditions) compared to patients admitted 6 or 7 days earlier (Table 2.1). The probability distributions of DRGs were similar between groups ($p = 1.00$ by the Kolmogorov-Smirnov test; **Figure 2.S1**), suggesting similar reasons for hospitalization.

Table 2.1: Characteristics of study population

	Full sample	Patients with high likelihood of physician handoff ^a	Patients with low likelihood of physician handoff ^a	p-value for difference
	(N = 153,974)	(N = 44,627)	(N = 38,296)	
Age, mean (SD), y	75.8 (13.3)	75.3 (13.5)	76.03 (13.2)	<0.001
Female, No. (%)	84,686 (55.0%)	24,188 (54.2%)	21,178 (55.3%)	0.001
White race, No. (%)	127,644 (82.9%)	36,907 (82.7%)	31,709 (82.8%)	0.75
Comorbidities, mean (SD)	5.9 (3.1)	5.8 (3.1)	6.055 (3.2)	<0.001
Comorbidities, No. (%)				
Coronary artery disease	8,915 (5.8%)	2,575 (5.8%)	2,348 (6.1%)	0.03
Alzheimer’s dementia	32,950 (21.4%)	9,104 (20.4%)	8,617 (22.5%)	<0.001
Atrial Fibrillation	26,484 (17.2%)	7,408 (16.6%)	6,778 (17.7%)	<0.001
Chronic Kidney Disease	51,581 (33.5%)	14,504 (32.5%)	13,327 (34.8%)	<0.001
Chronic obstructive pulmonary disease	38,032 (24.7%)	10,889 (24.4%)	9,765 (25.5%)	0.001
Diabetes	60,050 (39.0%)	17,137 (38.4%)	15,318 (40.0%)	<0.001
Congestive Heart Failure	55,123 (35.8%)	15,530 (34.8%)	14,131 (36.9%)	<0.001
Hyperlipidemia	84,532 (54.9%)	24,366 (54.6%)	21,178 (55.3%)	0.04
Hypertension	120,100 (78.0%)	34,363 (77.0%)	30,177 (78.8%)	<0.001
Prior Stroke/Transient Ischemic Attack	79,759 (51.8%)	22,849 (51.2%)	20,182 (52.7%)	<0.001
Cancer	19,709 (12.8%)	5,668 (12.7%)	4,902 (12.8%)	0.62

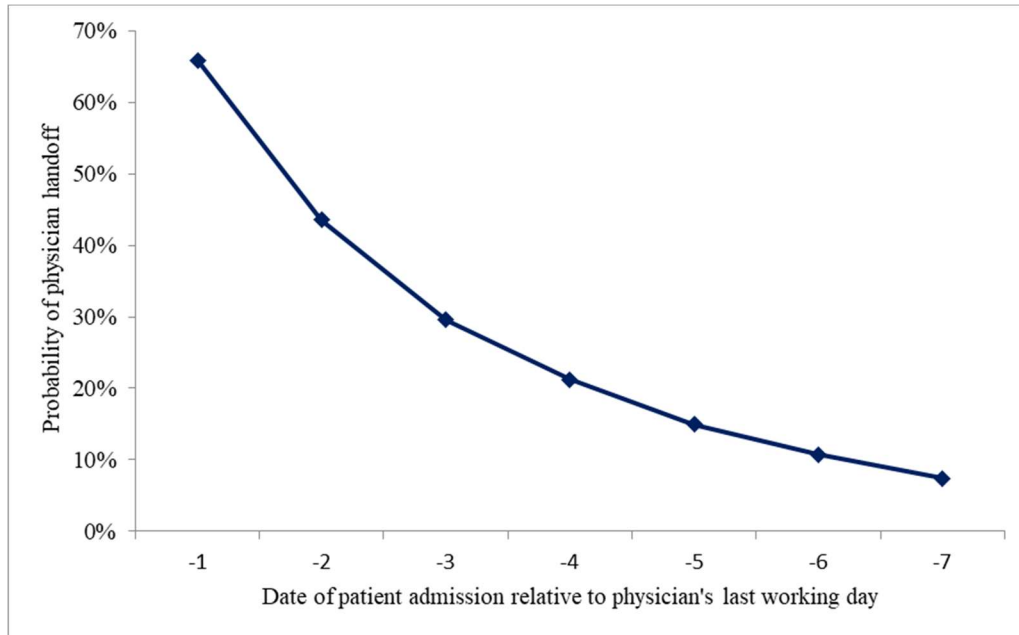
Notes: ^a Patients with a high likelihood of physician handoff were defined as those admitted in the 2 days prior to the attending hospitalist’s last working day in a shift block (days -1/-2), while patients with a low likelihood were defined as those admitted in the 6 or 7 days prior (days -6/-7).

Figure 2.S1: Diagnosis related group (DRG) cumulative distribution, according to likelihood of physician handoff



Notes: Figure shows cumulative distributions of the admitting Diagnosis-Related Groups (DRG) for admissions in the study sample, separated by the likelihood of physician handoff (patients admitted on days -1/-2 are at high probability of physician handoff, orange dashed line; patients admitted on days -6/-7 were at low probability of physician handoff, black line). Even though DRG numbers are categorical values representing separate diagnoses, we graphed the cumulative distribution on a continuous scale to visualize the case-mix of admissions across hundreds of DRGs. Therefore, the overlap between the TJC survey and non-TJC survey week distributions can reveal any subtle differences in case-mix across these many diagnoses. Distributions were not statistically significantly different in a 2-sample Kolmogorov-Smirnov test for equality of distribution functions ($p = 1.00$).

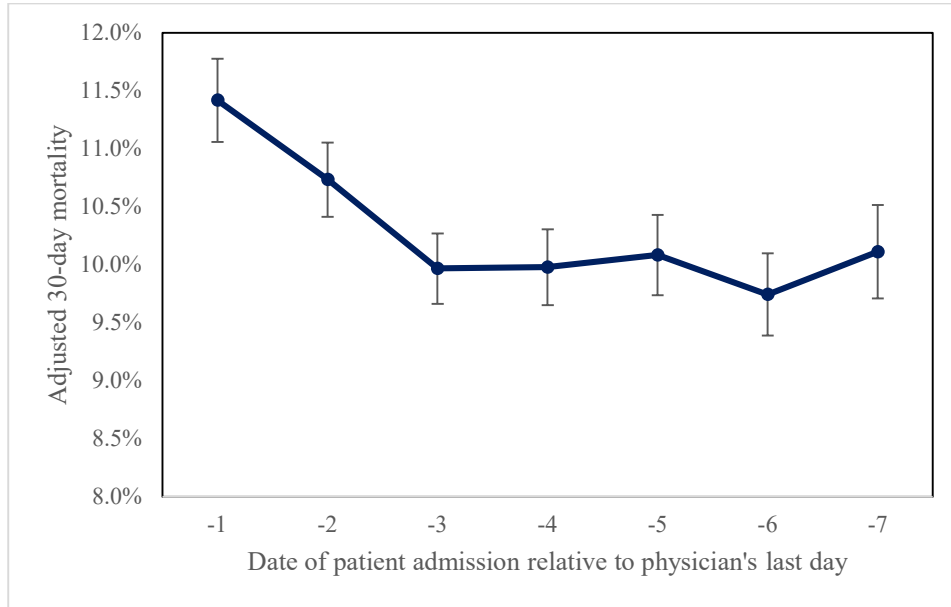
Figure 2.1: Physician handoff and date of patient admission relative to last working day in a physician’s shift block



Notes: Figure plots the probability of physician handoff according to the date a patient was admitted relative to the last working day (day 0) in a physician’s shift block (e.g., day -1 refers to 1 day prior to the last working day; day -2 refers to 2 days prior; etc.).

Adjusted 30-day mortality increased with the probability of physician handoff and was highest for patients admitted the day prior to a hospitalist’s last working day in a shift block, for whom the probability of handoff was highest (Figure 2.2). For example, the adjusted 30-day mortality rate for patients admitted on day -1 (the day before a hospitalist’s last working day in a shift block) was 11.4% (95% CI 11.1% to 11.8%) and on day -2, 10.7% (95% CI 10.4% to 11.1%), compared to 9.7% (95% CI 9.4% to 10.1%) and 10.1% (95% CI 9.7% to 10.5%) for patients admitted on days -6 and -7, respectively. This relationship was strongest among patients with high predicted mortality (Figure 2.S2). For instance, among patients in the top quartile of predicted mortality, the 30-day mortality rates for patients admitted on days -1 and -2 were 34.2% (95% CI 33.0% to 35.4%) and 32.5% (95% CI 31.4% to 33.6%), respectively, compared to 27.8% (95% CI 26.7% to 29.0%) and 28.9% (95% CI 27.5% to 30.2%) on days -6 and -7.

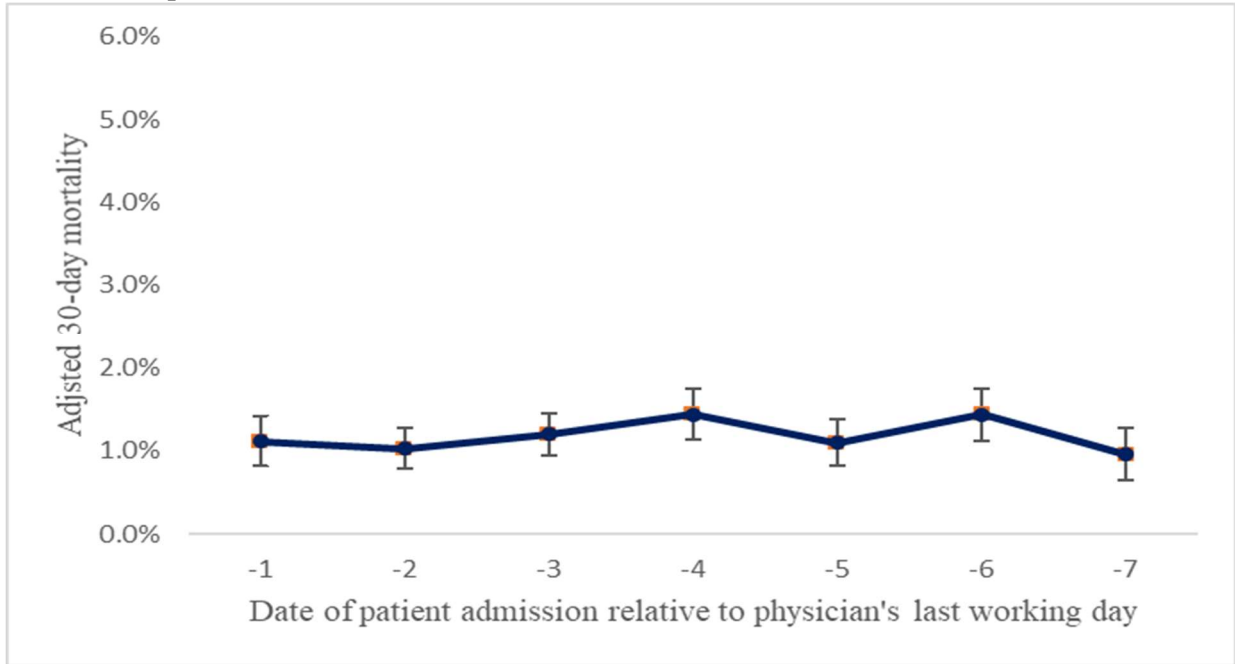
Figure 2.2: Adjusted 30-day mortality and date of patient admission relative to last working day in a physician's shift block



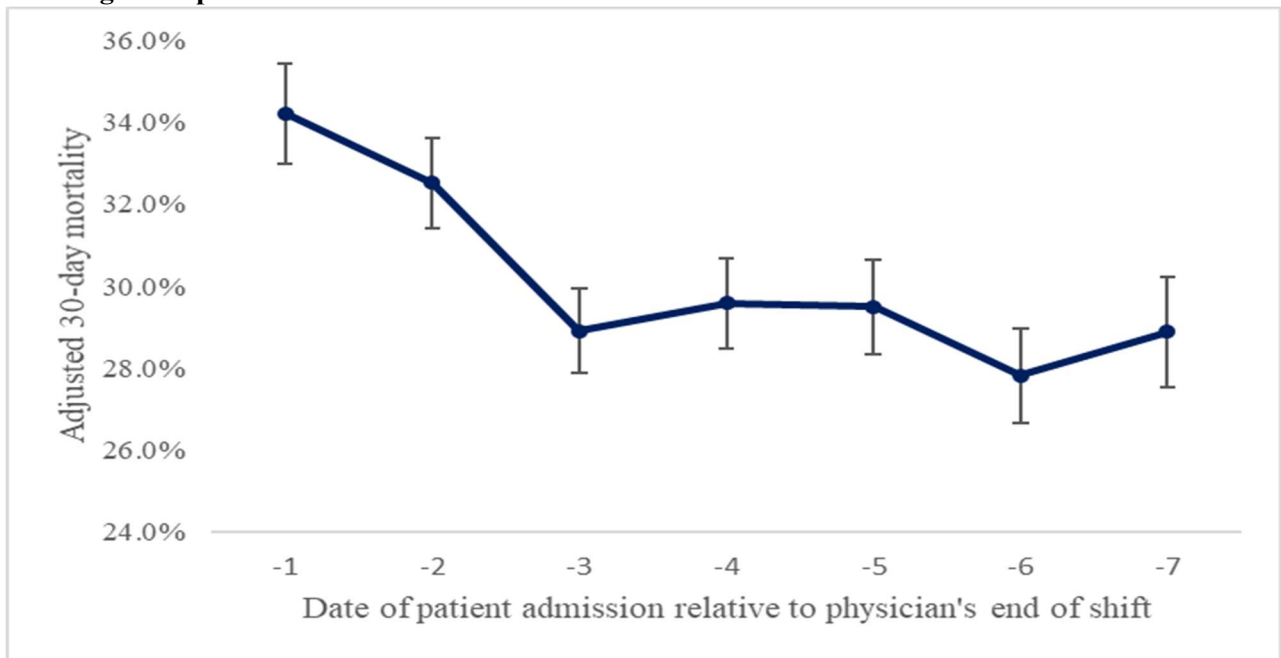
Notes: Figure plots adjusted patient 30-day mortality according to the date a patient was admitted relative to the last working day (day 0) in a physician's shift block. A hospitalization-level multivariable linear regression model was estimated in which the dependent outcome was 30-day mortality and the key independent variables were a set of relative date indicators (i.e., indicator variables for day -1, day -2, etc., until day -7), with other covariates described in the Methods. Bars represent 95% confidence intervals.

Figure 2.S2: Adjusted 30-day mortality and date of patient admission relative to last working day in a physician’s shift block, according to patient predicted mortality risk

A. Low-risk patients



B. High-risk patients



Notes: Figure plots adjusted patient 30-day mortality according to the date a patient was admitted relative to the last working day (day 0) in a physician’s shift block, by patient mortality risk. A hospitalization-level multivariable linear regression model was estimated in which the dependent outcome was 30-day mortality and the key independent variables were a set of relative date indicators (i.e., indicator variables for day -1, day -2, etc., until day -7), with other covariates described in the Methods. Handoff was interacted with predicted mortality risk

(defined below) to allow for a formal test of interactions. Low-risk patients were defined as those in the bottom quartile of predicted 30-day mortality and high-risk patients as those in the top quartile of predicted 30-day mortality. Bars represent 95% confidence intervals.

In a mortality comparison between patients with high vs. low likelihood of physician handoff (Table 2.2), thirty-day mortality was greater among patients admitted in the two days prior to the admitting hospitalist’s last working day in a shift block (days -1/-2) versus the six or seven days prior (days -6/-7) (unadjusted mortality, 10.8% (4,806/44,627) vs. 10.4% (3,986/38,296); adjusted mortality, 11.2% (95% CI 11.0% to 11.3%) vs. 10.0% (95% CI 9.7% to 10.2%), absolute adjusted difference 1.2% (95% CI 0.8% to 1.6%), $p < 0.001$; relative adjusted difference, 12.0%). Results were comparable in logistic regression models that excluded hospital fixed effects (Table 2.S1).

Table 2.2: Adjusted 30-day mortality according to likelihood of physician handoff

30 Day Mortality	Unadjusted, % (No.)		Adjusted, % (95% CI)		Adjusted difference, % (95% CI)
	Likelihood of physician handoff ^a		Likelihood of physician handoff ^a		
	High	Low	High	Low	
All patients (N = 82,923)	10.8% (4,806/44,627)	10.4% (3,986/38,296)	11.2% (11.0% to 11.3%)	10.0% (9.7% to 10.2%)	1.2% (0.8% to 1.6%)
Low risk patients ^b (N = 20,865)	1.0% (109/11,060)	1.3% (128/9,805)	1.1% (0.9% to 1.2%)	1.2% (1.0% to 1.4%)	-0.1% (-0.5% to 0.2%)
High risk patients ^b (N = 20,725)	33.4% (3,606/10,811)	29.2% (2,895/9,914)	33.8% (33.1% to 34.5%)	28.7% (27.9% to 29.4%)	5.1% (3.7% to 6.6%)

Notes: ^a Patients with a high likelihood of physician handoff were defined as those admitted in the 2 days prior to the attending hospitalist’s last working day in a shift block (days -1/-2), while patients with a low likelihood were defined as those admitted in the 6 or 7 days prior (days -6/-7). A hospitalization-level multivariable linear regression model was estimated in which the dependent outcome was 30-day mortality and the key independent variable was a binary indicator for whether a patient was at high vs. low likelihood of physician handoff, with other covariates described in the Methods. Handoff was interacted with predicted mortality risk (defined below) to allow for a formal test of interactions. ^b Low-risk patients were defined as those in the bottom quartile of predicted 30-day mortality and high-risk patients as those in the top quartile of predicted 30-day mortality.

Table 2.S2: Adjusted 30-day mortality according to likelihood of physician handoff, sensitivity analysis using logistic model

30 Day Mortality	Adjusted, % (95% CI)		Adjusted Odds ratio, % (95% CI)
	Likelihood of physician handoff ^a		
	High	Low	
All patients (N = 82,923)	10.6% (10.3% to 10.8%)	9.4% (9.1% to 9.6%)	1.19 (1.13 - 1.26)
Low risk patients ^b (N = 20,865)	1.1% (0.9% to 1.3%)	1.3% (1.1% to 1.5%)	0.88 (0.67 - 1.16)
High risk patients ^b (N = 20,725)	31.4% (30.6% to 32.3%)	26.8% (26.0% to 27.6%)	1.30 (1.21 - 1.39)

Notes: ^a Patients with a high likelihood of physician handoff were defined as those admitted in the 2 days prior to the attending hospitalist’s last working day in a shift block (days -1/-2), while patients with a low likelihood were defined as those admitted in the 6 or 7 days prior (days -6/-7). A hospitalization-level multivariable logistic regression was estimated in which the dependent outcome was 30-day mortality and the key independent variable was a binary indicator for whether a patient was at high vs. low likelihood of physician handoff, with other covariates described in the Methods. Hospital fixed effects were not included in the model due to a failure of the model to converge. Handoff was interacted with predicted mortality risk (defined below) to allow for a formal test of interactions. ^b Low-risk patients were defined as those in the bottom quartile of predicted 30-day mortality and high-risk patients as those in the top quartile of predicted 30-day mortality.

In sub-group analysis based on patients’ illness severity (Table 2.2), the difference in 30-day mortality between patients with a high vs. a low likelihood of physician handoff was largest among patients at high predicted risk of mortality. For example, among patients in the top quartile of predicted mortality, unadjusted 30-day mortality was 33.4% (3,606/10,811) among patients admitted on days -1/-2 vs. 29.2% (2,895/9,914) among patients admitted on days -6/-7 (adjusted mortality, 33.8% (95% CI 33.1% to 34.5%) vs. 28.7% (95% CI 27.9% to 29.4%); absolute adjusted difference 5.2% (95% CI 3.7% to 6.6%; relative adjusted difference, 18.1%). The likelihood of handoff was not associated with 30-day mortality for patients in the lowest quartile of predicted mortality ($p < 0.01$ compared to high-risk patients in a formal test of interactions). The relationship between physician handoff and 30-day mortality was similar in teaching and non-teaching hospitals (Table 2.S2).

Table 2.S2: Relationship between adjusted 30-day mortality and likelihood of physician handoff, according to teaching hospital status

Teaching hospital status	Adjusted, % (95% CI)		Adjusted difference, % (95% CI)
	Likelihood of physician handoff ^a		
	High	Low	
Teaching	11.0% (10.8% to 11.2%)	9.6% (9.3% to 9.9%)	1.4% (0.8% to 2.0%)
Non-teaching	11.3% (11.0% to 11.6%)	10.3% (10.0% to 10.6)	1.0% (0.4% to 1.6%)

Notes: ^a Patients with a high likelihood of physician handoff were defined as those admitted in the 2 days prior to the attending hospitalist’s last working day in a shift block (days -1/-2), while patients with a low likelihood were defined as those admitted in the 6 or 7 days prior (days -6/-7). A hospitalization-level multivariable linear regression model was estimated in which the dependent outcome was 30-day mortality and the key independent variable was a binary indicator for whether a patient was at high vs. low likelihood of physician handoff, with other covariates described in the Methods. The handoff variable was interacted with indicator variables for teaching hospital status, allowing for a formal test of interactions to assess whether the relationship between mortality and likelihood of physician handoff varied by teaching status. Teaching hospitals were identified from the 2015 American Hospital Association Annual Survey.

Similar findings were observed in longer-term follow-up (Table 2.3). For example, the adjusted absolute mortality difference at 60 days was 1.1% (95% CI 0.7% to 1.5%) among patients admitted on days -1/2 vs. days -6/-7; at 180 days, 1.1% (95% CI 0.6% to 1.6%); and at 365 days, 0.9% (95% CI 0.4% to 1.5%). Long-term associations between handoffs and mortality were also largest among patients in the top quartile of predicted mortality for whom admission on days -1/2 vs. days -6/-7 was associated with absolute adjusted increases in 60-day, 180-day, and 365-day mortality of 4.6% (95% CI 3.1% to 6.1%), 4.5% (95% CI 3.0% to 6.0%) and 4.2% (95% CI 2.7% to 5.7%), respectively, reflecting adjusted relative increases in mortality of 13.7 percent, 10.5 percent, and 8.4 percent, respectively.

Table 2.3: Adjusted 60-day, 180-day, and 365-day mortality according to likelihood of physician handoff

Mortality	Unadjusted, % (No.)		Adjusted, % (95% CI)		Adjusted difference, % (95% CI)
	Likelihood of physician handoff ^a		Likelihood of physician handoff ^a		
	High	Low	High	Low	
All patients (N =82,923)					
60-day mortality	13.1% (5,835/44,627)	13.1% (5,016/38,296)	13.6% (13.4% to 13.8%)	12.5% (12.3% to 12.7%)	1.1% (0.7% to 1.5%)
180-day mortality	18.5% (8,234/44,627)	18.9% (7,246/38,296)	19.2% (18.9% to 19.4%)	18.1% (17.8% to 18.4%)	1.1% (0.6% to 1.6%)
365-day mortality	23.1% (10,296/44,627)	24.0% (9,190/38,296)	23.9% (23.7% to 24.2%)	23.0% (22.7% to 23.3%)	0.9% (0.4% to 1.5%)
Low-risk patients (N = 20,865) ^b					
60-day mortality	1.8% (202/11,060)	2.2% (220/9,805)	2.0% (1.8% to 2.3%)	2.0% (1.8% to 2.3%)	0.03% (-0.4% to 0.5%)
180-day mortality	4.0% (438/11,060)	4.5% (445/9,805)	4.3% (4.0% to 4.6%)	4.2% (3.8% to 4.5%)	0.1% (-0.6% to 0.8%)
365-day mortality	6.4% (706/11,060)	6.8% (668/9,805)	6.8% (6.4% to 7.2%)	6.3% (5.9% to 6.8%)	0.5% (-0.3% to 1.3%)
High-risk patients (N = 20,725) ^b					
60-day mortality	37.6% (4,060/10,811)	34.1% (3,385/9,914)	38.1% (37.4% to 38.8%)	33.5% (32.8% to 34.3%)	4.6% (3.1% to 6.1%)
180-day mortality	46.5% (5,031/10,811)	43.4% (4,299 /9,914)	47.2% (46.4% to 47.9%)	42.7% (41.9% to 43.5%)	4.5% (3.0% to 6.0%)
365-day mortality	53.2% (5,750/10,811)	50.7% (5,023/9,914)	54.0% (53.3% to 54.7%)	49.8% (49.0% to 50.6%)	4.2% (2.7% to 5.7%)

Notes: ^a Patients with a high likelihood of physician handoff were defined as those admitted in the 2 days prior to the attending hospitalist’s last working day in a shift block (days -1/-2), while patients with a low likelihood were defined as those admitted in the 6 or 7 days prior (days -6/-7). A hospitalization-level multivariable linear regression was estimated in which the dependent outcome was mortality within a given time period (60-, 180-, or 365-days after hospital admission) and the key independent variable was a binary indicator for whether a patient was at high vs. low likelihood of physician handoff, with other covariates described in the Methods. Handoff likelihood was interacted with predicted mortality risk (defined below) to allow for a formal test of interactions. ^b Low-risk patients were defined as those in the bottom quartile of predicted 30-day mortality and high-risk patients as those in the top quartile of predicted 30-day mortality.

4. Discussion

In a large national sample of Medicare beneficiaries hospitalized with a general medical condition and treated by a hospitalist physician during 2008-2012, 30-day and longer-term mortality were significantly greater among those patients who were likely to experience a physician handoff during hospitalization, due to admission occurring by chance near the end of the treating physician's scheduled work block when handoff to a second physician routinely occurs. This relationship was strongest among patients with the greatest illness severity, among whom patients with a high likelihood of physician handoff (those admitted in the two days prior to the hospitalist's last working day in a work block) had an adjusted 30-day mortality rate of 33.8% compared to 28.7% among patients with a low likelihood of handoff, an absolute difference of 5.1% and a relative mortality increase of 18.1%.

Although care transitions have been associated with greater adverse events, prior studies of handoffs have largely focused on trainees, despite the fact that handoffs are common in the clinical practice that occurs once physicians complete their training (91;101; 102). Hospitalists, for example, now provide the majority of general medical care in inpatient settings and typically work contiguous days in which handoff of patients to another physician occurs at the end of a scheduled block. Despite the recognized importance of safe handoffs in hospital medicine, (91) no research has used national data to evaluate whether handoffs in this setting are, in fact, associated with adverse events such as higher mortality. Additionally, research on the relationship between handoffs and quality of care in the non-trainee setting has been limited to specific diseases, single institutions, or on outcomes such as length of stay as opposed to mortality (83; 90).

Our analytic approach to studying the relationship between physician handoff and patient mortality was based on the assumption that patients treated by a given hospitalist at the beginning versus the end of a work block would otherwise be similar but for the significantly greater likelihood of

physician handoff at the end of a work block, a quasi-experimental analysis. If, instead, patients who were admitted towards the end of a work block were at higher risk of mortality due to observable or unobservable factors, our estimates of increased mortality would be confounded and biased upwards. Patient characteristics were, however, clinically similar between those at high vs. low likelihood of physician handoff. If anything, patients in our data who were admitted towards the end of a work block were slightly healthier based on comorbidities, which could be consistent with the preferential assignment of lower-risk patients to those hospitalists whose work block was just about to end. In this case, our estimated relationship between mortality and the likelihood of physician handoff would be biased downwards, not upwards.

Our findings, if causal, suggest that transitions in care that commonly occur in inpatient medical settings may be associated with greater patient mortality. Despite this, most efforts to improve and monitor the safety of handoffs have focused on trainees. For example, while the ACGME requires formal training in handoffs and monitoring of handoff quality (103) the quality of handoff strategies is not systematically assessed in existing measures of hospital quality. Moreover, a number of interventions have been tried among trainees to target vulnerabilities in the handoff process, one example being I-PASS (illness severity, patient summary, action list, situation awareness and contingency plans, and synthesis by receiver) which has been associated with significant reductions in medical errors and adverse events. Our findings suggest the need to evaluate these tools and strategies more broadly in the hospital medicine setting since the risks associated with handoff are not confined to trainees. Our findings also suggest the potential importance of patient triage as a way to mitigate the risks of physician handoff. For example, because we observed the relationship between the likelihood of handoff and mortality to be strongest among patients with high predicted mortality, it is possible that

systematic triage of high-risk patients to hospitalists who are at the beginning, versus the end, of a scheduled work block may be reduce overall mortality associated with handoffs.

Our study had several limitations. First, the study was observational and although patients with high vs. low likelihood of handoff were similar on a range of characteristics, including reason for admission, residual confounding may be present. Second, any effect of physician handoff cannot be empirically distinguished from potential adverse effects of physician fatigue, owing to working a continuous stretch of days in the hospital, on patient outcomes (104). Third, our study focused on mortality rather than other medical errors or adverse events. Fourth, we evaluated an important but common set of handoffs that occur in the hospital setting, the handoff at the end of hospitalist service block. Handoffs occur in other specialties and within all inpatient specialties, daily handoffs occur between day and night providers. Fifth, we lacked data on the quality of handoff processes in individual hospitals, making it impossible to identify what specific processes of care within hospitals were associated with better patient outcomes after physician handoff.

In conclusion, in a large national sample of Medicare beneficiaries hospitalized with a general medical condition and treated by a hospitalist physician, mortality was significantly greater among those patients who were likely to experience a physician handoff during hospitalization. Our findings suggest the need for systematic measurement and evaluation of handoff processes within hospitals.

Chapter 3: The Extremely Under and Overcompensated in Individual Health Insurance Markets

Monica Farid and Professor Thomas McGuire

1. Introduction

In individual health insurance markets in the U.S. and around the world, health plans are paid a risk-adjusted amount for each enrollee. By paying plans more for enrollees likely to be high-cost and less for those likely to be low-cost, risk adjustment improves incentives to plans to enroll and serve sick, costly individuals as well as healthy, low-cost individuals. In the presence of a risk-adjusted payment, the important outcomes of a payment system -- plan profit and losses, incentives to enroll and serve -- stem not from spending per se, but from the residual spending not accounted for by risk adjustment. The focus of our study are the individuals who contribute most to residuals, the extremely over or undercompensated, who have an outsized effect on incentives and performance of health plan payment systems.

Our first set of analyses is descriptive. What are the diagnoses and what are the services used by the people underpaid by hundreds of thousands or in some cases millions of dollars? And on the other side of the residual distribution, what causes someone to be overpaid by hundreds of thousands of dollars? Our second set of analyses investigates how the tail people play into incentives for insurance market performance; specifically, we investigate the predictability of falling into the extremes. If membership in the tails is unpredictable by individuals or plans (e.g., caused by a one-time expensive and unanticipated surgical procedure) then very high residuals affects ex post profits to a plan, but has a small effect on the ex ante incentives related to adverse selection. On the other hand, if membership in the tails is highly predictable, the tail people interfere with the functioning of health insurance markets.

Our data are an updated version of the data used to calibrate the payment system in state-level Marketplaces created by the Affordable Care Act (2010). We characterize the top 10%, 1% and, the top .1% of residuals created by the Marketplace risk adjustment system, a population that accounts for a disproportionate share of plan losses and highly disproportionate share of the unexplained variance. We also study tail people on the other side of the distribution of residual spending, those for whom the revenue a plan receives in a risk-adjusted payment greatly exceeds the amount the plan spends on them. We have found little research on the extreme residuals on the left-hand side of the residual distribution.

An extensive literature in health economics studies persistence of high spending in individual health insurance markets. This literature, however, is mostly focused on the right tail of the distribution, on the top 10%, and studies spending rather than residuals. Hirth et al (2015) use 2003 to 2008 MarketScan employer claims data and find that membership in the top 10% of the spending distribution is persistent; 43.4% of those in the top 10% in 2003 were in the top decile one year later. Some persistence remains even after five years. Of those in the top 10% in 2003, 34.4% were in the top decile five years later (105). Similarly, Figueroa et al (2019) use a 20% sample of Medicare beneficiaries from 2012 to 2014 to analyze persistently high-cost spenders in the Medicare setting. They find that 28.1% of individuals are in the top 10% of spending for three consecutive years (106). These findings align with Cohen and Yu (2012) and Monheit (2003) who use data from the Medical Expenditure Panel Study (MEPS). Cohen and Yu observe 40% of those in the top decile of spending in 2009 remain in the top decile in 2010 and Monheit (2003) find similar persistence using older data (107;108) Focusing on drug spending, Pauly and Zeng (2004) use 1994-1998 claims of 140,000 individuals privately insured individuals and find that drug spending is both highly skewed and persistent. Among those in the top quintile of drug spending in 1994, 76% were in the top quintile the following year (109) Drug spending may be particularly persistent.

Studies of Medicare spending broadly align with findings among the privately insured. Garber et al. (1998) and Riley (2007), among others, study the right tail of the Medicare spending distribution (defined as the top 5% or top 1%) and find similar levels of persistence (110;111) Garber et al, for example, use 1987-1995 Medicare claims for a random sample of beneficiaries and find that, 15% remain in the top 5% of spending year-to-year.

Spending persistence is less problematic if risk adjustment performs well in predicting expenditures. Study of persistence of spending residuals, i.e., spending net of risk adjustment, takes account of any mitigation effect of risk adjustment on persistence of high spending. There exists a body of literature exploring the profitability of selection post risk adjustment models, however, it is older and is usually in the context of more basic risk adjustment models (112;113;114;115). We build on this work using a sophisticated risk adjustment model with recent commercial claims data to i) describe the characteristics of the highly profitable and highly unprofitable and to ii) to study the persistence of ‘profits’ and ‘losses’ to better gauge incentives for selection that remain after risk adjustment.

The rest of our paper proceeds as follows. Section 2 describes the right- and left-side tail people. Interestingly, those on the right and the left share many of the same diagnoses. Section 3 conducts a series of analyses of the persistence of residuals over time and the degree to which spending and residuals might be predictable to individuals and plans at the extremes of the residual distribution. We find that profits and losses are persistent, and they are particularly persistent for those at the tails implying strong incentives to underserve the highly undercompensated, the efficiency problem studied by Ellis and McGuire (2007) among others (116). On the demand side, we find that spending an individual might predict based on their age, sex and prior spending is correlated with their profitability after risk adjustment, setting up the efficiency problems studied by Einav and Finkelstein (2010) among others (117). Finally, we study the spending patterns of those with extreme and persistent residuals, and

find that for the consistently highly underpaid, spending on specialty drugs represents a disproportionate proportion of expenditures.

Taken together, our findings point to the need to pay special attention to both the very high and low residuals when considering the incentive properties of a health plan payment model. The conclusion of the paper, Section 4, presents some preliminary ideas for accommodating the tail people in health plan payment system design.

2. Spending, Risk Adjustment, Residuals

Data and Risk Adjustment Methodology

We use the 2015-2016 Truven MarketScan Commercial Claims and Encounters database to measure spending and the 2016 HHS-HCC risk adjustment methodology to define the risk adjustment payment for each person (118;119). Drawn from large insurers and employers, these data are a more recent version of the health insurance claims data used by Kautter et al. (2014) to develop the HHS-HCC Marketplace payment system (120). The HHS-HCC is a concurrent (rather than prospective) model which produces 15 sets of risk adjustment coefficients, three age-specific models (adult, child and infant) that include HCCs most appropriate for each age group, and five metal-specific models (since expenditure conditional on risk may vary based on patient liability for cost sharing). Adults are those over 20 years of age. Following HHS criteria, our analytic sample is comprised of individuals who had both prescription drug and mental health coverage and who had no negative or claims with a capitation payment. In addition, we also restrict our study population to those continuously enrolled for twelve months and who were in a non-HMO plan in the first and last month. For analysis of persistence we further restrict the sample to those who were also enrolled the entirety of the prior year. After applying these exclusion criteria we have 9,774,301 individuals available for one year and 7,185,977 individuals

for the two-years. We estimated risk-adjusted payments using the 2016 adult HHS-HCC risk adjustment model for silver plans.

Profiles of Tail People

Table 3.1 contains some characteristics of the population in 2016 overall and broken out by residuals percentile buckets, where residuals are defined as spending net of risk adjustment payment. The average overall annual health care expenditure is about \$6,400, of which 56% is in the outpatient setting. About 52% of the population is female and the average age is 44. Only about a fifth of the population is coded with any of the HCCs included in the HHS-HCC model. We find similarities in demographics and some aspects of spending patterns between individuals on the left and right extremes of the residual distribution. Both groups are older than the population average (46 - 51 years compared to an average of 43.6), tend to have a higher proportion of their spending in the inpatient (IP) setting, and a slightly lower proportion of spending on drugs compared to the population average.

Table 3.1: Descriptive Statistics by Residual Percentile Buckets

Variable	Full Population	0 -0.1th percentile	0.1 -1st percentile	1-10th percentile	90- 99th percentile	99-99.9th percentile	> 99.9th percentile
Population count	9,774,301	9,774	87,969	879,687	879,688	87,969	9,774
Average spending	\$6,433	\$55,749	\$21,160	\$5,972	\$25,767	\$113,836	\$434,620
Average over/underpayment	\$0	-\$135,254	-\$44,174	-\$11,131	\$16,115	\$83,080	\$341,609
Average age	43.6	51.2	50.6	48.9	46.4	49.8	49.0
Percent female	52.4%	47.0%	56.0%	58.0%	59.0%	55.0%	51.0%
Average percent of total spending in IP setting	20.3%	46.0%	32.3%	18.5%	19.0%	35.2%	37.0%
Average percent of total spending on drugs	23.9%	11.7%	16.8%	26.3%	25.2%	20.8%	14.7%

Proportion with any HCC	21.4%	100.0%	100.0%	100.0%	38.0%	72.0%	92.0%
Average number of HCCs	0.31	6.04	2.95	1.35	0.56	1.60	3.58

Note: Residuals are calculated as the difference between actual and predicted spending. The 0-0.1st, 0.1-1st and 1-10th bucket present individuals who are most overpaid, while the last three columns represent those who are most underpaid. The ‘average percent of total spending’ in each setting is calculated by taking the average of the proportion of spending in drug/ip setting across all individuals in the percentile bucket. The average number of HCCs is for HCCs that are included in the 2016 HHS adult risk adjustment model.

The average proportion spent on drugs and in inpatient and outpatient settings masks some important heterogeneity among those with the highest residual spending. For instance, about 25% of expenditures of those between the 90th and 99th percentiles of residuals are on drugs and 19% are in the inpatient setting. However, more than a third of this population has the large majority their expenditures (> 80%) in either the drug setting or the IP setting., i.e. there appears to be ‘two ways’ to be a high residual spender, expensive hospitalizations and expensive drugs. We explore the contribution of drug spending to the persistence in spending and residuals in Section 3.

To be highly overpaid, individuals must be coded with many and expensive HCCs and we find that the top 0.1% in terms of overpayment have on average 6 HCCs (compared to a population average of 0.31). In contrast, those most underpaid often have no HCCs coded. Although they incur about \$26k in health expenditures on average, only 38% of those in the 90-99th percentile bucket are coded with any HCC. Finally, both those on the left and right are high spenders. All groups except for the 1-10th residual group incur spending greater than the 90th percentile of spending (\$14k).

In terms of HCCs disproportionately found among those in the tails of residual spending, again we find similarities on either extreme of the residual distribution (Table 3.2). Some HCCs are over-represented in the right and the left tails: hemophilia, stem cell and bone marrow transplants and tracheostomy, among others. To place people in both tails, these HCCs must have a large variance in

cost within the HCC such that a weight set at average cost leaves both some very underpaid and some very overpaid. For instance, individuals with hemophilia, tracheostomy status or myelodysplastic syndromes/aplastic anemia, have a spending standard deviation that is 13 to 17 times the full population standard deviation and 51 times the spending standard deviation of individuals with no HCC coded. (About 80% of the full population is not coded with an HCC). High spending variance within an HCC may give rise to selection incentives if a plan is able to discriminate between those likely to be winners and losers with a given HCC.

Table 3.2: Disproportionately Common HCCs Among the Top 1% and Bottom 1% of Residuals

Rank among most underpaid (top 1% of residuals)	HCC	Label	Prevalence among most underpaid (top 1% of residuals) relative to full population	Rank among most overpaid (bottom 1% of residuals)
1	66	Hemophilia	29.5	3
2	251	Stem Cell, Including Bone Marrow, Transplant Status/Complications	27.7	10
3	8 interacted with 'severity' dummy	Severe Metastatic Cancer	26.9	29
4	159	Cystic Fibrosis	25.8	15
5	9 interacted with 'severity' dummy	Severe Lung/Brain Cancer	24.2	25
6	125	Respirator Dependence/Tracheostomy Status	23.9	6
7	67 or 67 interacted with 'severity' dummy	Severe Myelodysplastic Syndromes and Myelofibrosis or Aplastic Anemia	23.9	8
8	8	Metastatic Cancer	23.4	27
9	253 interacted with 'severity' dummy	Artificial Openings for Feeding or Elimination	22.9	32

10	145 interacted with 'severity' dummy	Severe Intracranial Hemorrhage	22.8	17
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Note: The severity indicator is on if the enrollee is coded with any of the following severe conditions: sepsis, peritonitis/GI perforation, seizure disorders and convulsions, non-traumatic coma, respirator dependence/tracheostomy status, heart assistive device/artificial heart, cardio-respiratory failure and shock and pulmonary embolism. The HCC conditions are ordered by ratio of prevalence in the top 1% of residuals (most underpaid individuals) relative to the rest of the population. For instance, hemophilia is 29.5 times more likely among the most the most underpaid individuals relative to the rest of the population. The right most column shows how these conditions rank using the same ratio, among the most overpaid in the population.

3. Extreme Residuals: Persistence and Predictability

The large gains and losses associated with the tail people bear on the functioning of individual health insurance markets where risk adjustment is intended to contend with selection incentives. In this section we analyze the magnitude of demand-side and supply-side selection incentives implied by the persistence and predictability of spending and residuals.

Demand-Side Selection Incentives

Accurate anticipation of spending on the part of individuals is behind the adverse selection problems studied by Einav and Finkelstein (EF) building on work by Culter and Reber (1998) (117;121;122). EF show that in the presence of community-rated premiums, if individuals with above average plan spending tend to sort into more generous plans, zero-profit premiums for the more generous plans are too high in equilibrium, causing too few enrollees to join the more generous plans. In context of risk adjustment, the EF mechanism for inefficient sorting among plan types comes into play when the spending individuals predict is correlated with losses to the plan (positive residuals).

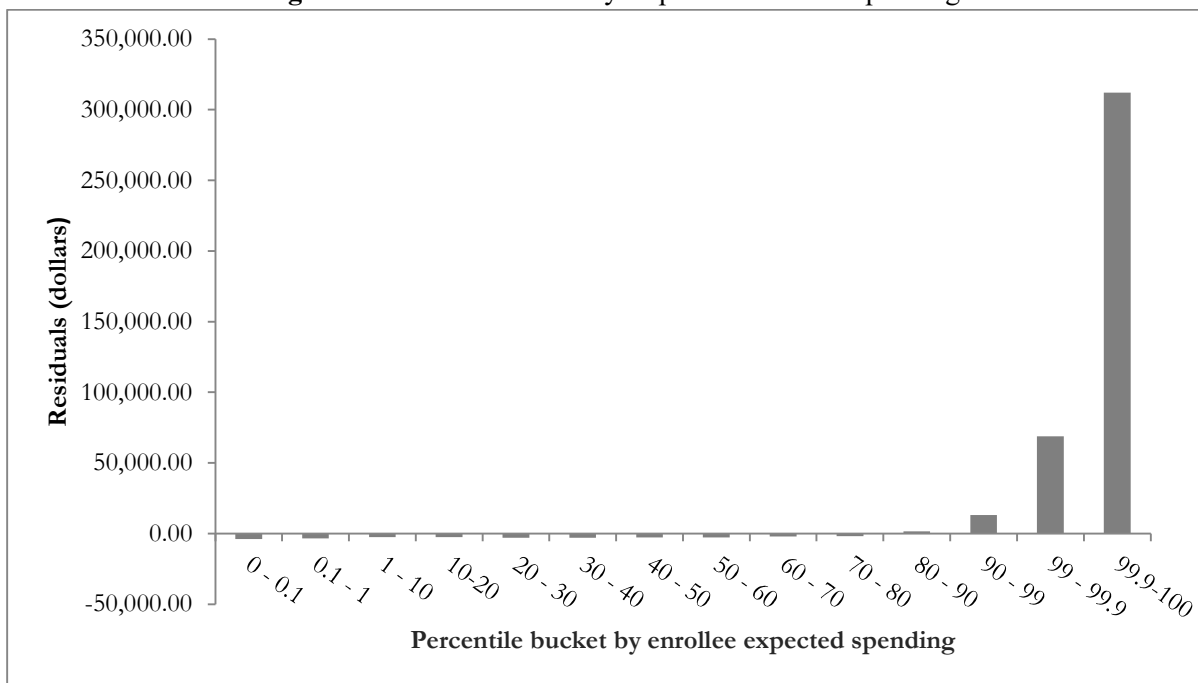
In this section we use predicted spending as proxy for expected spending and assume individuals can predict spending on the basis of age, gender and their previous spending in three categories: inpatient, outpatient and drugs. Implicit in these analyses is the assumption that predicted spending is a good approximation of willingness to pay for certain plan types. Our assumptions about predictability

may be conservative in terms of what people predict on (they may know more) but too strong in terms of what people can do with the information (they may not be able to run a regression in their heads).

We run separate prediction models for each decile of the spending distribution and find that, interestingly, predictability of spending is highest at the extremes, particularly in the right tail. Among those in the middle of the spending distribution, age, gender and prior spending in three categories explains little of the variation in next year's spending (R-square close to 0) while those in the highest categories of spending have an R-square of about 0.20. (Since the 10th percentile of the spending distribution is 0, we group those in the first decile together). Predictability of high spending is problematic for the functioning of insurance markets if risk adjustment fails to "pick up" the spending individuals can predict, forcing more generous plans to raise premiums to cover the unpaid selection and interfering with efficient consumer sorting among plan types. To check this, we examine the relationship between spending residuals and individual expected spending to observe whether there are significant plan gains or losses associated with individuals who might have strong preferences about coverage generosity (that is, individuals who have relatively high or low expected spending).

Figure 3.1 graphs the mean residual for each level of spending predicted by an individual (using own age, gender and categories of spending in the previous year). For the bulk of the expected spending distribution -- up to the 80th percentile of predicted spending -- the average residual is small and negative; plans make money on those individuals with low predicted spending. However, those with the highest expected spending would impose large plan losses and could activate the EF-type incentive problem and leading to too few consumers joining a more generous plan. Individuals in the top 1% and top .1% of the expected spending distribution do the damage in terms of demand-side selection incentives.

Figure 3.1: Mean Residual by Expected Enrollee Spending



Note: this figure shows the average amount of overpayment or underpayment resulting from conventional risk adjustment for groups of enrollees ordered by their expected spending. Expected spending is defined as the predicted spending from the OLS regression of spending on demographics and prior year's spending information. Negative values represent overpayments and positive values represent underpayments. For instance, those whose predicted spending puts them above the 99.9th percentile of the expected spending distribution are highly unprofitable post risk-adjustment; conventional risk adjustment underpays by about \$312,000 dollars on average for this group.

In sum, the large bulk of the demand-side selection incentives are created by the very few individuals in the extreme right-side of the predicted spending distribution.

Supply-Side Selection Incentives

Accurate anticipation of residuals on the part of plans is behind the adverse selection problems studied by Ellis and McGuire and others. If plans can anticipate which groups of individuals represent large losses or gains, plans can structure their offerings to deter the losers and attract the winners. In contrast with individuals, plans do know the risk-adjustment formula and are in a position to anticipate residuals. To investigate the importance of this efficiency problem, we check the persistence of

residuals over the range of the residual distribution. We measure persistence in two ways: the correlation of current year to past year residuals and probability that a person in a certain range of the distribution this year was in the same range the previous year

Table 3.3 contains the results, beginning with the second column which shows the size of the residual at the upper threshold value of the bucket; individuals at the 0.1th percentile of the distribution are overpaid by \$92k while the most underpaid individual in our data represents more than \$8.5m in losses. The last two columns report our persistence measures. We find that residuals are highly persistent, particularly in the tails of the residual distribution. 21% of the bottom 0.1% of the residual distribution in 2016 were also in the same category the previous year, while 24.5% of the top 0.1% were in the same category. If residual spending were distributed independently across years we would expect just 0.1% persistence in these buckets. Similarly, residuals at the tails of the distribution exhibit high correlation with prior year residuals. Both of these empirical findings run counter to a regression to the mean.

Table 3.3: Persistence of Residual Spending

2016 Residual percentile bucket	Upper threshold value	Correlation	Simple persistence**
0 - 0.1	-\$91,927	0.049	21.0%
0.1 – 1	-\$27,889	0.097	23.8%
1 – 10	-\$5,680	0.047	39.0%
10-20	-\$3,307	-0.036	44.2%
20 – 30	-\$2,707	0.022	33.3%
30 – 40	-\$2,109	0.012	26.8%
40 – 50	-\$1,647	0.020	29.6%
50 – 60	-\$1,265	0.005	35.3%
60 – 70	-\$525	0.020	21.5%

70 – 80	\$1,147	0.029	18.8%
80 – 90	\$5,881	0.046	21.8%
90 – 99	\$51,193	0.150	29.8%
99 - 99.9	\$182,164	0.154	18.5%
99.9 – 100	\$8,529,292	0.521	24.5%

**If residuals are random then persistence would be about 0.1% for the extreme 0.1% buckets (0-0.1th percentile and 99.9 -100th percentile), 0.9% for the 99-99.9th and 0.1-1th percentile buckets and 10% for the non-extreme buckets (eg, 10-20th, 20 -30th, 30th-40th percentiles etc). Hence the persistence measures are not directly comparable across the buckets; a persistence of 24.5% among the top 0.1% implies much higher stickiness in residuals than a similar persistence in the 10 percentile range buckets.

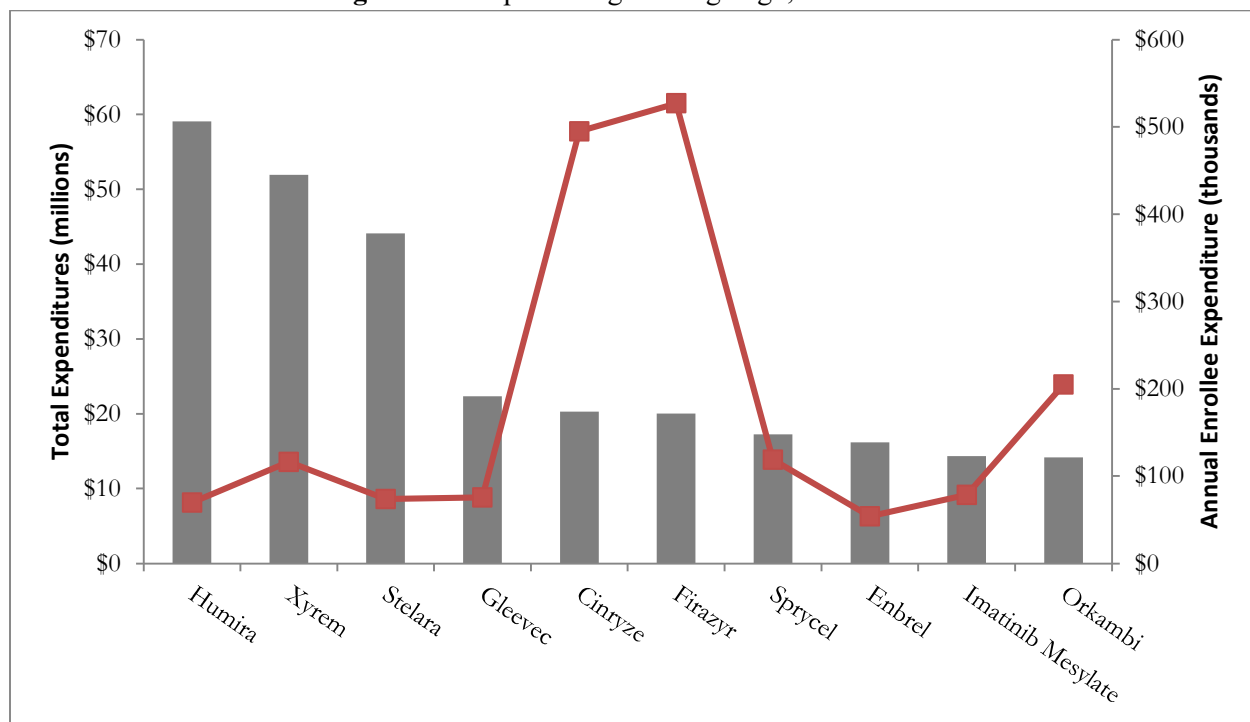
Note: The population is restricted to those who were enrolled for the full year in 2015 and 2016. Individuals are placed into one of fourteen buckets based on the percentile of their residual in 2016. The upper threshold value represents the percentile value at the right cutoff; for instance, -\$91,926.87 is the 0.1th percentile of residuals in 2016 among individuals who were fully enrolled in 2015 and 2016. The correlation column shows Pearson correlation coefficients of 2016 and 2015 residuals. Finally the simple persistence column shows the proportion of people in each of the 2016 percentile buckets who were in the same bucket the previous year. For instance, 21% of individuals in the lowest residual bucket in 2016, also had 2015 residuals that placed them in the 0-0.1th percentile of 2015 residuals.

The persistence of these large losses and gains is a troubling from a regulator’s perspective, signaling the ability of plans to identify ex ante who will be highly profitable or unprofitable the following year and, if adequate anti-selection mechanisms are not in place, to inefficiently distort their contracts or use other methods to attract or deter these enrollees.

We next examined more closely the spending patterns of those who are persistently in the extreme ends of the residual distribution beginning with the most underpaid. 23% of those in the top 1% of residuals in 2016 were in the same residual percentile in the previous year (16,367 enrollees). (As a benchmark, if residuals were distributed independently each year we would expect only 1% persistence in this bucket). We find that this group has a relatively larger proportion of their total spending on drugs -- 30% compared to 25% among all individuals enrolled for two years. Figueroa et al (2019) also find that persistently high cost Medicare beneficiaries (those defined as being in the top 10% of spending from 2012 through 2014) have a relatively larger proportion of their spending on drugs. Figure 3.2 show

the top 10 drugs in terms of spending on the drug for these people. The highest expenditure drug, Humira, a specialty drug targeting autoimmune diseases such as rheumatoid arthritis and Crohn’s disease, represented \$60 million dollars of spending among this group. On the other hand, the drug with the highest annual average cost per enrollee (\$527,118) was Firazyr (indicated for hereditary angioedema). We recognize that spending on drugs from claims does not take account of consumer coupons or rebates manufacturers provide to plans and pharmacy benefit managers (PBMs), and hence these numbers likely exceed actual spending.

Figure 3.2: Top 10 Drugs among High, Persistent Residuals



Note: this figure shows the top ten drugs in terms of total expenditure for those whose residuals are high and persistent. This group is defined as the subset of individuals in the top 1% of the 2016 residual distribution who were also in the top 1% of the 2015 residual distribution. The grey bars show total expenditures in millions for this group while the red line shows the annual average spending per enrollee in thousands for users of these drugs.

We next turn to spending patterns of the persistently highly overpaid individuals. 29% of those in the bottom 1% of residuals in 2016 were in the same residual range in the previous year (20,485 enrollees), an even higher proportion than among the top 1% of residuals (23%). The defining feature of this group is the high prevalence of transplant-related HCCs. Table 3.4 shows the top 10 HCCs

disproportionately found among persistent bottom 1% of residuals in 2016. They are mostly comprised of flags for ‘transplant status’ (for instance, kidney, liver or heart transplant status) and encompass all seven of the transplant HCCs that are included in the HHS-HCC risk adjustment model. The other three HCCs disproportionately represented among this group are ESRD, hemophilia and lung, brain and other severe cancers. The third column shows the ratio of prevalence among this group (persistent highly overpaid individuals) relative to the full population. Transplant HCCs are highly overrepresented, between 98 to 172 times more likely in this group compared to the full population.

Table 3.4: Disproportionately Common HCCs Among the Persistent Bottom 1% of Residuals

Rank among persistent bottom 1% of residuals (N=20,485)	HCC	Label	Prevalence among most persistent bottom 1% relative to full population	Proportion with HCC in 2015, among those with HCC in 2016 (N=24,758)	Proportion with HCC in 2015, among those with HCC in 2016 and in persistent bottom 1% residuals (N=7,011)
1	G14	Heart Transplant and Heart Assistive Device/Artificial Heart	172.0	66%	98%
2	158	Lung Transplant Status/Complications	145.4	67%	92%
3	34	Liver Transplant Status/Complications	135.0	65%	93%
4	18	Pancreas Transplant Status/Complications	127.6	62%	80%
5	41	Intestine Transplant Status/Complications	125.6	60%	80%
6	251	Stem Cell, Including Bone Marrow, Transplant Status/Complications	112.8	44%	75%
7	66	Hemophilia	105.4	57%	94%
8	184	End Stage Renal Disease	101.5	54%	88%

9	183	Kidney Transplant status	98.2	76%	94%
10	9	Lung, Brain, and Other Severe Cancers, Including Pediatric Acute Lymphoid Leukemia	96.4	50%	91%

Note: The HCC conditions are ordered by ratio of prevalence in the persistent bottom 1% of residuals (persistent overpaid individuals) relative to the rest of the population. For instance, Heart Transplant and Heart Assistive Device is 172 times more likely among persistently highly overpaid individuals relative to the rest of the population. The persistent bottom 1% are defined as individuals whose residuals put them below the 1st percentile of the residual distribution in 2015 and 2016. The fourth column shows the proportion of enrollees that have the HCC on in 2015 among those who had it on in 2016. The fifth column reports the same metric except that the population is further restricted to those who are persistently highly overpaid (i.e. they are in the bottom 1% of residuals in 2015 and 2016).

The role of transplant procedures in contributing to persistence may be surprising given that transplants are one-time procedures. However, the definition of transplant HCCs encompasses the transplant procedure, complications such as organ rejection, as well as less specific diagnoses codes such as ‘encounter for aftercare following organ transplant’ and ‘transplant status’. “Transplant status” can remain in effect over time, at least partly explaining why transplant flags persist. The fourth and fifth column of Table 3.4 show, for each of the top 10 HCCs, the proportion of enrollees who have the HCC on in 2015 among those who had it on in in 2016.

There were 24,758 individuals with any of the transplant indicators or Hemophila, ESRD, Lung, Brain and Severe cancer indicators on in 2016. We find that between 44% to 67% of those who had a transplant indicator on in 2016, had it on in the prior year. When focusing on the subset of individuals among this group who are persistently overpaid, we find that this proportion rises substantially; 75% to 98% of this group also had the HCC on in the prior year.

4. Conclusion and Discussion

Our analysis aimed to shed light on some of the characteristics of the tail people, those in the extreme right and left tail of the residual distribution. We found that, unsurprisingly, the residual

distribution is right-skewed, but perhaps less well-anticipated, there is a significant left tail as well. We found some similarities in the demographics and comorbidities of those on the extreme ends. High spending variance within an HCC classification puts members with that indication on both extremes of the residual distribution. Brown et al (2014) noted that high variance within an HCC creates the potential for within HCC selection (123). For instance, a payor may try to differentiate between different types of patients with hemophilia and select against the riskier types via formulary design (Geruso et al, 2016) or via other mechanisms (124;125).

High residuals (or large potential losses and gains to a plan) are cause for concern if plans can predict who these people will be. It turns out that high residuals persist year-to-year likely giving plans the information they need to predict who will spend much more than the plan is paid year-after-year. We find that risk adjustment underpays for enrollees who might select into generous plans based on what they know about their health risk. This is largely a problem in the right tail of the predicted spending distribution. Using a simple model for prediction, we show that enrollees who predict high subsequent year expenditures are associated with large residuals. This implies that if beneficiaries differentially sort into plans based on their expected spending, plans will set premiums too high, interfering with efficient consumer sorting among plan types.

Persistent ‘winners’ from a plan perspective are disproportionately coded with transplant HCCs. Because of how these HCCs are defined, it is possible for these flags to turn on and stay on, thus grouping individuals who had a transplant sometime in the past with those who underwent the procedure in the current year. The huge and persistent overpayments for this group of individuals points to the need to reconsider the risk adjustment algorithm for assigning payment weights to individuals with past transplants.

On the other hand, persistent ‘losers’, those with high spending less payment, spend disproportionately on drugs; and, in particular, use specialty drugs and biologics. The top ten drugs in terms of expenditure were all specialty drugs and targeted hereditary conditions, autoimmune diseases and cancer. The 2018 HHS risk adjustment model introduced drug groupings and drug interactions as additional covariates in the model. There are only nine groupings, however, and they generally are comprised of the more commonly prescribed drugs (eg insulin and anti-HIV agents). (126) The problem of how to deal with growth in specialty drugs and associated ‘unpredicted’ spending within a health plan payment model in an individual health insurance market is yet unresolved.

Reinsurance is one possibility for compensating plans for some of the individuals with high losses. McGuire, Schillo and Van Kleef (2018) show that basing reinsurance on residuals rather than spending (as is conventional) is a more efficient way to compensate plans for losses and to mitigate selection incentives, and that, in data from Germany, The Netherlands and the U.S., devoting a small share of funds to reinsurance can have a large impact on reducing residual sum of squares of spending post payment (127).

The role of expensive drugs in accounting for extreme and persistent residual spending is worthy of special attention, absence of rebate information in claims data notwithstanding. Growth in costs of biologics and specialty drugs will put more of the users of these drugs in the tail of the residual spending distribution and keep them there, increasing selection-related incentives in individual health insurance markets and further concentrating the source of these adverse selection incentives in the people in the tails of the residual spending distribution.

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