Plugging Gaps in Payment Systems: Evidence from the Take-Up of New Medicare Billing Codes[*]

Jeffrey Clemens[†]
Jonathan M. Leganza[‡]
Alex Masucci[⁋]

July 20, 2021

Abstract

Over the last decade, the U.S. Medicare program has added new billing codes to enhance the financial rewards for Chronic Care Management and Transitional Care Management. We show that the take-up of these new billing codes is gradual and exhibits substantial variations across markets and physician groups, indicating that frictions to take-up may delay the impacts of payment reforms. We show that patterns of care and billing code substitution and complementarity can be important for assessing the costs and care access impacts of payment reforms. In our particular context, we estimate that the new Transitional Care Management codes had substantial impacts on the overall provision of evaluation and management services, flu vaccinations, and other recommended services, while the new Chronic Care Management codes did not. These patterns of complementarity shape both the costs and benefits of the introduction of these payment reforms, including the effects of the new billing codes on the overall return to specializing in primary care.

[*] We thank Kate Antonovics, Julian Betts, Todd Gilmer, and Gaurav Khanna for helpful comments and conversations. All three of the authors were employed by the University of California, San Diego, for the bulk of the time during which this paper was written. Leganza and Masucci have subsequently changed affiliations, as detailed below.
[†] University of California, San Diego. (Email: clemens.jeffrey@gmail.com)
[‡] Clemson University. (Email: jleganz@clemson.edu)
[⁋] Amazon. This work was completed prior to Alex joining Amazon. (Email: amasucci@amazon.com)

1 Introduction

Health care payment models shape the financial incentives physicians and hospitals face while delivering care. Payment models can thus have important implications for the health system's efficiency. Importantly, the patterns of service provision that constitute cost-effective health care are not static. That is, efficient health care will tend to evolve dynamically with a population's underlying health needs, with the development of new technologies, and with changes in the organization of medicine. Payment models may also need to adapt to these changes.

Maintaining an efficient health care payment model requires adapting to the health care landscape. To that end, the Centers for Medicare & Medicaid Services (CMS) regularly revises its physician fee schedule to incorporate new billing codes. In this paper, we show that the effects of such reforms can depend on a rich set of factors. First, for new codes to influence patterns of care provision, they must be recognized and adopted by physicians' practices. Second, the impact of new codes on spending and care provision can depend on the extent to which they substitute for or complement existing services. Importantly, patterns of complementarity and substitutability can involve subtle mixes of changes in bill coding, on the one hand, and real care provision, on the other. Through an analysis of new primary care billing codes, we provide evidence that take-up frictions, code complementarity, and code substitutability can all be highly relevant for assessing the welfare impacts of the introduction of new billing codes.

To provide evidence on code adoption, coding substitutes, and coding complements, we analyze the Medicare program's introduction of new codes for the management of care for patients with complex conditions. In particular, we analyze the 2013 introduction of new codes for billing Transitional Care Management services and the 2015 introduction of new codes for billing Chronic Care Management services. The introduction of these sets of codes played an important role in a broader effort by CMS to a) increase the financial rewards to providing primary care and b) improve incentives for managing the care of patients with high health care needs.

Our empirical analysis proceeds in two steps. We begin by providing descriptive evidence on patterns in the adoption of the Transitional and Chronic Care Management codes by primary care physicians. Simple time series reveal that the adoption of the new codes is a gradual process, suggesting substantial take-up frictions. We show that the use of both the Transitional and Chronic Care Management codes escalated substantially over the first 4 years following each code's introduction. We also show substantial variation in take-up across space, some of which is correlated with variations in the prevalence of chronic conditions, but much of which is not.

We then explore several dimensions of heterogeneity in new code adoption across physicians. The most striking pattern is that new code take-up is far more rapid among mid-career than among early-career or late-career physicians. Rapid take-up by mid-career physicians may be both assisted by their accumulated fluency with code processing and spurred by the horizon over which they will realize the gains to investing further in code-billing proficiency. Additionally, we find that take-up is strongest among physicians who operate in mid-sized groups that consist entirely of primary care physicians. Overall, the patterns we document are consistent with the idea that the adoption of new codes requires physicians to make investments in their practices' mastery of bill coding, which is a form of organizational or entrepreneurial capital.

Next, we analyze patterns of complementarity and substitutability between the adoption of new codes and either the billing or provision of additional services. We use a set of complementary regression frameworks to study the effects of new code adoption at the county level. We begin by estimating fixed effect models that exploit all panel variation in the intensity with which new codes are billed across counties. For our estimates to capture the causal effect of new code take-up, the key assumption is that differential rates of new code take-up were uncorrelated with differential counterfactual trends in overall health care needs and utilization. We provide evidence on the validity of this assumption using two sets of robustness analyses. First, we show that our initial estimates are robust to controlling for a rich set of time-varying demographic and health characteristics of the Medicare beneficiaries in each county. Second, we estimate event study models for which we match high and low take-up counties on baseline levels of health care utilization. By comparing high take-up counties to low take-up counties, the event study models allow us to shed light on whether trends in care provision had diverged prior to the introduction of the new codes. Together, these analyses provide evidence that our estimates are unaffected by divergent trends associated with variations in population health and health care utilization either at baseline or over the course of our sample period.

We begin our analysis of patterns of care complementarity and substitutability by presenting relatively clear illustrations of code substitution, on the one hand, and code complementarity on the other. First, we find that the adoption of Transitional Care Management services has partially crowded out the billing of standard office visits during the weeks following hospital discharges. Second, we find that both Transitional and Chronic Care Management services quite strongly predict increases in the provision of Annual Wellness Visits. Finally, we find that Transitional Care Management services predict a much broader increase in the billing of "complex" office visit codes.

After illustrating these cases of substitution and complementarity, we analyze the relationship between new code billing and billing patterns across broad categories of care. We find that Transitional Care Management billing predicts substantial increases in overall care provision. These increases occur primarily within Evaluation & Management services and a category of "Other" services that includes vaccinations, but not in the provision of Procedures, Imaging, or Tests. By contrast, Chronic Care Management billing predicts no net increase in overall billing and a modest decrease in the provision of Imaging services. These findings suggest that the Chronic Care Management code may, in large part, have rationalized the coding of services that had previously been delivered and billed using less lucrative codes, whereas the Transitional Care Management codes appear to generate substantial increases in patients' interactions with their doctors. This is consistent with CMS's goal in introducing the Transitional Care Management codes, namely to enhance the coordination of care for discharged patients with complex conditions. Finally, we find that the adoption of the Transitional Care Management codes predicts increases in influenza vaccinations, pneumonia vaccinations, and mammograms, which are strongly recommended services. While a comprehensive cost-benefit analysis is beyond this paper's scope, our findings illustrate the relevance and potential importance of several nuanced pieces of the puzzle.

Our analysis makes several contributions to existing literatures. First, we show that patterns of complementarity and substitutability in bill coding and service provision can play important roles in shaping a payment reform's effects on overall cost and care delivery. Our analysis provides clear illustrations demonstrating that new service codes introduced by Medicare can both complement and substitute for existing service codes. We emphasize two policy relevant aspects of these findings. First, code substitution and code complementarity will tend to impact claims-dependent systems of quality measurement and/or risk adjustment. Carey (2017), for example, shows that the entry of new drugs creates challenges for risk-adjustment models.[1] The introduction

[1] New drugs alter affected patients' expected costs, which changes their profitability net of risk adjustment. Carey (2017) finds that the design of Medicare Part D plans responds to the incentives associated with the introduction of

of new service codes can have similar implications. Second, the existence of complementarities in real service provision can have straightforward effects on both the cost and health benefits of introducing new service codes. A comprehensive analysis of the costs and benefits of introducing new codes must account for these spillovers.

Second, a long literature has analyzed the effects of financial incentives on the services physicians provide to their patients. One set of papers in this literature estimates standard impacts of reimbursement levels on the supply of services (see, for example, Alexander and Schnell, 2019; Clemens and Gottlieb, 2014; Gruber, Kim, and Mayzlina, 1999). Other papers have investigated margins including physicians' preferences over taking new patients (Chen, 2014; Clemens, Gottlieb, and Hicks, 2020; Garthwaite, 2012), prescription patterns (Carey et al., 2020), and choices over where to establish their practices (Khoury et al., 2021). Relatively recent research on this rich variety of margins has provided evidence that health care becomes more widely accessible, and sometimes to a substantial degree, when physicians are paid more generously to provide it. Still other research has demonstrated important roles for additional factors including intrinsic motivation (Kolstad, 2013) and team environments (Chan, 2016). We contribute to this literature by showing that the effects of incentives on the supply of services can depend importantly on physicians' awareness of those incentives and on the time horizons over which they adapt. Our analysis points to a novel dimension of physicians' organizational or entrepreneurial capital: their mastery of the billing systems that shape their practices' profitability. We show that the take-up of the new codes we analyze unfolds quite gradually. So too do the care complementarities associated with the Transitional Care Management code's incentives for better managing the care of patients who have recently been discharged from hospitals.

Finally, while frictions have received little attention in prior research on physicians' labor supply, they have received substantial attention in other lines of research. Frictions play an important role, for example, in research on the causes of incomplete take-up of benefits among individuals who are eligible for Medicaid and other forms of public assistance (Aizer, 2007; Bhargava and Manoli, 2015; Manoli and Turner, 2014). Research has also demonstrated an important role for information frictions in shaping responses to the tax code (Chetty and Saez,

new drugs. Geruso, Layton, and Prinz (2019) and Lavetti and Simon (2018) provide related evidence on the strategic responses of firms to the incentives created by risk adjustment mechanisms for drug benefits. Brown et al. (2014) develop related findings in the context of Medicare Advantage plans.

2013; Chetty, Friedman, and Saez, 2013).[2] We highlight that frictions may be important for understanding differences between physicians' short- and long-run responses to non-trivial changes in incentives they face. The complexity of physicians' contracts and reimbursement procedures has been examined elsewhere (Clemens and Gottlieb, 2017; Clemens, Gottlieb, and Molnar, 2017; Gottlieb, Shapiro, and Dunn, 2018; Dunn et. al, 2021). Our analysis finds that the physician workforce's awareness of reforms to the payment models in these contracts, as well as the investments they make to adapt, can be essential for such reforms to have their intended effects.

The remainder of this paper proceeds as follows. In Section 2 we present background information on the introduction of new billing codes for Chronic and Transitional Care Management. In Section 3 we describe the data used in our analyses. In Section 4 we present our descriptive analysis of the take-up of these new billing codes. In Section 5 we present our empirical research designs for estimating the effects of new billing code take-up on other billing and service provision. Section 6 presents the results of these analyses, and Section 7 concludes.

2 Background

2.1 Primary Care and the Fee for Service Payment System

Primary care physicians play an important role in health care systems. They often serve as initial points of contact for undiagnosed patients and provide continued treatment to patients with health conditions that need to be regularly managed and evaluated. The evidence suggests that strong primary care systems are linked to better population health outcomes across OECD countries (Macinko et al., 2003) and that reorienting health systems towards primary care in general is likely to be beneficial for health outcomes and health care costs (Friedberg et al., 2010). Along these lines, the Centers for Medicare & Medicaid Services has recently "recognized primary care and care coordination as critical components in achieving better care for individuals, better health for individuals, and reduced expenditure growth" (CMS, 2012).

Despite playing such an integral role, an emerging body of evidence highlights how primary care physicians often provide services that are left out of the Physician Fee Schedule (PFS). In an important sense, they are thus not paid in full for the services they deliver to patients

[2] Adjustment frictions may explain important differences between short- and long-run labor supply elasticities as well as between micro and macro labor supply elasticities (Chetty, 2012).

(Gottschalk et al., 2005; Farber et al., 2007; Dyrbye et al., 2012; Tai-Seale et al., 2017). The new codes that we study were intended to address exactly this problem. In the final rule for the Medicare Physician Fee Schedule for 2018, CMS states that the PFS has traditionally not appropriately captured and accounted for services physicians provide in the context of general care coordination and management. The report states: "In the years since 2012, we have acknowledged the shift in medical practice away from an episodic treatment-based approach to one that involves comprehensive patient-centered care management, and have taken steps through rulemaking to better reflect that approach in payment under the PFS. In CY 2013, we established new codes to pay separately for transitional care management (TCM) services. Next, we finalized new coding and separate payment beginning in CY 2015 for chronic care management (CCM) services…" (CMS, 2018).

Whereas improvements in technology naturally result in additions to the billing schedule in categories such as imaging and tests, codes for evaluation and management services must be added more intentionally to adapt to the health needs of the beneficiary population, which may evolve over time. The TCM and CCM codes represent the first major component of the recent efforts by CMS to expand and improve the provision of primary care services by introducing new billing codes for underprovided services.

By adding these new billing codes, CMS has adjusted the PFS by explicitly paying physicians for TCM and CCM services. CMS has done so in order to either compensate doctors more fully for the complex primary care services they were already providing or, where primary care needs were going unmet, to increase incentives for physicians to provide such services. The new billing codes are the result of policy makers aiming to make the provision of primary care more financially attractive (Burton et al., 2017). They capture the essence of a broader CMS agenda to "improve the payment for, and encourage long-term investment in, primary care and care management services" (CMS, 2012).

2.2 Transitional Care Management

The Transitional Care Management (TCM) codes are designed to pay physicians for the care management services they provide to patients following a discharge out of an inpatient setting, such as a hospital or skilled nursing facility. The goal of these care management services is to reduce preventable readmissions and improve patient health by better coordinating the provision of follow-up care.

CMS introduced two new billing codes for physicians who provide TCM. Billing code 99495 is for Transitional Care services of moderate medical decision complexity. It requires initial communication with the patient (or caregiver) within two days of the patient discharge date as well as a face-to-face visit within 14 days of the discharge. Billing code 99496 is for Transitional Care services of high medical decision complexity. It requires initial communication within two days of the discharge as well as a face-to-face visit within 7 days of the discharge.

These new codes were first eligible to be billed in 2013. The reimbursement rates were set by CMS, taking into consideration the input and feedback from committees and stakeholders such as the American Medical Association RVS Update Committee, and using similar existing codes to guide the rate-making process. In 2013, TCM associated with code 99495 paid roughly $164, which compares favorably to a similar office visit ($107), and TCM associated with code 99496 paid roughly $231, which again is higher than a comparable office visit ($143).[3]

2.3 Chronic Care Management

The Chronic Care Management (CCM) codes are designed to pay physicians for care coordination and care management for patients with multiple chronic conditions, such as Alzheimer's disease, dementia, asthma, cancer, cardiovascular disease, chronic obstructive pulmonary disease, depression, diabetes, or hypertension, among others. Chronic conditions are common among Medicare beneficiaries, and spending on patients with these afflictions is substantial. Approximately 85% of U.S. national health care spending is associated with people with chronic conditions (Anderson, 2010). Moreover, a recent report analyzing the Medical Expenditure Panel Survey found that 42% of adult Americans had multiple chronic conditions and that the prevalence of multiple chronic conditions was even higher (81%) for Americans 65 years and older (Buttorff et al., 2017).

Recognizing the pressing need for the health care system to provide appropriate care for Medicare patients afflicted with chronic conditions, CMS created the new CCM billing codes. CCM code 99490 pays for care management of at least 20 minutes of clinical staff time per month.

[3] We report dollar amounts for reimbursement purposes that correspond to national payments in a non-facility setting, which can be found here: https://www.cms.gov/medicare/physician-fee-schedule/search/overview.

Eligible patients are those who have multiple chronic conditions that are expected to last at least twelve months or until death and that create a significant risk of death or functional decline. This code was first eligible to be billed in 2015. As with the TCM codes, payment rates were determined by CMS with input from stakeholders. In 2015, reimbursement was roughly $43.

At first, the process of billing CCM was met with a few burdens and complexities. An initiating office visit was originally required for all patients before commencing CCM, and advanced patient consent had to be obtained. In a recent analysis of health care provider interviews, O'Malley et al. (2017) document that some providers reported administrative barriers to billing—such as the need to maintain certified electronic health records and to have the ability to share records with other providers outside their practice—while others reported that the modest reimbursement rate was not sufficient to cover upfront investments in staffing and infrastructure required to provide CCM. With the goal of further increasing the provision of care for patients with chronic conditions, CMS responded to provider concerns. In 2017, CMS relaxed various administrative requirements for billing CCM—such as simplifying patient consent procedures, only requiring initiating office visits for new patients or patients not seen within the previous year, and reducing documentation rules (CMS, 2017). In 2017, CMS also introduced two additional CCM codes with higher reimbursement rates: code 99487 ($94), for CCM that involves moderate or high complexity medical decision making, and code 99489 ($47), for each 30 minutes of additional CCM time (no matter the complexity).

2.4 New Billing Codes in Practice

The implementation of new billing codes that pay physicians for TCM and CCM create financial incentives to provide these services to beneficiaries. However, the extent to which physicians ultimately respond to financial incentives depends on several factors. First, physicians must be aware of the new codes and the rules governing their use. Second, they must weigh the costs and benefits of adjusting their billing and care provision patterns in response to the incentives the codes create. As discussed above, this can require navigating the general administrative complexities associated with billing procedures in the U.S. health care system (Gottlieb et al., 2018).

The effectiveness of new billing codes can be limited by the administrative burdens associated with their use. Adapting to new codes may or may not be worthwhile, if the new codes represent a relatively modest refinement to an otherwise large and complex fee for service payment model. It is thus important to understand the pace of new code adoption, as well as variations in take-up across physicians, physician groups, and geographic regions. As take-up occurs, it is then important to evaluate empirically how the use of new billing codes impacts broader billing patterns and the overall provision of care.

3 Data

To study how physicians respond to the introduction of the new Medicare billing codes, we make use of several data sources from CMS. Using three physician-level datasets, we build a panel of physicians from 2012 to 2018 that contains information on physician characteristics and physician billing. We also make use of three additional county-level datasets that contain information on patient demographics, population health, and health care utilization.

3.1 Constructing the Physician Panel

Our base dataset is the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* (MPUP). The MPUP is a provider-level panel dataset that covers health care professionals who bill services to Medicare Part B. It spans the years 2012 to 2018. The data are derived from administrative claims data from CMS and allow us to observe almost all physicians who bill Medicare. (Physicians who do not bill any HCPCS code at least 10 times in a given year are omitted from the data for that year.) The MPUP contains unique physician identifiers called National Provider Identifiers (NPIs), information on physician specialties, and information on billing, including billing of the new codes. We focus most of our analysis on primary care physicians (PCPs), which we define to be physicians with a specialty of Internal Medicine, Family Medicine, General Practice, or Geriatric Medicine.

We supplement these data with two other datasets from CMS, which we link to the MPUP using the unique NPIs. From the *National Plan and Provider Enumeration System* (NPPES), a dataset published by CMS that identifies and enumerates all physicians, we obtain information on physician practice location.[4] This information allows us to study physician groups, which we define as physicians practicing at the same address. Then, from the *Physician Compare* dataset, a dataset CMS publishes to provide patients with information on doctors who accept patients

[4] Specifically, the NPPES data record a primary practice location for each physician, for each month. We use practice location as of December for each calendar year.

covered by Medicare, we pull information on physician medical school attendance and graduation dates.[5] We use these data to categorize physicians based on medical school ranking (using rankings of medical schools for primary care from the 2018 U.S. News & World Report) and career stage. We define early-career PCPs as those who graduated from medical school 5 to 24 years prior, mid-career PCPs as those who graduated 25 to 39 years prior, and late-career PCPs as those who graduated 40 or more years prior.[6] After adding the information from the NPPES data and the Physician Compare data to the MPUP, we have a detailed panel dataset of physicians over time.

3.2 County-Level Data

We use three additional datasets to facilitate our county-level analyses. From the *CMS Geographic Variation Public Use File*, a dataset that CMS publishes for researchers and policy makers to assess geographic variation in health care services, we extract information on basic demographics. Specifically, we utilize county-level variables that report total beneficiary counts, the percent of beneficiaries that are female, the percent of beneficiaries that are eligible for Medicaid, and the average age of beneficiaries.

We also use the *CMS Chronic Conditions Files*, which are datasets published by CMS that report county-level statistics on the prevalence of, and Medicare spending for, twenty-one different chronic conditions. We use these data to construct a normalized index that reflects the overall prevalence of chronic conditions, which we use as a proxy for patient health. Our index is based on the prevalence of eight major chronic conditions (arthritis, kidney disease, COPD, diabetes, heart failure, hyperlipidemia, hypertension, and ischemic heart disease).[7]

Finally, we use the *Dartmouth Atlas Post-Discharge Events* data from 2010 to 2017, which provide county-level rates of the incidence of various health care related events experienced by beneficiaries after being discharged from the hospital. These rates are calculated as a percentage of all hospital discharges in the county in each year. This data set provides particularly relevant

[5] CMS began publishing the Physician Compare data in 2014. We use all available data from 2014 through 2018 to define medical school and graduation date. The information is time-invariant, and most physicians appear in all waves of the data; however, we are missing information on medical school and graduation date for physicians who appear in our data only before 2014.
[6] Our definition of early-career PCPs is driven by the data: very few physicians are assigned an NPI until 5 years after finishing medical school, likely due to time spent in residencies.
[7] More details on the construction of this index are available in Appendix B.

outcomes for studying the effect of Transitional Care Management, since this service is directly used to provide managed care for patients after a hospital discharge.

3.3 Analysis Sample and Summary Statistics

Our analysis sample is the near-universe of Medicare-billing physicians between 2012 and 2018, and our objective is to describe how physicians respond to the introduction of the new billing codes. We present baseline summary statistics in Table 1. That is, Table 1 provides a descriptive overview of our key variables before the implementation of any of the new Medicare billing codes. Of the 175,408 PCPs in our data in 2012, 19.6% are sole practitioners, 15.3% are early-career, and 32.3% attended a ranked medical school. Evaluating and managing patient health makes up a large fraction of PCP billing: average billing for standard office visits amounts to roughly 44% of average total billing for PCPs.

4 The Take-Up of New Medicare Billing Codes

We begin by documenting the take-up of the new Medicare billing codes. First, we show how the adoption of the codes evolved over time. Second, we investigate geographic variation in new code usage, exploring how the take-up of the new codes is diffused across space. Third, we analyze how new code usage varies by physician characteristics.

4.1 New Code Billing Over Time

Figure 1 plots the time series on national billing of both the TCM and CCM codes, and it highlights that the adoption of new codes is a gradual process. Panel A plots total billing, in dollars, for both TCM and CCM, where total billing for TCM (CCM) is defined as the sum of the billing for all relevant new codes classified as TCM (CCM). The graphs show how billing for the new codes ramps up steadily over time, and neither type of new code billing seems to have leveled off over the time horizon of our data.

Panel B plots the fraction of PCPs billing TCM and CCM. A similar pattern emerges: the fraction of PCPs billing the codes increases over time at a relatively stable rate. By 2018, which is six years after the introduction of the TCM codes and four years after the introduction of the CCM codes, 12.3% of PCPs bill TCM and 4.5% of PCPs bill CCM. (For another relevant comparison, note that 8.8% of PCPs bill TCM in 2016, which is four years after the introduction of the codes.)

Panel C plots new code billing as a share of a physician's total billing, conditional on billing the new code. For PCPs who bill TCM, the new code billing increases to about 4% of total billing in 2018; for PCPs who bill CCM, the new code billing increases to about 8% of total billing in 2018. While more PCPs bill TCM overall, CCM billing ultimately makes up a greater share of total billing for those PCPs who do bill CCM. This pattern is consistent with the idea of CCM-intensive billing practices emerging as a result of physicians undertaking significant investments in staffing and infrastructure in order to provide care that complies with CCM requirements (O'Malley et al., 2017).

4.2 Regional Variation in New Code Billing

There is significant regional variation in the take-up of new codes. We document this in Figure 2, which graphs Hospital Referral Region (HRR) new code billing per PCP in 2018 for each of TCM (panel A) and CCM (panel B). TCM billing is much lower in the western parts of the U.S. and is more heavily concentrated in both the Northeast and the Southeast. CCM billing is relatively sparse throughout the northern regions and appears to be concentrated all along the southern parts of the U.S., both in the South but also throughout the Southwest. Underlying health conditions across regions explain some of this variation. New code billing is indeed correlated with our constructed chronic condition index, which we illustrate in Figure 3; the regression model in panel A explains 19.5% of the variation in HRR-level TCM billing, and the regression model in panel B explains 19.2% of the variation in HRR-level CCM billing.

4.3 New Code Billing by Physician Characteristics

Table 2 displays new code billing rates by physician characteristics. The table reports the fraction of physicians billing TCM (column 1) and CCM (column 2) during 2018, the last year of our data, and each row corresponds to a different physician characteristic. Panel A documents billing rates across specialties and shows that PCPs are much more likely to bill the new codes than non-PCPs. The first row reproduces findings from the time series graphs, whereas the second row shows that billing rates for TCM and CCM are less than 1% for all non-PCPs.

Panel B breaks down billing rates by physician career stage. The likelihood of billing the new codes is higher (for both TCM and CCM) for mid-career PCPs compared to early-career or late-career PCPs. In panel A of Figure 4, we provide a more granular look at how billing rates vary over career stage. PCPs with more experience are more likely to adopt the new codes, until reaching the later stages of their career. The "inverse U" shape exhibited here conforms with economic intuition for how the propensity to undertake billing-related investments is likely to vary across the career life cycle. Physicians at the beginning of their careers are likely to be facing a set of more fundamental business-related investment decisions and may lack the entrepreneurial capital necessary to profitably build the capacity to bill the new codes. The declining rate of new code adoption over the latest of career stages is consistent with the idea that physicians approaching retirement will have less time over which they can capture the returns on investments associated with learning how to bill the new codes or how to carry out procedures that will qualify as TCM or CCM.

Panel C of Table 2 reports billing rates by physician medical school. The results suggest similar billing rates for PCPs from ranked and unranked schools, although PCPs who attended the highest ranked medical schools appear slightly less likely to bill the new codes than other PCPs. The more granular evaluation of medical school rankings displayed in panel B of Figure 4 points to generally similar conclusions, especially for TCM billing. The fact that PCPs who attended the highest ranked medical schools differ in their propensity to adopt the new codes connects to and complements the few existing studies that investigate how physician practice styles differ based on initial medical school quality (Doyle et al. 2010, Schnell and Currie 2018).

Panel D and panel E of Table 2 break down billing rates by physician group characteristics. In general, we see that PCPs belonging to groups are more likely to bill the new codes than sole practitioners, except for PCPs in the largest groups, which is consistent with the idea that larger groups face more bureaucratic barriers to providing CCM (O'Malley et al. 2017). Moreover, we see that PCPs in PCP-only groups are particularly likely to bill the new codes, which may reflect stronger incentives to make investments in new code billing for groups composed entirely of physicians for whom the new codes are designed.

Note that large groups themselves are more likely than groups of other sizes to have at least one PCP billing the new code, which we show in Table 3, as large groups are made up of more doctors. This shows that it is not the case that information about the new codes fails to reach large groups at all, but rather that a smaller fraction of the PCPs who make up large groups actually bill the new codes.

Finally, panel F shows how new code billing rates differ by other billing behaviors. New code billing rates are higher for PCPs who also bill standard office visits. We also see that billing rates for one type of new code are substantially higher than average for PCPs who bill the other new code: 40.9% of PCPs who bill CCM also bill TCM, and 14.8% of PCPs who bill TCM also bill CCM. In addition, we see that billing rates for the new codes are higher for PCPs who also bill Annual Wellness Visits (AWVs), which were first introduced as a part of the Affordable Care Act (ACA), and which aim to provide patients with a standard wellness check and a plan for upcoming preventive care. We explore the relationship between the new codes and AWVs further in Figure 5. Panel A illustrates the correlation between AWV billing in 2012 and new code billing in 2018 and points to a relatively weak initial relationship. Panel B illustrates a shift in the relationship: new code billing in 2018 is strongly correlated with AWV billing in 2018. This is suggestive of a phenomenon we consider more fully later, namely that the adoption of new codes is complementary with the billing and/or provision of additional, related codes. This complementarity may tend to be strongest when the documentation required to bill one code overlaps significantly with the documentation required to bill another code.

Overall, the descriptive facts and patterns presented in this section provide some initial insight into how physicians respond to the introduction of new billing codes. Take-up of new codes occurs gradually over time and across space. In exploring heterogeneity in take-up rates, we find patterns consistent with the idea that the adoption of new codes requires ongoing learning and investments related to bill-coding proficiency. Correlations between new code billing rates and other billing behaviors lead us to the next part of our analysis, where we investigate the impact of new code adoption on physician billing and provision of care.

5 Empirical Framework for Analyzing the Effects of New Code Adoption

In the next phase of our analysis, we use a complementary set of regression frameworks to estimate the effects of new code take-up on broader patterns of bill coding and care provision. Within each framework, we implement robustness checks to gauge the relevance of threats to interpreting the estimated relationships between new code billing and outcomes of interest as causal. The first regression framework we consider exploits all panel variation in the intensity with which new codes are billed at the county level. That is, we estimate the equation below, where *c* denotes counties and *t* denotes years:

$$Outcome_{c,t} = \beta_1 New\ Code\ Billing\ Per\ PCP_{c,t} + X_{c,t}\,\gamma$$
$$+\alpha_{1c}\, County_c + \alpha_{2t}\, Time_t + \varepsilon_{c,t}. \quad (1)$$

Equation (1) controls for county fixed effects ($County_c$), time fixed effects ($Time_t$), and time-varying county characteristics ($X_{c,t}$).

When we estimate equation (1), the primary coefficient of interest is β_1, which describes the relationship between the outcome of interest and the dollar value of new code billing per primary care physician. For β_1 to be an unbiased estimate of the effect of new code adoption, new code billing would need to be as good as randomly distributed. This may, of course, seem implausible given that the new codes are intended for use when patients have chronic conditions, and will thus be more intensively used in counties where many patients have such conditions. Here, it is crucial that the new codes did not exist during the first year of our sample, which allows us to use county fixed effects to effectively control for baseline variations in counties' outcomes. The key assumption is that variations in the intensity with which new codes were adopted were uncorrelated with other sources of divergence in counties' outcomes. Our robustness analyses are designed to provide checks for the relevance of threats to this key assumption.

A first set of robustness checks we implement operates within the basic estimation framework described by equation (1). We explore the robustness of our estimates to whether we control for time-varying county characteristics that describe the health of the Medicare population. Specifically, we construct indices for the prevalence of a variety of chronic conditions. We then estimate regressions both with and without these covariates included in $X_{c,t}$, which provides evidence on whether our estimates are sensitive to controlling for proxies for variation in the evolution of the patient population's health.

In a second set of robustness checks, we transition from equation (1) to an event study estimator. For the event-study approach, we divide counties into groups based on the intensity with which they adopted the new billing codes. High intensity adopters are implicitly our "treatment" group while low intensity adopters and non-adopters are implicitly our "control" group.[8] Using this grouping of counties, we then estimate regressions of the form:

$$Outcome_{c,t} = \sum_{p(t)\neq -1} \beta_{p(t)} High\ Intensity\ New\ Coder_c \times Event\ Year_{p(t)} + X_{c,t}\,\gamma$$

$$+\alpha_{1c}\, County_c + \alpha_{2t}\, Time_t + \varepsilon_{c,t}. \qquad (2)$$

In equation (2), we interact a set of "event time" dummy variables with an indicator for whether a county was a high intensity adopter of the new billing code. The event time dummy variables are coded to correspond with specific numbers of years relative to the new code's introduction, which corresponds with 2015 when we analyze the Chronic Care Management codes and 2013 when we analyze the Transitional Care Management codes. We omit the interaction for the time period describing the year immediately prior to the new code's introduction, which we define as year $p(t) = -1$. The coefficients of interest can thus be interpreted as differential changes in the outcome of interest from the year prior to the new code's introduction to the reference year. For reference years less than 0, the point estimates thus provide evidence on whether divergent trends in the outcome had occurred prior to the new code's introduction. This provides evidence on the relevance of concerns related to divergent pre-existing trends. Estimates for years following the new code's introduction track the dynamics with which the outcome subsequently evolved.

Note that equation (2) provides a natural check for one of the sources of bias that might be relevant to our estimate of β_1 in equation (1). The absence of divergent pre-existing trends would provide evidence that outcomes of interest were on parallel paths in the high take-up counties relative to low take-up counties. One might still worry, however, that differential shocks may have occurred in later years in ways that correlate with high intensity take-up. This motivates us to implement one additional check.

As shown in Section 4, high intensity take-up of the new codes is, as was intended, correlated with the prevalence of chronic conditions. More generally, high take-up is correlated

[8] Specifically, we first drop counties that do not meet a size threshold of having over 10 total PCPs in 2012. We then order the remaining counties in our sample by average post-implementation annual new code billing per PCP. The top half of these counties is defined as the treatment group, and the bottom half is defined as the control group.

with more intensive utilization of services. We thus implement a final robustness check that limits our sample to high and low intensity take-up counties with similar levels of overall health care utilization at baseline. That is, we match "high" and "low" intensity counties on their baseline total allowed amounts.[9] By estimating equation (2) on the resulting matched sample, we provide a final check for the problem of divergent pre-existing trends in high vs. low take-up counties with populations that had similar levels of overall utilization at baseline.

6 Analysis of the Effects of New Code Adoption on Subsequent Coding and Care Provision

In this section we present the results of the analyses described in Section 5. For each outcome of interest, we report estimates for both equation (1) and equation (2). In the main text we present estimates of equation (1) both with and without the inclusion of demographic and health related covariates. In the main text we also present event study estimates of equation (2) using our matched sample of counties. Estimates for equation (2) using the unmatched sample are shown in the Appendix. We are careful to differentiate between outcomes for which our estimates are robust across this set of specifications and outcomes for which our findings exhibit sensitivity.

In Section 6.1, we show the difference in new code take-up between the treatment and control groups in our event study estimation strategy. In Section 6.2, we present evidence from a clear case in which the new billing codes acted as a (partial) substitute for other service codes. In Section 6.3, we present evidence from clear cases in which the adoption of new codes was complementary to the provision and billing of additional services. In Section 6.4, we present a more comprehensive analysis of the effects of the adoption of the Transitional Care Management and Chronic Care Management codes on a broader set of coding and care provision outcomes. Finally, in Section 6.5, we present analyses of the effects of new code adoption on proxies for patient receipt of best practice care.

[9] The treatment group in the matched strategy is identical to the treatment group that is defined using the unmatched strategy. To generate our control group, we match to each treatment county the three counties from the unmatched control group that are closest to it in terms of total PCP billing per PCP in the year before the implementation of the new code of interest.

6.1 New Code Billing in High vs. Low Take-Up Counties

Figure 6 presents an analysis of TCM and CCM billing for the counties we identify as high take-up counties (the "treatment" group) relative to the counties we identify as low take-up counties (the "control" group) for our matched event-study design. We see that the treatment groups for both new codes exhibit a widening gap in new code usage relative to the control groups. For TCM, the gap appears to stabilize in 2018, the final year of our sample and the sixth year of usage for that code, leaving treatment counties with about $1,370 more in TCM billing per PCP. For CCM, the gap is about $2,120 per PCP in 2018. Figure A1 reveals quite similar differentials for the full sample event-study analysis. Note that 2018 is the fourth year of CCM availability, and the gap between the treatment and control groups has not clearly leveled off at this point. For our event study analyses, these differences in new code billing between the "treatment" and "control" counties can be viewed as similar to an underlying "first stage;" the magnitude of the differential utilization of the new codes should be kept in mind for scaling the variations we observe in the outcomes we analyze in Sections 6.2 through 6.5.

6.2 A Case of Code Substitution

In this section we begin our analysis of the effect of the new codes on overall billing and service delivery. An initial effect of interest involves the possibility that the introduction of new billing codes may lead to substitution away from other service codes. This could involve either real changes in service provision or pure coding substitution. The TCM and CCM codes were introduced to improve compensation for physicians who are responsible for designing and implementing complex care management plans. One possibility is that, prior to the new codes' introduction, physicians may have billed more basic office visit codes that, in a relevant sense, would have undercompensated them for the work performed. The transition to new codes may also come with increases in the intensity of a fixed number of patient-physician interactions. (Later, we consider the possibility of complementary care, in which the adoption of new codes alters care management plans and, as a result, increases the number of patient-physician interactions.)

Figure 7 presents an illustrative example of code substitution in practice. Panel A shows the fraction of beneficiaries that have a traditional office visit within two weeks of discharge from the hospital, split by treatment status for TCM.[10] Panel B shows the fraction of beneficiaries with a traditional post-discharge office visit with a Primary Care Physician specifically, as opposed to with a Nurse Practitioner or Physician Assistant. Both panels reveal a clear relative decline, comparing "treatment" and "control" counties, in the fraction of beneficiaries receiving a traditional post-discharge office visit in the treatment group relative to the control group. By 2017, this amounts to a 4.3 percentage point decline in the fraction of beneficiaries receiving these visits and a decline of 6.3 percentage points in the fraction of beneficiaries receiving these visits from PCPs in particular. The corresponding estimates for the full sample event study analysis, as presented in Figure A2, are moderately smaller, at 3 and 5.2 percentage points, respectively. Recall from Section 6.1 that PCPs in high take-up counties were, by 2018, billing an average of $1,370 more for TCM than were PCPs in low take-up counties. The full-sample differentials thus amount to roughly 2.2 and 3.8 percentage point declines per thousand dollars in TCM billings per PCP. The pre-treatment trends in both outcomes are flat, indicating that these outcomes were not diverging across our treatment and control counties prior to the treatment counties' take-up of the TCM code.

Note that these variables come from the Dartmouth Atlas of Health Care, which allows us to track this particular set of outcomes from 2010 through 2017, whereas the bulk of our analysis involves variables that extend from 2012 through 2018. This is relevant in part because our analysis of the TCM code is unable to provide clear evidence on the potential relevance of divergent pre-existing trends for all variables. For key variables from the Dartmouth Atlas, however, we find no evidence of divergent trends.

Table 4 shows estimates of β_1 from equation (1) for these outcomes. These specifications regress the outcome of interest on the county-level volume of new code billing per PCP; the analysis thus allows us to exploit all of the available variation in our county-level panel to estimate the effects of new code billing. We find that an additional thousand dollars of TCM billing per PCP predicts a 1.2 percentage point reduction in the fraction of beneficiaries receiving a traditional post-discharge visit with any care provider. We similarly estimate a 1.9 percentage point reduction in the fraction of beneficiaries receiving such a visit from a PCP. These estimates are moderately smaller, though not dramatically so, than the declines per thousand dollars in TCM service billing

[10] The visits included in this variable are those corresponding to HCPCS codes 99201-99205, 99211-99215, 99381-99387, 99391-99397, 99241-99245, and 99271-99275.

as estimated using the event study framework. Table A1 shows the year-by-year point estimates, and we see that the magnitude of the estimates rises over time, in particular for the latter outcome, as new code take-up expands in prevalence.

Figure 7 and Table 4 provide clear evidence of a case of code substitution. Office visits provided within two weeks of a hospital discharge, as tracked by the Dartmouth Atlas, would convert quite readily into TCM services. We emphasize two additional points of interest with respect to this particular instance of code substitution. First, the amount of code substitution appears to be quite modest, implying a non-trivial net increase in post-discharge visits. For example, our estimates imply a reduction of one traditional post-discharge visit with a PCP for every 17 additional TCM visits.[11] This implies that while TCM is substituting for some care that was previously being provided, the bulk of TCM visits represent an increase in real post-discharge care that is taking place because of the introduction of the TCM codes. On this point, we note that a key purpose of TCM services is to aid in coordinating a patient's care across providers. Successful management of this sort may manifest itself through a non-trivial increase in the total quantity of care delivered. We consider such effects directly in Sections 6.3 and 6.4.

Second, we highlight that both code substitution and code complementarity can have subtle implications for claims-dependent measures of care quality and claims-dependent measures of risk adjustment. Metrics like those analyzed here, namely post-discharge visits with primary care physicians, are sometimes interpreted as measures of care quality. Our estimates reveal that a stagnant measure of post-discharge care, meaning a measure constructed entirely from the codes for standard office visits, would have penalized the physicians or health systems who were quickest to adopt the TCM code. This highlights that quality metrics that use billing codes to assess a provider's compliance with recommended care delivery must adapt to changes in coding systems. Changes in coding patterns can also have implications for risk adjustment models that take prior years' coding patterns as inputs.[12]

---

[11] To arrive at these figures, we take $1,000 of new code billing per PCP, multiply it by the average county-level stock of PCPs in our sample (58.42), and divide the resulting figure by the average billed amount for a TCM visit ($190.08). This tells us that $1,000 of additional new code billing per PCP represents 307.34 TCM visits on average. The average county-level count of discharged patients in our sample is 965.67. Comparing 1.2-percentage-point and 1.9-percentage-point declines in this figure to the total increase in TCM visits with which these declines are associated yields the figures above.

[12] This point relates quite directly to insights from Carey (2017). Carey points out that because new drugs alter affected patients' expected costs, their introduction can alter patients' relative profitability to drug plans when risk adjustment is based on prior years' claims. Carey shows further that the design of Medicare Part D plans is responsive to these

6.3 A Case of Complementary Coding and Service Provision

We might also expect the new codes to serve as complements to other primary care services. This could happen for distinct reasons that, as above, may blend changes in real service provision with changes in coding practices. For instance, on the one hand, the TCM codes were explicitly intended to reimburse services that would help with the coordination of post-discharge care. Once successfully integrated into physicians' practices, TCM billing might thus result directly in an increase in patients' contact with other physicians and an increase in care that would have otherwise not been provided. On the other hand, the need to integrate the new codes into a practice could lead a physician group to simply update their coding procedures more generally, or perhaps to hire a coding specialist, which could lead to changes in billing that come from reclassifying care that would have otherwise been provided.

An example of a service that acts as a complement to both TCM and CCM is the Annual Wellness Visit. The Annual Wellness Visit was first introduced as a part of the Affordable Care Act. It describes an office visit during which a patient receives a standard wellness check and works with a physician to plan for upcoming preventive care. In Figure 8, we see that the introduction of TCM is associated with an increase in the billing of Annual Wellness Visits in the treatment counties relative to the control counties. According to Table 5, this relationship amounts to an additional $1.28 of Annual Wellness Visit billing per PCP for every additional dollar of TCM billing per PCP. We estimate a far more modest complementarity of 13 cents in Annual Wellness Visit billing per PCP for each dollar of CCM billing per PCP (see Panel B of Table 5). The magnitude of the relationship between Annual Wellness Visits and TCM is particularly interesting given that the codes are meant to serve the complementary purpose of expanding the quantity and quality of primary care received by Medicare beneficiaries.

The implications of the complementarity of TCM with another recently introduced code should be considered in the context of its complementarity with traditional office visits. Table 6 shows the relationship between both new codes and the billing of office visits of 5 levels of complexity, where level 5 represents the most intensive office visits.[13] We see in Table 6 that TCM

incentives. Geruso, Layton, and Prinz (2019), Lavetti and Simon (2018), and Brown et al. (2014) also provide evidence that firms respond strategically to the incentives created by risk adjustment mechanisms.

[13] The office visit complexity categories are defined by factors such as the degree of detail of the medical history and examination involved, the complexity of the medical decision making, and the length of the visit.

complements office visits overall and that this is primarily driven by an additional $2.35 in level 4 office visit billing per PCP for each dollar of TCM billing per PCP. This relationship is shown in the event study specification in Figures 9 and 10 as well. The event studies for the unmatched sample (Figures A4 and A5) reinforce the positive relationship between TCM billing and complexity level 4 visits, although we do not estimate a statistically significant effect for total office visit billing for this sample.

The fact that there is some evidence of a relationship between CCM and Annual Wellness Visits, but not of one between CCM and complex office visits, may indicate that some of the Annual Wellness Visit complementarity stems from learning about coding and adopting more sophisticated billing practices that take advantage of the high payments available for recently introduced codes. But the strong link between TCM and complex office visits also suggests that there is a real care complementarity that is occurring independent of any increase in coding sophistication, and some of this additional care may be spilling over into Annual Wellness Visits. A mix of these stories is also plausible, where physicians provide more primary care visits in general and more intently provide an Annual Wellness Visit for each of their patients due to increased coding knowledge.

Increased coding sophistication could also partially explain the complementarity of TCM with traditional office visits that are of high complexity. Of course, this relationship could simply reflect the needs of the patients that TCM-billing PCPs are seeing. But it is also plausible that greater knowledge about coding, whether provided by a billing specialist or otherwise, would lead to an increase in the share of office visits provided that are classified as the more complex and higher-paying codes. Our estimates in Table 6 indicate a complementarity between TCM and level 5 office visits that is similar to the level 4 complementarity in terms of its percentage increase from the baseline. The point estimate for level 3 office visits is negative and relatively large, and there is a negative relationship for office visits of levels 1 and 2 as well. These facts suggest that office visits for TCM-billing physicians are being moved up in terms of their billed complexity. Physicians may be changing the real care provided during their visits to target the higher-paying complexity levels, or they may be billing higher complexity codes for visits that already would have met the necessary requirements.

6.4 The Overall Effects of New Code Adoption on Patterns of Coding and Care Provision

In this section we describe the effects of new code adoption on overall patterns of physician billing and care provision. The associations between TCM take-up, CCM take-up, and broad categories of billing are shown in Table 7. TCM exhibits substantial complementarity with the overall volume of services provided by PCPs. In total, each thousand dollars of TCM billing predicts an additional $5,240 of additional billing per PCP. The estimates in Table 7 are reinforced by the event study evidence in Figure 11 and Figure A6. Panel A of Figure 11 reveals that as of the last three years of our sample, PCPs in the high take-up counties in our matched sample were billing a substantial $13,330 more in services than PCPs in low take-up counties. The corresponding estimates for the full sample event study analysis, as presented in Figure A6, is a substantially more modest $2,280. Recall from Section 6.1 that PCPs in high take-up counties were, by the end of our sample, billing an average of about $1,370 more for TCM than were PCPs in low take-up counties. The full sample differential thus amounts to roughly $1,660 in additional billings per thousand dollars of TCM billing ($2,280 scaled by 1.370), while the matched sample differential amounts to roughly $9,730 per thousand dollars of TCM billing ($13,330 scaled by 1.370). While our event study and full panel estimates all imply substantial complementarity between the adoption of TCM and the provision of other services, the variations in estimates across our estimation strategies makes us cautious in advancing one specific quantitative estimate.[14]

Of the additional $5,240 in total billings, Table 7 shows that $3,620 comes from Evaluation & Management services, which encompasses many of the most basic and essential primary care services. The bulk of this increase is driven by Annual Wellness Visits and office visits, as described above. The "Other" category contains codes that are not easily categorized. As shown below, this includes a complementarity between TCM services and the delivery of flu and pneumonia vaccines.

[14] While we are cautious in advancing a particular quantitative estimate, the pattern of estimates gives us confidence that a substantial amount of complementary care provision is appropriately interpreted as a causal consequence of TCM code take-up. There are two principal reasons for this assessment. First, the overall point estimates in our panel framework are completely insensitive to whether or not we include a rich set of demographic and health controls in the regression model. This casts doubt on the alternative interpretation that complementary expenditures have been driven by differential shocks to the health care needs of counties with high relative to low levels of TCM take-up. Second, the largest implied complementarities come from what is arguably our "most controlled" specification, namely the event study analysis in which we both include our extensive sets of covariates and restrict the sample such that the high and low take-up counties have similar levels of billing per beneficiary at baseline.

In contrast with TCM, we find that CCM billing predicts little net increase in overall billing. Like TCM billing, CCM billing predicts increases in "Other" billing, including vaccinations. Unlike TCM billing, CCM billing predicts no net increase in Evaluation & Management services. Interestingly, CCM billing predicts a modest but statistically significant decline in Imaging billing. We present event study evidence for the Evaluation & Management and Imaging categories in Figures 12 and 13. The corresponding estimates for the outcomes in this section for the unmatched sample, which exhibit less precision than the estimates for the matched sample, are shown in Figures A6-A8.

The evidence presented thus far describes care provided by PCPs only. To assess the impacts of TCM and CCM billing on total care provision, we must also consider the care provided by physicians in other specialties. Appendix Tables A2 and A3 present the relevant evidence. Evidence on billing by non-PCP physicians reinforces key aspects of our findings on the care delivered by PCPs. Counties with high levels of TCM billing exhibit increases in the provision of care by non-PCPs, which augments the increase in care provision by PCPs. Once again, increases in Evaluation & Management services and "Other" services account for the majority of the overall increase. For CCM, we see no net increase in care provided by non-PCPs. Further, we see that declines in the utilization of Imaging services by PCPs are reinforced by declines in the utilization of Imaging services by non-PCPs.

The evidence summarized above reveals that the adoption of the TCM codes is associated with a substantial increase in overall care provision. This is consistent with the rationale for TCM services, which was to improve incentives for the coordination of post-discharge care. TCM services predict substantial increases in office visits by both PCPs and non-PCPs, suggesting systematic increases in patients' contact with their physicians after discharge. Importantly, these increases cannot be purely a function of coding, as the billing of additional Evaluation & Management services requires additional office visits to take place. In contrast with TCM billing, CCM billing predicts essentially no change in overall care billing. We take this as suggestive that CCM billing may, in large part, involve a rationalization of the coding for services that had previously been billed as moderately less lucrative codes. Take-up of CCM codes predicts modest shifts in care provision. This includes a reduction in Imaging services and an increase in Other services, including rates of vaccination.

6.5 New Code Provision and Receipt of Recommended Care

In this section we discuss the effect of the new codes on distinct examples of recommended preventive care to beneficiaries. In Table 8 we show evidence of complementarity of TCM with billing for flu vaccinations and billing for pneumonia vaccinations. This amounts to 18 cents of flu vaccine billing per PCP and 43 cents of pneumonia vaccination billing per PCP for each dollar of TCM billed per PCP. The corresponding event study graphs are shown in Figures 14 and 15. These examples are striking for a couple of reasons. These services represent unambiguous increases in care provision in that, in contrast with shifts in the complexity of office visits, billing for vaccinations cannot plausibly arise through the reclassification of care that was already being delivered. Additionally, flu vaccination in particular is a basic primary care service that is nearly universally recommended for the elderly.

Flu vaccination billing ramps up temporally for the treatment group as TCM take-up and usage increases. For pneumonia vaccinations, there is evidence of an increase in the first two years of TCM availability. In 2015, the Advisory Committee on Immunization Practices updated its recommendations to significantly expand the portion of the elderly whom it recommends to be vaccinated against pneumonia. The resulting spike in pneumonia vaccinations in 2015 hits the treatment group to a greater extent than the control group. The difference between the groups subsides from this peak but remains present through the last year of our sample. As with our evidence on broader categories of care provision, the evidence of the effects of CCM billing is mixed and points towards low levels of care complementarity. The contrast between TCM and CCM is, once again, quite striking.

In Table 8 we also see evidence of complementarity between TCM and billing for mammograms. The point estimate of 2 cents of mammogram billing per PCP for each dollar of TCM billing per PCP, while small in magnitude, is precisely estimated relative to a comparatively small baseline mean. This complementarity is reflected in the event study in panel A of Figure 16 as well. The relationship between TCM and the primary care services mentioned in this section meshes well with the fact that TCM seems to drive higher levels of Evaluation & Management services overall. The increases in the provision of these services, however, provides clear evidence that TCM brings about additional real care that does not simply represent a re-coding of care that was already being provided before the introduction of TCM.

7 Discussion and Conclusion

Maintaining an efficient health care payment system requires adapting to changes in the health care landscape. In recent years, this has required confronting the challenge of designing and managing care plans, in particular for patients with complex conditions. In this context, we analyze the U.S. Medicare program's introduction of new billing codes for the provision of Chronic Care Management and Transitional Care Management. Our analysis points to and assesses several economic margins that can complicate the jobs of insurance administrators as they design and implement such reforms.

We show why the successful implementation of basic payment reforms requires attending to a broad set of issues including take-up frictions, substitution across billing codes, and complementarities in both code billing and care provision. We first provide evidence on take-up patterns for the Chronic Care and Transitional Care Management codes we analyze. For care provision to respond to payment reform, it is essential that physicians recognize the nature of the payment reform and the incentives it creates, then respond to those incentives in their medical practices. We show that take-up is quite gradual, suggesting an important role for frictions in mediating the take-up of new billing codes. We next provide evidence that the billing codes we analyze substitute for some baseline service billing, while complementing and augmenting others. These patterns of substitution and complementarity have implications for the total cost of new code implementation as well as for the overall impact of new codes on the care received by patients. Each of these outcomes can be important for understanding the new code's financial costs and health care benefits. We show, for example, that the total care billed by PCPs rises by roughly $5 for each dollar of Transitional Care Management billed to Medicare. This additional spending comes with additional service provision including Annual Wellness Visits, additional office visits, vaccinations, and mammograms.

A complete analysis of the costs and benefits of payment reform must assess its impacts on health outcomes as well as on expenditures. While we analyze the relationship between new code adoption and several indicators of "recommended" care, we do not provide a comprehensive cost-benefit analysis. A full cost-benefit analysis would require long-run evidence on patient-level outcomes, which is beyond the scope of our study.

The Chronic and Transitional Care Management codes we analyze fit into a long-running effort by the Centers for Medicare and Medicaid Services to improve the rewards for providing primary care. These codes constitute an important tool in policy makers' toolkits, namely the ability to expand the set of services that are recognized and rewarded within fee-for-service payment schedules. In addition to the issues of take-up, substitution, and complementarity that we emphasize, we conclude by highlighting longer-run margins of interest. A crucial question for the payment reforms we analyze is how they shape the overall returns to specializing in primary care. Over the long run, reforms that increase the returns to practicing in primary care will tend to achieve their objectives if they induce more medical school students to make primary care their chosen specialty. More lucrative and more comprehensive payments for the services primary care practitioners deliver should be expected to have this effect.

References

Aizer, A., 2007. Public health insurance, program take-up, and child health. *The Review of Economics and Statistics*, *89*(3), pp.400-415.

Alexander, D. and Schnell, M., 2019. The impacts of physician payments on patient access, use, and health. *NBER Working Paper No. w26095*.

Anderson, G.F., 2010. *Chronic care: making the case for ongoing care*. Robert Wood Johnson Foundation.

Bhargava, S. and Manoli, D., 2015. Psychological frictions and the incomplete take-up of social benefits: Evidence from an IRS field experiment. *American Economic Review*, *105*(11), pp.3489-3529.

Bloink, J. and Adler, K.G., 2013. Transitional care management services: new codes, new requirements. *Family Practice Management*, 20(3), pp.12-17.

Brown, J., Duggan, M., Kuziemko, I. and Woolston, W., 2014. How does risk selection respond to risk adjustment? New evidence from the Medicare Advantage Program. *American Economic Review*, *104*(10), pp.3335-64.

Burton, R., Berenson, R.A. and Zuckerman, S., 2017. Medicare's evolving approach to paying for primary care. Washington, DC: Urban Institute.

Buttorff, C., Ruder, T. and Bauman, M., 2017. *Multiple chronic conditions in the United States* (Vol. 10). Santa Monica, CA: Rand.

CMS. 2012. Medicare Program; Revisions to Payment Policies Under the Physician Fee Schedule, DME Face-to-Face Encounters, Elimination of the Requirement for Termination of Non-Random Prepayment Complex Medical Review and Other Revisions to Part B for CY 2013. Final Rule with Comment Period. *Federal Register, Vol. 77, No. 222*, pp.68891-69380.

Carey, C., 2017. Technological change and risk adjustment: Benefit design incentives in Medicare Part D. *American Economic Journal: Economic Policy*, *9*(1), pp.38-73.

Carey, C., Lieber, E., and Miller, S. 2020. Drug firms' payments and physicians' prescribing behavior in Medicare Part D." *NBER Working Paper No. w26751*.

Chan, D.C., 2016. Teamwork and moral hazard: evidence from the emergency department. *Journal of Political Economy*, *124*(3), pp.734-770.

Chen, A., 2014. Do the poor benefit from more generous Medicaid physician payments?

Chetty, R., 2012. Bounds on elasticities with optimization frictions: A synthesis of micro and macro evidence on labor supply. *Econometrica*, *80*(3), pp.969-1018.

Chetty, R. and Saez, E., 2013. Teaching the tax code: Earnings responses to an experiment with EITC recipients. *American Economic Journal: Applied Economics*, *5*(1), pp.1-31.

Chetty, R., Friedman, J.N. and Saez, E., 2013. Using Differences in Knowledge across Neighborhoods to Uncover the Impacts of the EITC on Earnings. *American Economic Review*, *103*(7), pp.2683-2721.

Clemens, J. and Gottlieb, J.D., 2014. Do physicians' financial incentives affect medical treatment and patient health?. *American Economic Review*, *104*(4), pp.1320-49.

Clemens, J. and Gottlieb, J.D., 2017. In the shadow of a giant: Medicare's influence on private physician payments. *Journal of Political Economy*, *125*(1), pp.1-39.

Clemens, J., Gottlieb, J.D. and Hicks, J., 2021. How Would Medicare for All Affect Health System Capacity? Evidence from Medicare for Some. *Tax Policy and the Economy*, *35*(1), pp.225-262.

Clemens, J., Gottlieb, J.D. and Molnar, T.L., 2017. Do health insurers innovate? Evidence from the anatomy of physician payments. *Journal of Health Economics*, *55*, pp.153-167.

CMS. 2018. Medicare Program; Revisions to Payment Policies Under the Physician Fee Schedule and Other Revisions to Part B for CY 2019. Final Rule. *Federal Register, Vol. 83, No. 226*.

Doyle Jr, J.J., Ewer, S.M. and Wagner, T.H., 2010. Returns to physician human capital: Evidence from patients randomized to physician teams. *Journal of Health Economics*, *29*(6), pp.866-882.

Dunn, A., Gottlieb, J. D., Shapiro, A., Sonnenstuhl, D. J., an Tebaldi, P. 2021. A Denial a Day Keeps the Doctor Away. *NBER Working Paper No. w 29010*.

Dyrbye, L.N., West, C.P., Burriss, T.C. and Shanafelt, T.D., 2012. Providing primary care in the United States: the work no one sees. *Archives of Internal Medicine*, *172*(18), pp.1420-1421.

Farber, J., Siu, A. and Bloom, P., 2007. How much time do physicians spend providing care outside of office visits?. *Annals of Internal Medicine*, *147*(10), pp.693-698.

Friedberg, M.W., Hussey, P.S. and Schneider, E.C., 2010. Primary care: a critical review of the evidence on quality and costs of health care. *Health Affairs*, *29*(5), pp.766-772.

Garthwaite, C.L., 2012. The doctor might see you now: The supply side effects of public health insurance expansions. *American Economic Journal: Economic Policy*, *4*(3), pp.190-215.

Geruso, M. and Layton, T., 2020. Upcoding: evidence from Medicare on squishy risk adjustment. *Journal of Political Economy*, *128*(3), pp.984-1026.

Geruso, M., Layton, T. and Prinz, D., 2019. Screening in contract design: Evidence from the ACA health insurance exchanges. *American Economic Journal: Economic Policy*, *11*(2), pp.64-107.

Gottlieb, J.D., Shapiro, A.H. and Dunn, A., 2018. The complexity of billing and paying for physician care. *Health Affairs*, *37*(4), pp.619-626.

Gottschalk, A. and Flocke, S.A., 2005. Time spent in face-to-face patient care and work outside the examination room. *The Annals of Family Medicine*, *3*(6), pp.488-493.

Gruber, J., Kim, J. and Mayzlin, D., 1999. Physician fees and procedure intensity: the case of cesarean delivery. *Journal of Health Economics*, *18*(4), pp.473-490.

Khoury, S., Leganza, J.M. and Masucci, A., 2021. Health Professional Shortage Areas and Physician Location Decisions.

Kolstad, J.T., 2013. Information and quality when motivation is intrinsic: Evidence from surgeon report cards. *American Economic Review*, *103*(7), pp.2875-2910.

Lavetti, K. and Simon, K., 2018. Strategic formulary design in Medicare Part D plans. *American Economic Journal: Economic Policy*, *10*(3), pp.154-92.

Macinko, J., Starfield, B. and Shi, L., 2003. The contribution of primary care systems to health outcomes within Organization for Economic Cooperation and Development (OECD) countries, 1970–1998. *Health Services Research*, 38(3), pp.831-865.

Manoli, D.S. and Turner, N., 2014. Nudges and learning: Evidence from informational interventions for low-income taxpayers. *NBER Working Paper No. w20718*.

O'Malley, A.S., Sarwar, R., Keith, R., Balke, P., Ma, S. and McCall, N., 2017. Provider experiences with chronic care management (CCM) services and fees: a qualitative research study. *Journal of General Internal Medicine*, *32*(12), pp.1294-1300.

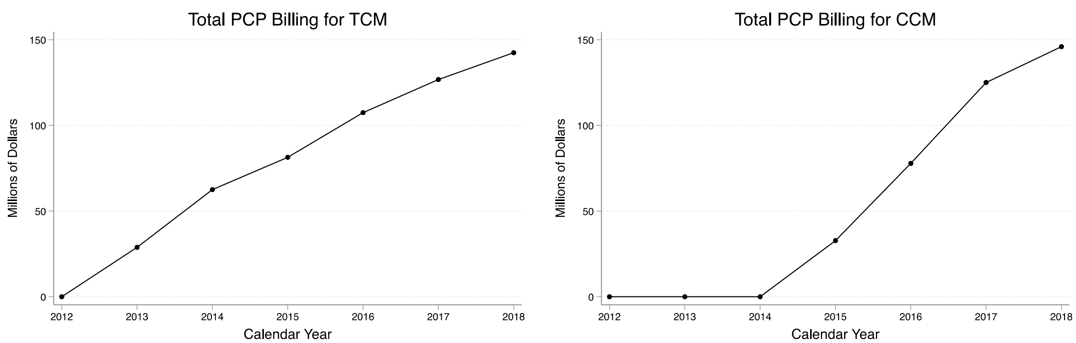
Schnell, M. and Currie, J., 2018. Addressing the opioid epidemic: is there a role for physician education?. *American Journal of Health Economics, 4(3),* pp.383-410.

Tai-Seale, M., Olson, C.W., Li, J., Chan, A.S., Morikawa, C., Durbin, M., Wang, W. and Luft, H.S., 2017. Electronic health record logs indicate that physicians split time evenly between seeing patients and desktop medicine. *Health Affairs*, *36*(4), pp.655-662.

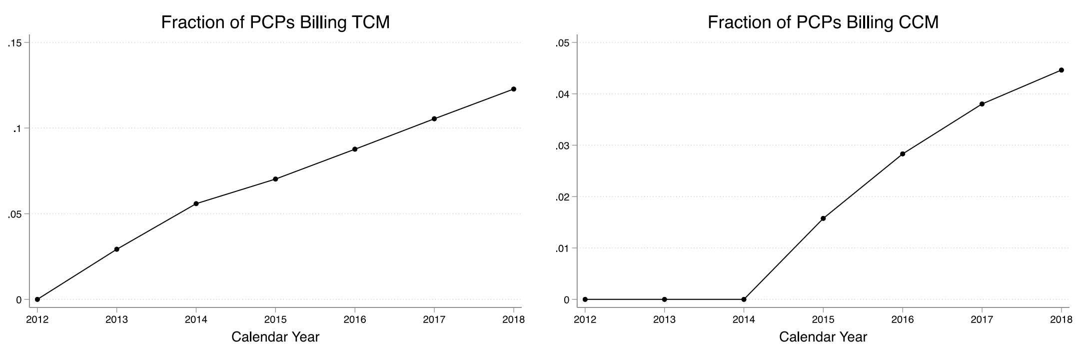
Figures and Tables

Figure 1: Take-Up of New Codes Over Time

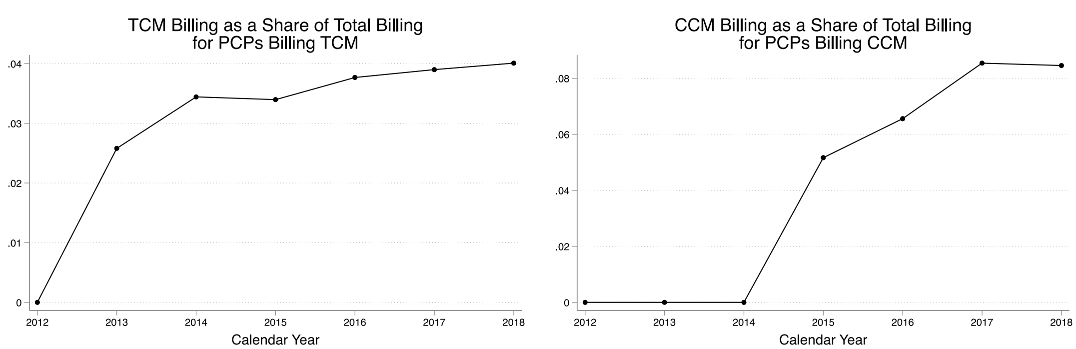
Panel A. Total New Code Billing



Panel B. Fraction of PCPs Billing New Codes



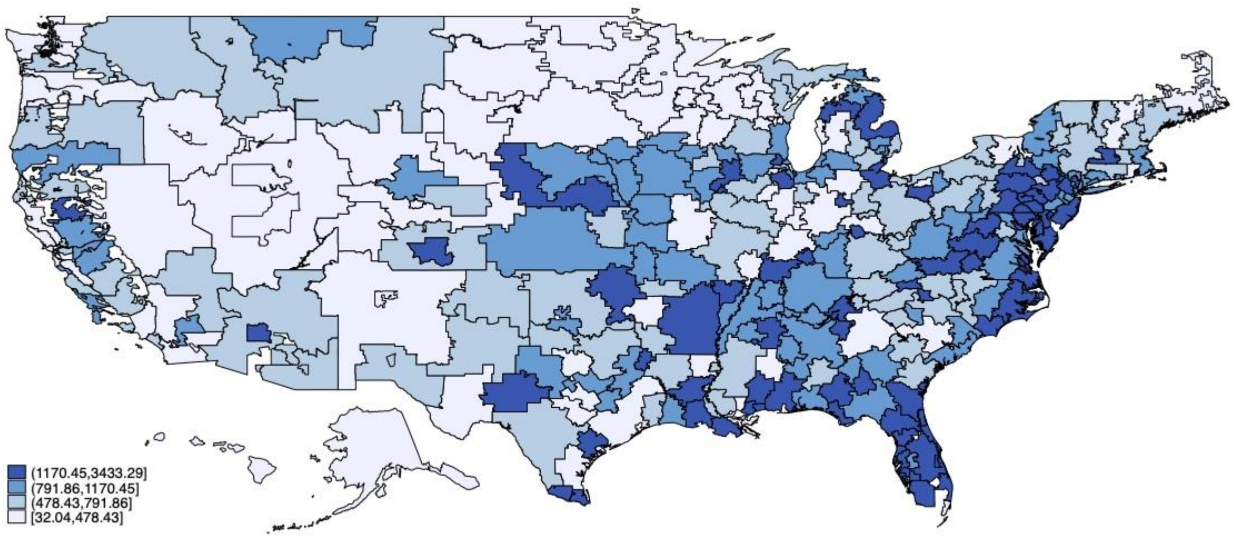
Panel C. New Code Billing as a Share of Total Billing



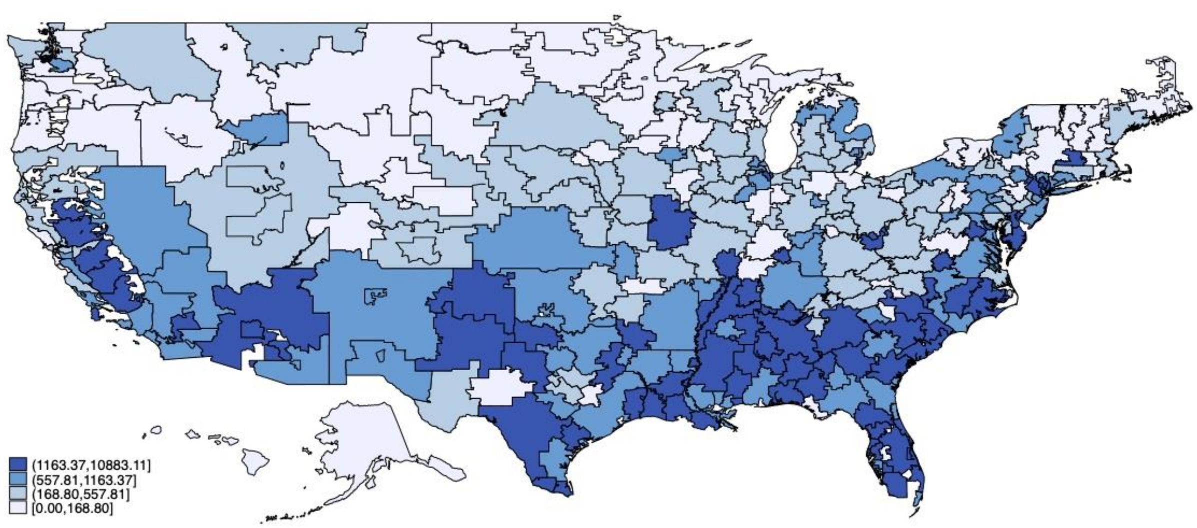
Notes: These graphs plot statistics related to the take-up of Transitional Care Management (TCM) and Chronic Chare Management (CCM) billing codes for primary care physicians (PCPs). We define PCPs to be physicians with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric Medicine. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from the Centers for Medicare & Medicaid Services.

Figure 2: Regional Variation in the Take-Up of New Codes

Panel A. TCM Hospital Referral Region Billing per PCP in 2018



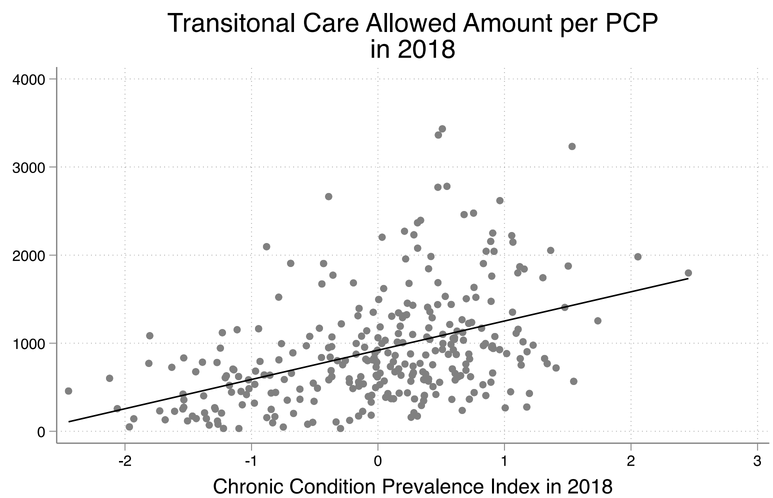
Panel B. CCM Hospital Referral Region Billing per PCP in 2018



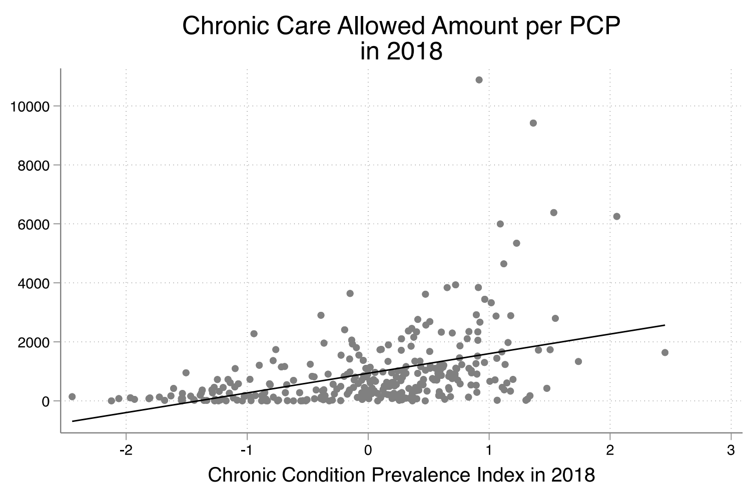
Notes: These heat maps illustrate regional variation in the take-up of Transitional Care Management (TCM) and Chronic Chare Management (CCM) billing codes. Each map plots new code billing per primary care physician (PCP) at the Hospital Referral Region (HRR) level in 2018, the final year of our sample. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from the Centers for Medicare & Medicaid Services.

Figure 3: Regional Variation in the Take-Up of New Codes by Chronic Condition Prevalence

Panel A. TCM Hospital Referral Region Billing per PCP in 2018



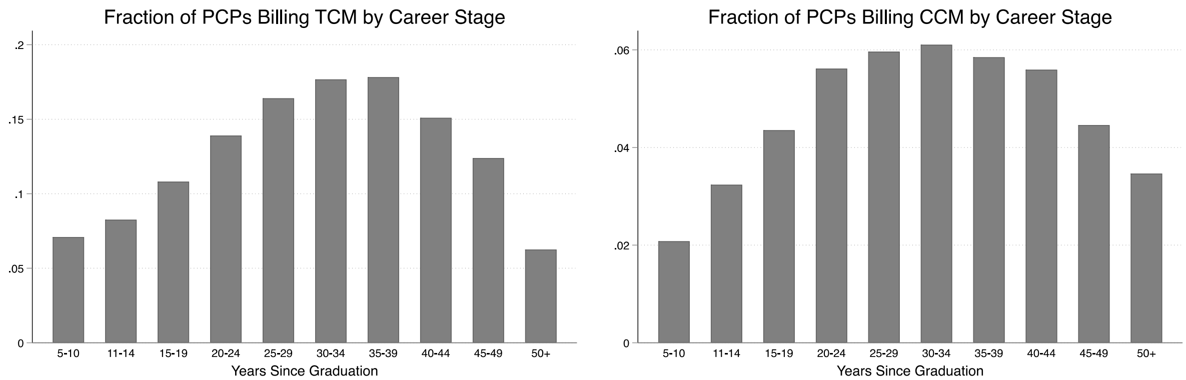
Panel B. CCM Hospital Referral Region Billing per PCP in 2018



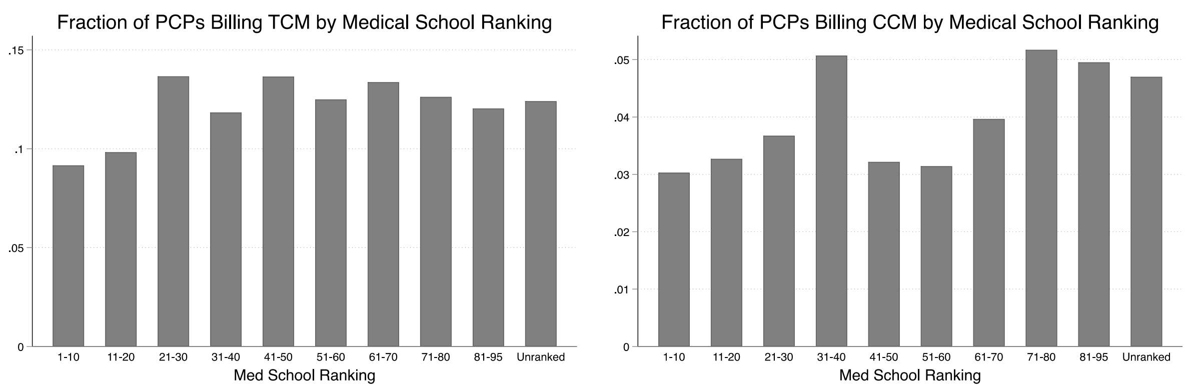
Notes: These scatter plots show how billing for Transitional Care Management (TCM) and Chronic Care Management (CCM) relate to the prevalence of chronic conditions in an area. Each graph plots new code billing per primary care physician (PCP) at the Hospital Referral Region (HRR) level against a constructed normalized index for chronic condition prevalence in 2018, the final year of our sample. The corresponding regression lines are also plotted. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from the Centers for Medicare & Medicaid Services. The chronic condition index is constructed by normalizing the prevalence rates of each of eight chronic conditions at the HRR level and averaging these eight values. See Appendix B for more details.

Figure 4: New Code Billing in 2018 by Career Stage and Medical School Ranking

Panel A. New Code Billing by Career Stage



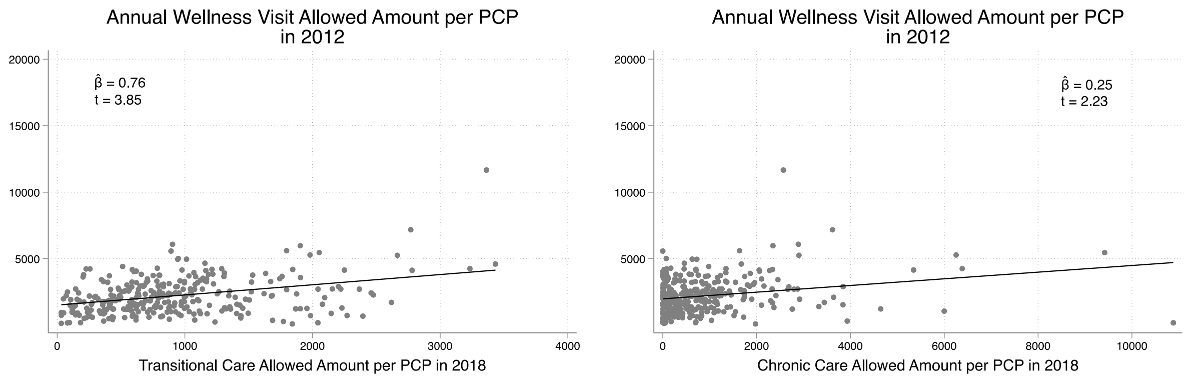
Panel B. New Code Billing by Medical School Ranking



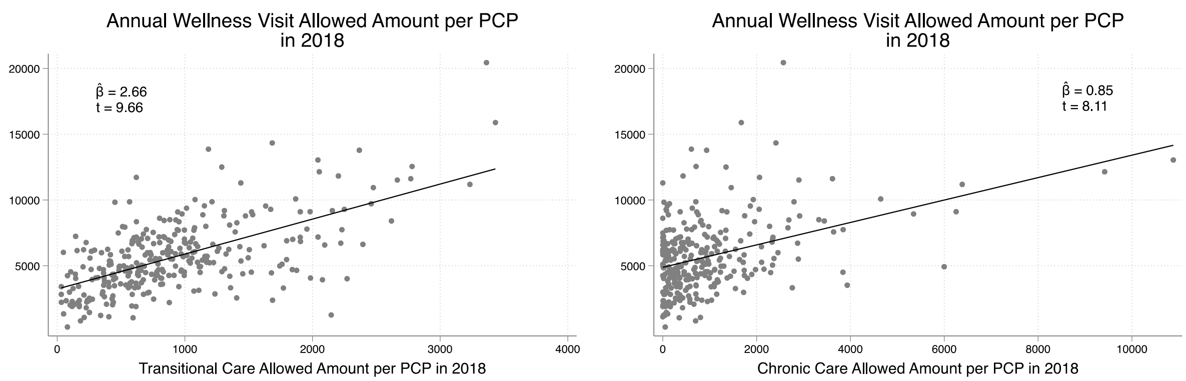
Notes: These bar graphs show how billing for Transitional Care Management (TCM) and Chronic Care Management (CCM) vary over career stages and across medical school rankings. Each graph plots the fraction of primary care physicians (PCPs) billing the new code for the various categories of career stage or medical school rankings in 2018, the final year of our sample. We define medical school rankings using the 2018 U.S. News & World Report rankings. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from the Centers for Medicare & Medicaid Services.

Figure 5: Correlations Between New Code Billing and Annual Wellness Visit Billing

Panel A. Correlations in 2012



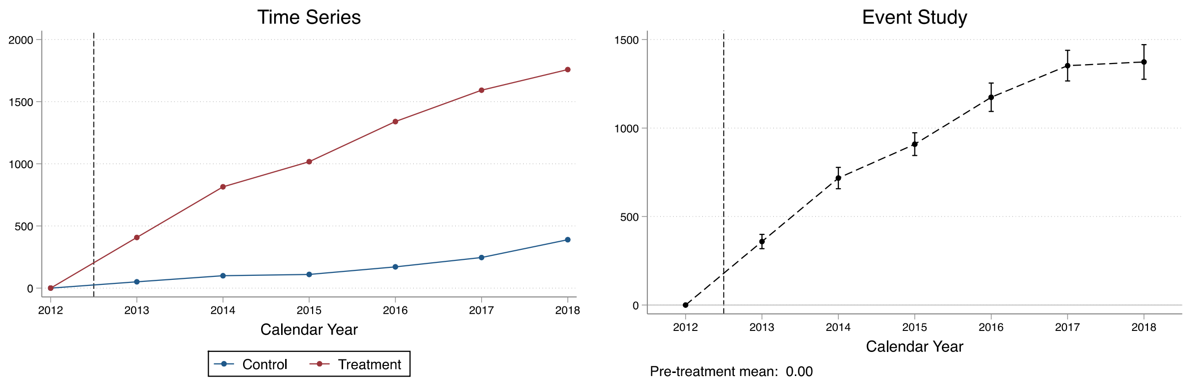
Panel B. Correlations in 2018



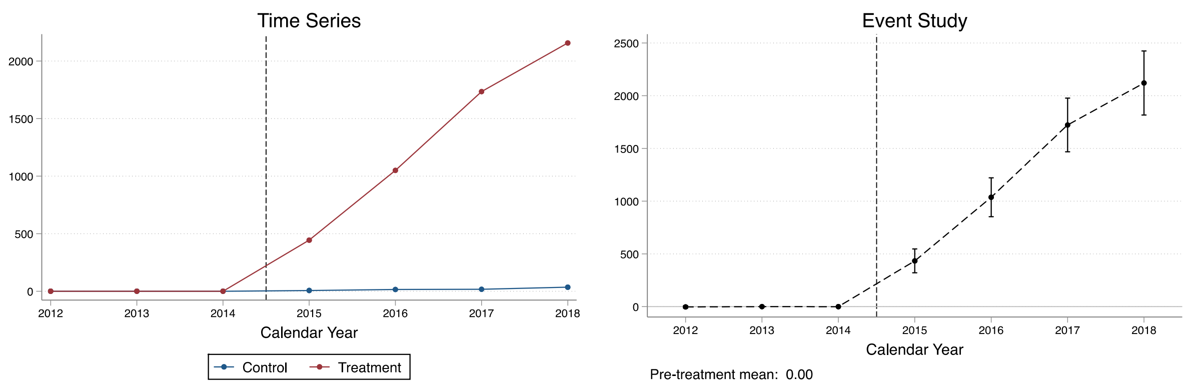
Notes: These scatter plots show how billing for Annual Wellness Visits relates to Transitional Care Management (TCM) and Chronic Care Management (CCM) billing. Each graph plots Annual Wellness Visit billing per primary care physician (PCP) against new code billing per PCP at the Hospital Referral Region (HRR) level. These plots are shown for 2012, the first year of our sample (before either new code was introduced), and 2018, the final year of our sample. The corresponding regression lines are also plotted. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from the Centers for Medicare & Medicaid Services.

Figure 6: New Code Allowed Amount by Treatment Status

Panel A. Transitional Care Management Billing per PCP, by TCM Treatment Group



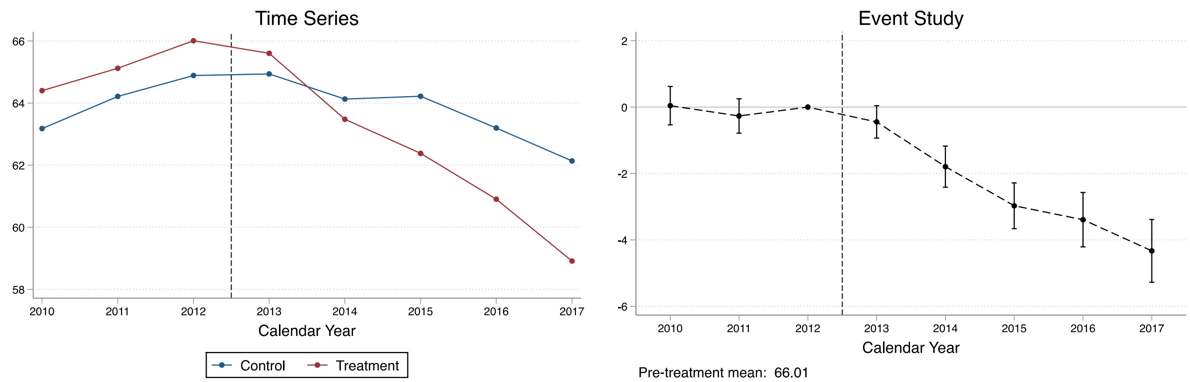
Panel B. Chronic Care Management Billing per PCP, by CCM Treatment Group



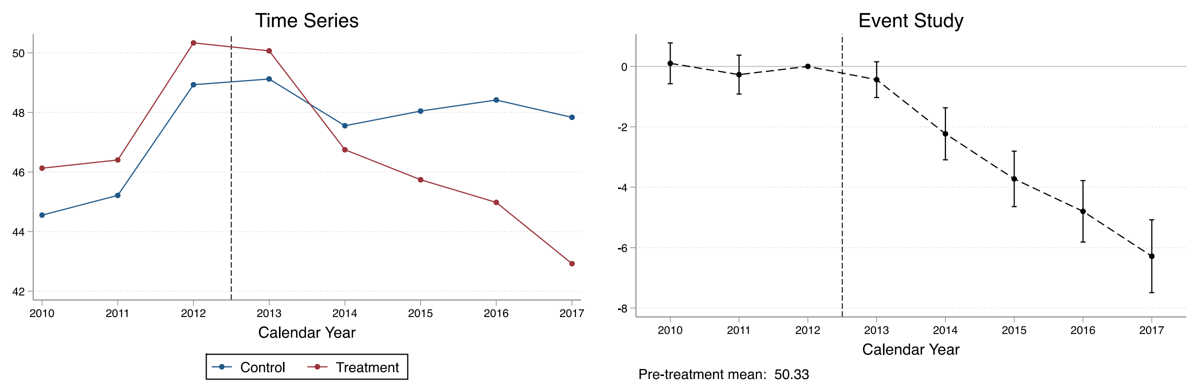
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable in panel A is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. The dependent variable in panel B is the county-level allowed amount for Chronic Care Management in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 7: An Example of Code Substitution

Panel A. Fraction of Beneficiaries with a Traditional Post-Discharge Ambulatory Visit, by TCM Treatment Group



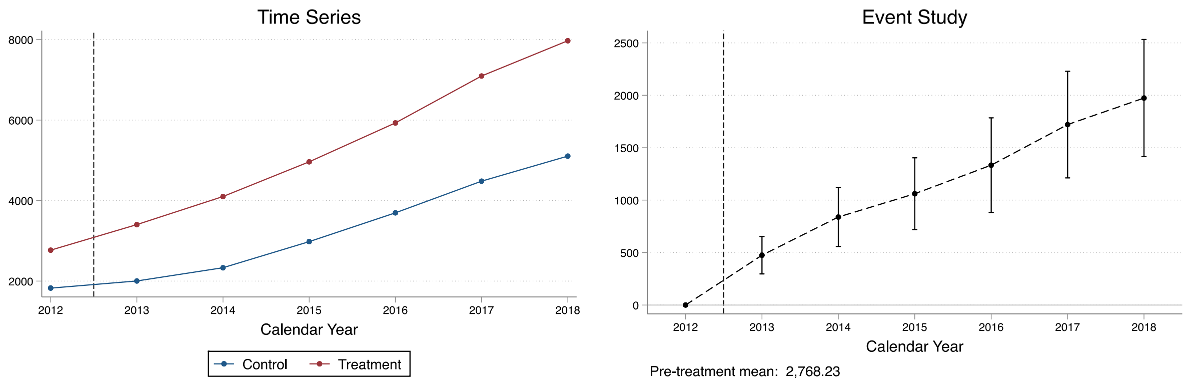
Panel B. Fraction of Beneficiaries with a Traditional Post-Discharge Visit with a PCP, by TCM Treatment Group



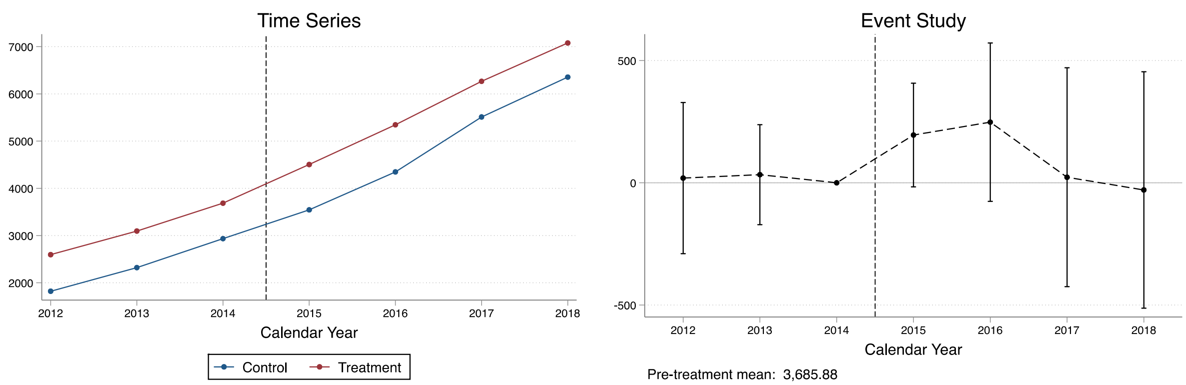
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2), estimated from our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable in panel A is the county-level fraction of beneficiaries with a traditional office visit within 14 days of a hospital discharge. The dependent variable in panel B is the county-level fraction of beneficiaries with a traditional office visit with a PCP within 14 days of a hospital discharge. Traditional office visits are defined in the data to include HCPCS codes 99201-99205, 99211-99215, 99381-99387, 99391-99397, 99241-99245, and 99271-99275. PCPs are defined in the data as any practitioners with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric Medicine. The denominator for both of these variables is the number of discharges in the given county-year. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 8: An Example of Complementarity with Another Recently Introduced Code

Panel A. Annual Wellness Visit Billing per PCP, by TCM Treatment Group



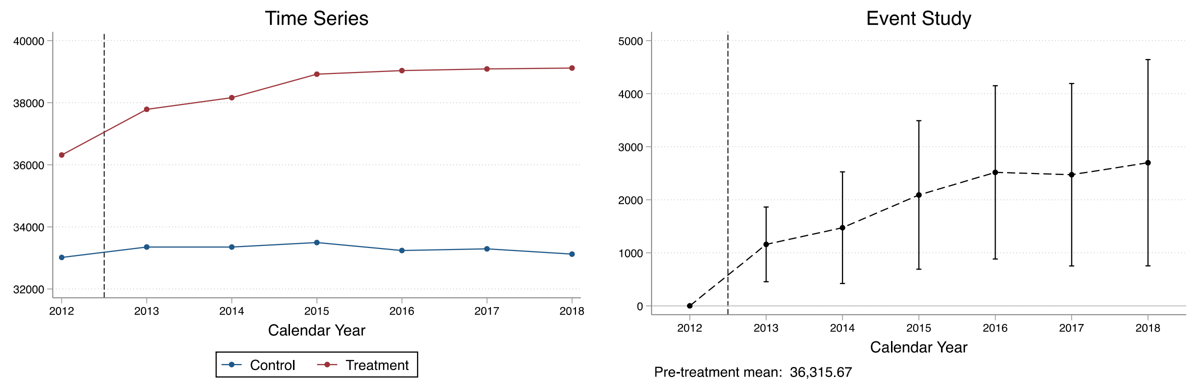
Panel B. Annual Wellness Visit Billing per PCP, by CCM Treatment Group



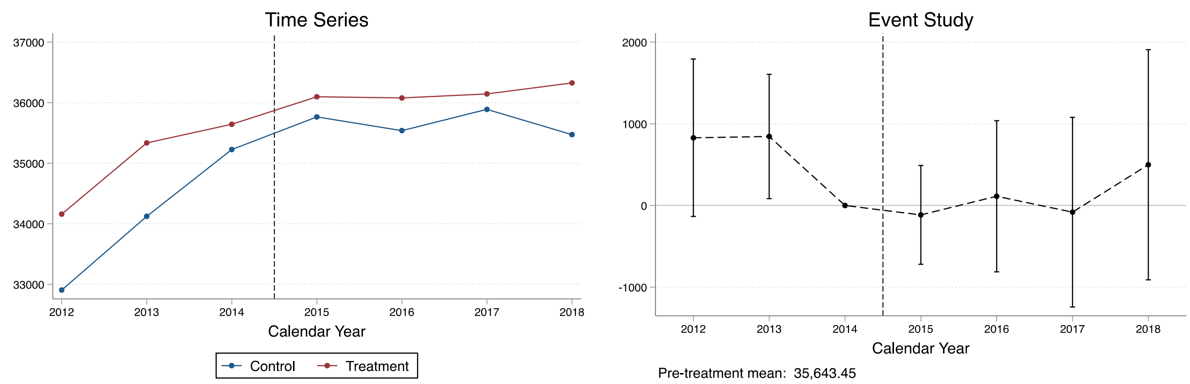
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for Annual Wellness Visits in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 9: An Example of Complementarity with a Traditional Primary Care Code (Complexity Level 4 Office Visit Billing)

Complexity Level 4 Office Visit Billing per PCP, by TCM Treatment Group



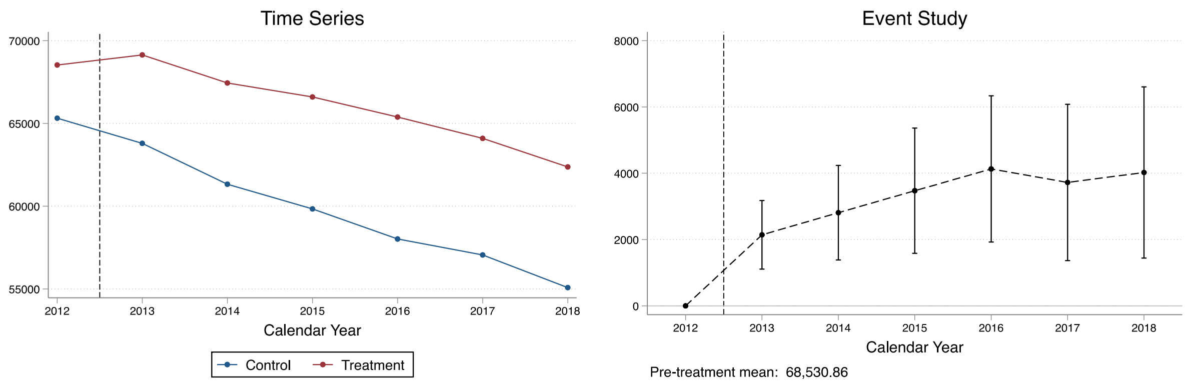
Complexity Level 4 Office Visit Billing per PCP, by CCM Treatment Group



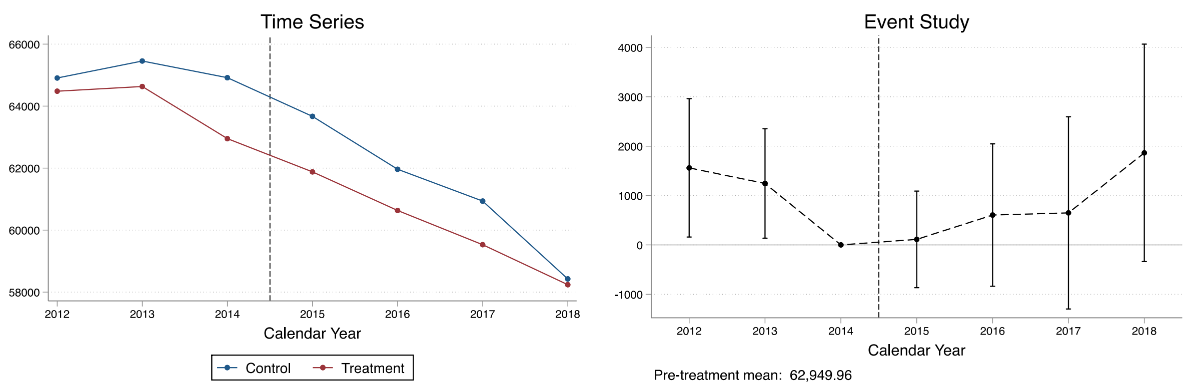
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for complexity level 4 office visits in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 10: An Example of Complementarity with a Traditional Primary Care Code (Total Office Visit Billing)

Total Office Visit Billing per PCP, by TCM Treatment Group



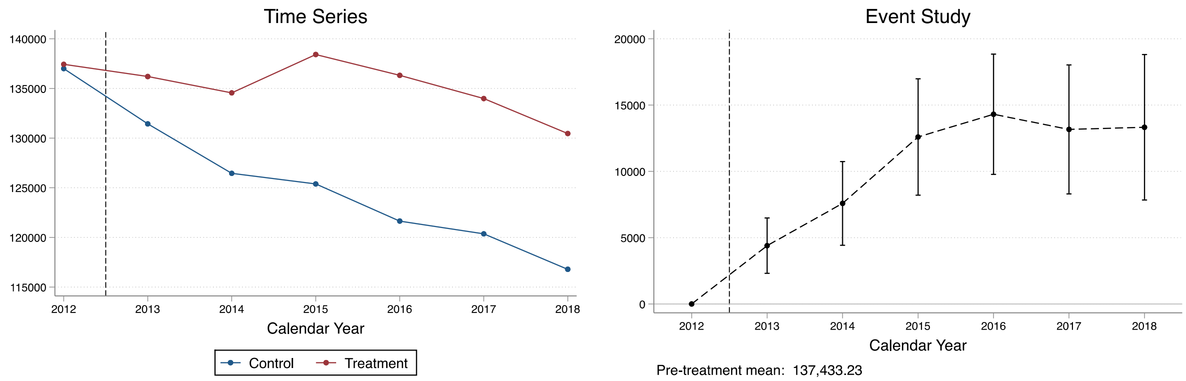
Total Office Visit Billing per PCP, by CCM Treatment Group



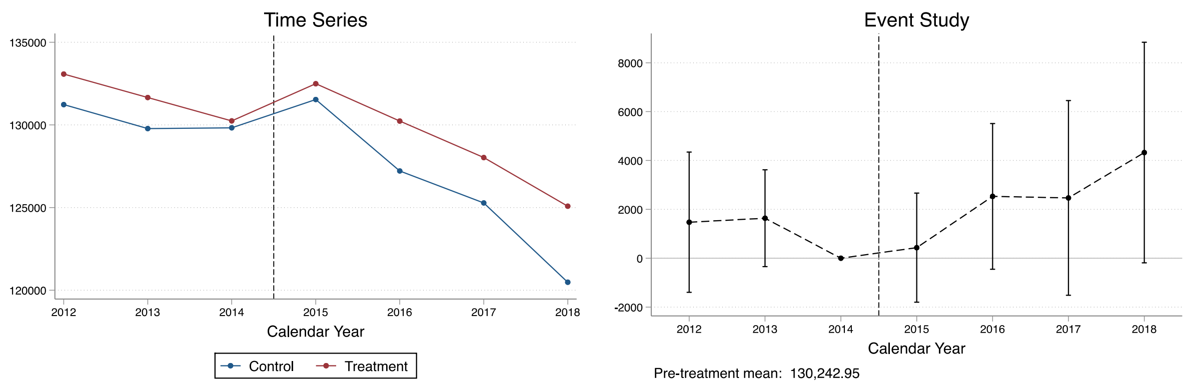
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for office visits in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 11: Total Billing

Panel A. Total Billing per PCP, by TCM Treatment Group



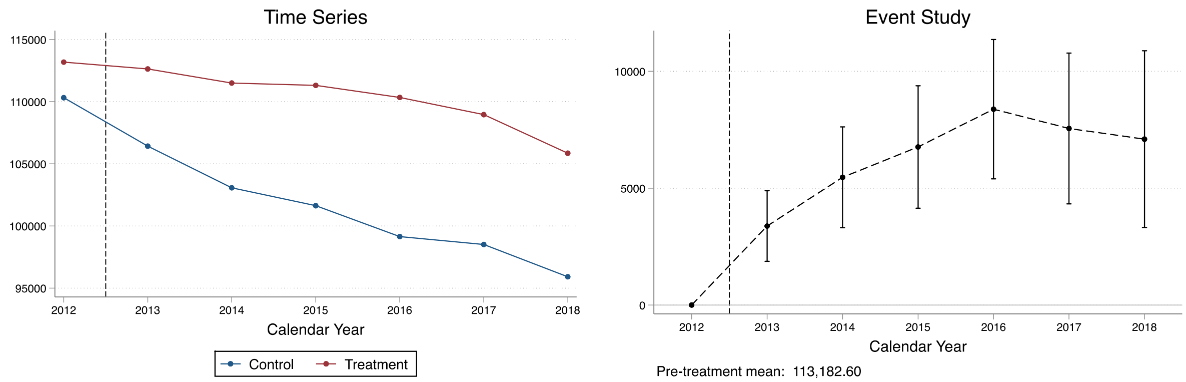
Panel B. Total Billing per PCP, by CCM Treatment Group



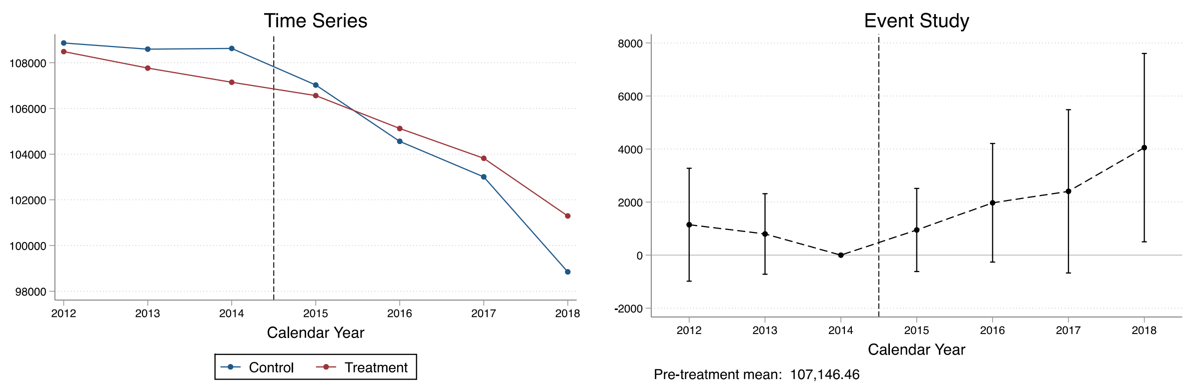
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level total allowed amount in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 12: Evaluation & Management Billing

Panel A. Evaluation & Management Billing per PCP, by TCM Treatment Group



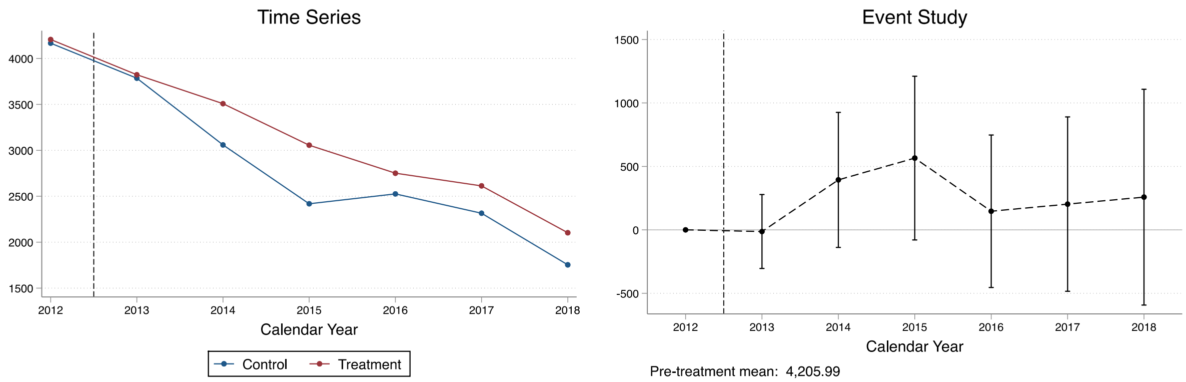
Panel B. Evaluation & Management Billing per PCP, by CCM Treatment Group



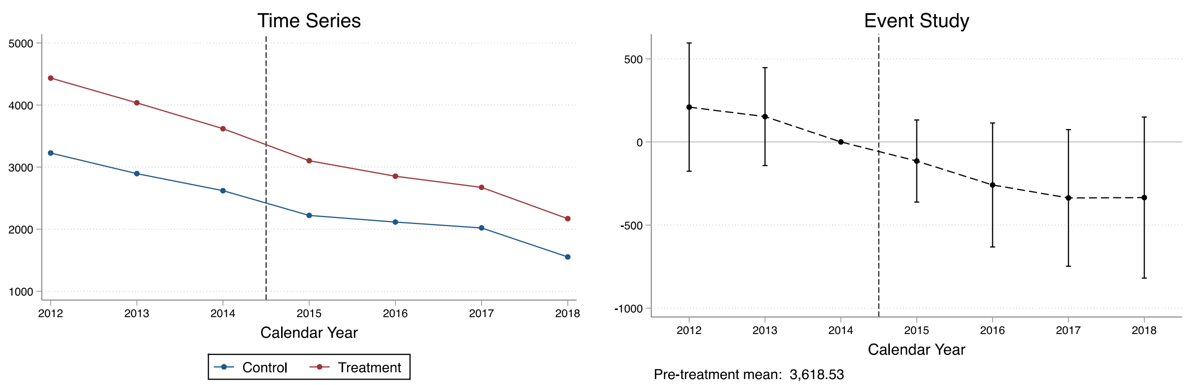
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for Evaluation & Management services in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 13: Imaging Billing

Panel A. Imaging Billing per PCP, by TCM Treatment Group



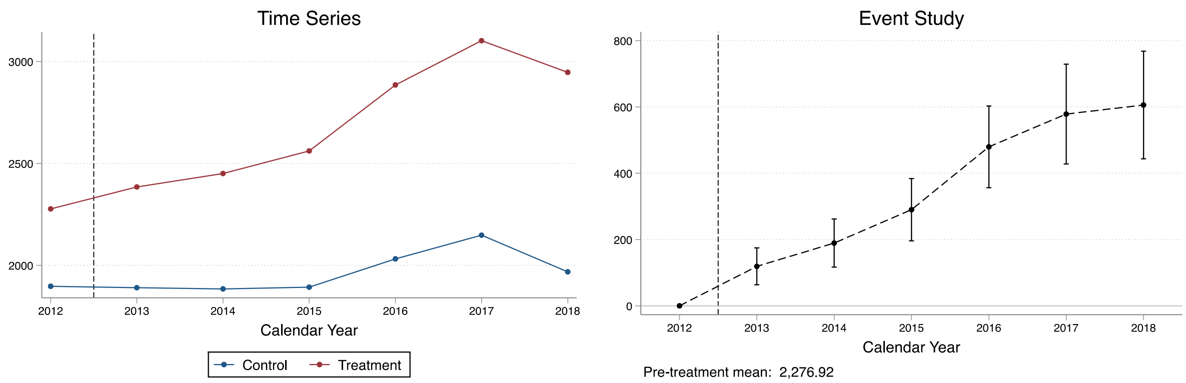
Panel B. Imaging Billing per PCP, by CCM Treatment Group



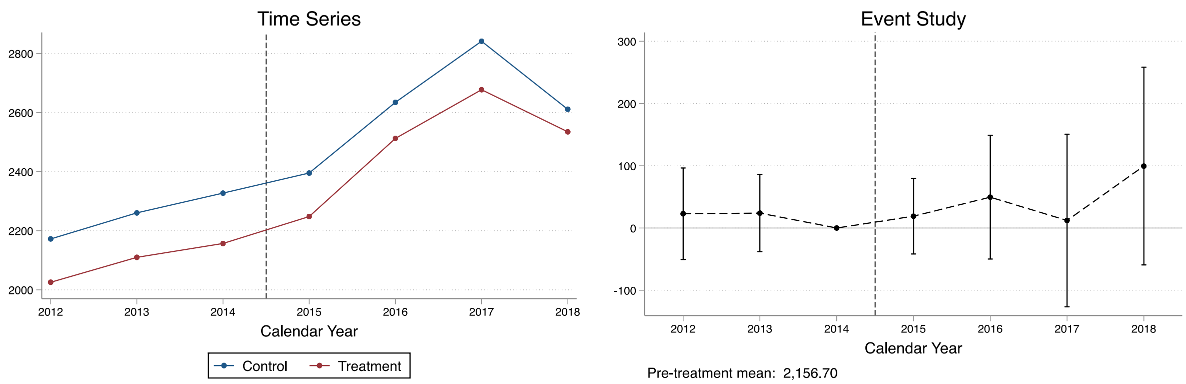
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for Imaging services in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 14: An Example of Complementarity with Recommended Primary Care Services: Influenza Vaccination

Panel A. Influenza Vaccination Billing per PCP, by TCM Treatment Group



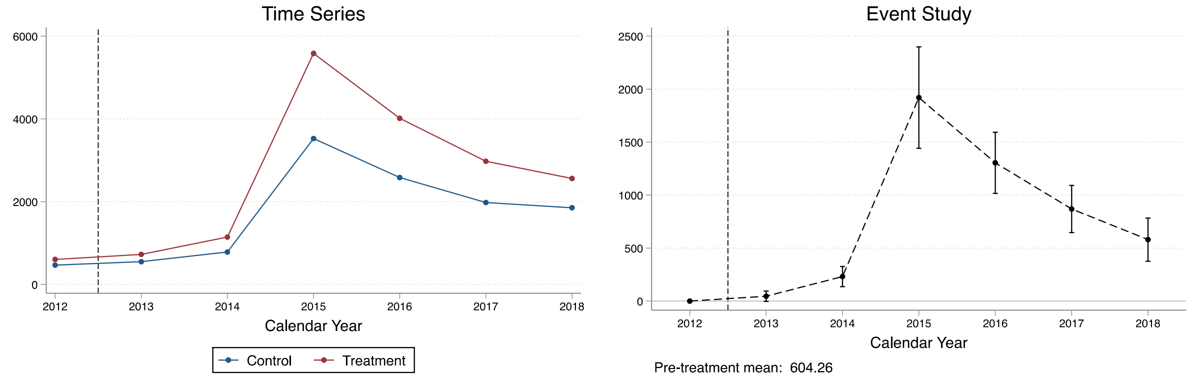
Panel B. Influenza Vaccination Billing per PCP, by CCM Treatment Group



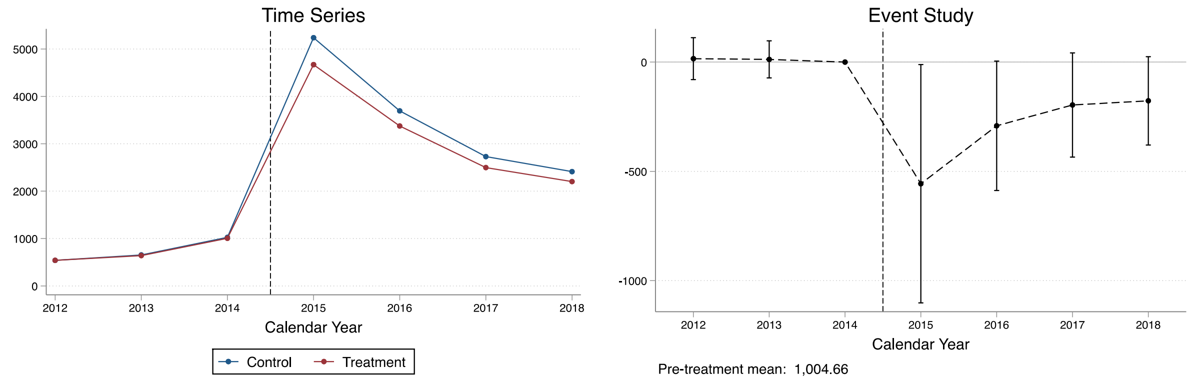
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for influenza vaccinations in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 15: An Example of Complementarity with Recommended Primary Care Services: Pneumonia Vaccination

Panel A. Pneumonia Vaccination Billing per PCP, by TCM Treatment Group



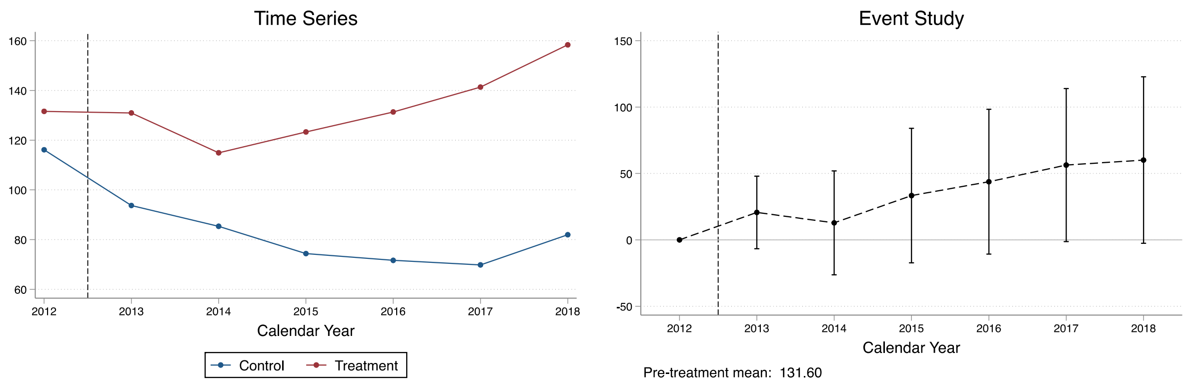
Panel B. Pneumonia Vaccination Billing per PCP, by CCM Treatment Group



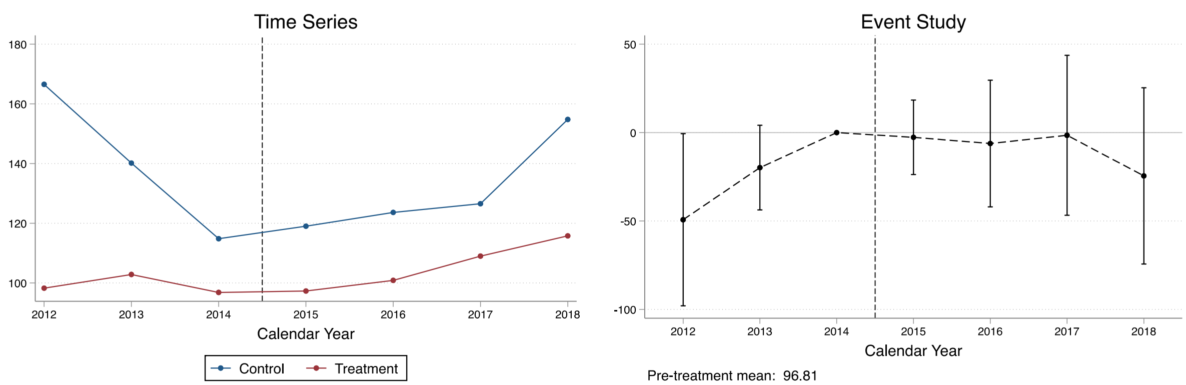
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for pneumonia vaccinations in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure 16: An Example of Complementarity with Recommended Primary Care Services: Mammograms

Panel A. Mammogram Billing per PCP, by TCM Treatment Group



Panel B. Mammogram Billing per PCP, by CCM Treatment Group



Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our matched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our matched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for mammograms in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Table 1: Summary Statistics Before the Introduction of the New Codes

	Statistic (1)
Panel A. PCP Counts	
Number of PCPs	175,408
Fraction Sole Practitioner	0.196
Fraction Early Career	0.153
Fraction Mid Career	0.654
Fraction Late Career	0.121
Fraction Ranked	0.323
Fraction Unranked	0.677
Panel B. PCP Billing	
Average Total Billing	\$101,967 (139,856)
Average Billing for Office Visits	\$45,186 (57,400)
Average Billing for Wellness Visit	\$2,100 (6,877)

Notes: This table displays summary statistics for our sample in 2012. We define primary care physicians (PCPs) to be physicians with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric Medicine. We define early-career, mid-career, and late-career physicians as those who graduated from medical school 5-24 years prior, 25-39 years prior, and 40+ years prior, respectively. We define medical school rankings using the 2018 U.S. News & World Report rankings. All billing statistics refer to Medicare billings. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from CMS.

Table 2: Likelihood of Billing New Codes in 2018

	Percent Billing TCM (1)	Percent Billing CCM (2)	Observations (3)
Panel A. Specialty			
PCPs	12.3%	4.5%	176,676
Non-PCPs	0.6%	0.4%	878,302
Panel B. Career Stage			
Early-Career PCPs	10.0%	3.8%	27,688
Mid-Career PCPs	17.3%	6.0%	109,269
Late-Career PCPs	12.9%	4.9%	30,588
Panel C. Medical School			
PCPs from Ranked Schools	12.0%	3.9%	52,049
PCPs from Unranked Schools	12.4%	4.7%	124,627
PCPs from Top 10 Schools	9.2%	3.0%	5,972
Panel D. Group Size			
Sole Practitioner PCPs	10.8%	5.0%	32,830
Small Group PCPs	15.4%	6.0%	44,915
Mid-Size Group PCPs	15.8%	5.3%	44,511
Large Group PCPs	7.8%	2.2%	54,420
Panel E. Group Size and Group Composition			
Small PCP-Only Group PCPs	16.5%	6.1%	29,396
Small Non-PCP-Only Group PCPs	13.1%	5.7%	15,519
Mid-Size PCP-Only Group PCPs	17.3%	6.1%	11,552
Mid-Size Non-PCP-Only Group PCPs	15.2%	5.0%	32,959
Large PCP-Only Group PCPs	10.3%	3.2%	533
Large Non-PCP-Only Group PCPs	7.8%	2.2%	53,887
Panel F. Other Billing Behaviors			
PCPs Billing Standard Office Visits	16.6%	5.7%	129,495
PCPs Billing the Other New Code	40.9%	14.8%	21,692 | 7,883
PCPs Billing Annual Wellness Visits	27.3%	9.3%	67,803

Notes: This table displays Transitional Care Management (TCM) and Chronic Care Management (CCM) billing propensities by various physician characteristics, in 2018, the final year of our sample. We define primary care physicians (PCPs) to be physicians with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric Medicine. We define early-career, mid-career, and late-career physicians as those who graduated from medical school 5-24 years prior, 25-39 years prior, and 40+ years prior, respectively. We define medical school rankings using the 2018 U.S. News & World Report rankings. We define small groups, mid-size groups, and large groups as groups with 2-5 practitioners, 6-20 practitioners, and 21+ practitioners, respectively. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from CMS.

Table 3: Group-Level Likelihood of Billing New Codes in 2018

	Percent Billing TCM (1)	Percent Billing CCM (2)	Observations (3)
Sole Practitioners	10.8%	5.0%	32,830
Small Group	21.3%	8.5%	26,801
Mid-Size Group	31.2%	11.5%	12,254
Large Group	36.8%	15.9%	4,821

Notes: This table displays group-level Transitional Care Management (TCM) and Chronic Care Management (CCM) billing propensities in 2018, the final year of our sample. We include all groups that have at least one primary care physician (PCP). We define PCPs to be physicians with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric Medicine. We define small groups, mid-size groups, and large groups as groups with 2-5 practitioners, 6-20 practitioners, and 21+ practitioners, respectively. We define a group to be billing the new code if at least one physician at the group bills the code in 2018. The underlying data source is our 2012–2018 panel of physicians, which we construct using primarily the *Medicare Provider Utilization and Payment Data: Physician and Other Supplier* dataset from CMS.

Table 4: Post-Discharge Outcomes

New Code	Fraction of Beneficiaries with a Traditional Post-Discharge Visit	Fraction of Beneficiaries with a Traditional Post-Discharge Visit with a PCP	Controls
Transitional Care Management (Thousands of $ per PCP)			
	-1.15***	-1.87***	No
	(.15)	(.19)	
	-1.21***	-1.93***	Yes
	(.15)	(.20)	
Dep. Mean	63.5	48.1	
N	16,760	16,051	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2017. The independent variable is the county-level allowed amount for Transitional Care Management in units of thousands of dollars billed by PCPs per PCP. Dependent variables are county-level rates where the denominator is the annual number of discharged patients. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Table 5: Annual Wellness Visits

New Code	Annual Wellness Visit Billing per PCP	Controls
Transitional Care Management ($ per PCP)		
	1.30***	No
	(.11)	
	1.28***	Yes
	(.11)	
Chronic Care Management ($ per PCP)		
	.14**	No
	(.06)	
	.13**	Yes
	(.06)	
Dep. Mean	3,051.80	
N	20,262	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2018. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. Similarly, the dependent variable is the county-level allowed amount for Annual Wellness Visits billed by PCPs per PCP. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Table 6: Office Visits by Complexity

New Code	Total Office Visit Billing per PCP	Level 1 Office Visit Billing per PCP	Level 2 Office Visit Billing per PCP	Level 3 Office Visit Billing per PCP	Level 4 Office Visit Billing per PCP	Level 5 Office Visit Billing per PCP	Controls
Transitional Care Management ($ per PCP)							
	2.02***	-.03**	-.03*	-.51	2.40***	.18***	No
	(.61)	(.01)	(.02)	(.37)	(.40)	(.07)	
	2.05***	-.03**	-.02	-.45	2.35***	.19***	Yes
	(.62)	(.01)	(.02)	(.37)	(.40)	(.07)	
Chronic Care Management ($ per PCP)							
	.07	.01	-.01	-.06*	.15	-.02	No
	(.12)	(.01)	(.004)	(.04)	(.09)	(.01)	
	.08	.01	-.003	-.04	.13	-.01	Yes
	(.12)	(.01)	(.004)	(.04)	(.09)	(.01)	
Dep. Mean	48,611.14	327.64	1,008.83	18,486.90	26,401.64	2,386.13	
N	20,262	20,262	20,262	20,262	20,262	20,262	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2018. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. Similarly, the dependent variable is the county-level allowed amount for the specified outcome billed by PCPs per PCP. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Table 7: PCP Billing by Category

New Code	Total Billing per PCP	Evaluation & Management Billing per PCP	Procedures Billing per PCP	Imaging Billing per PCP	Tests Billing per PCP	Durable Medical Equipment Billing per PCP	Other Billing per PCP	Controls
Transitional Care Management ($ per PCP)								
	5.24***	3.61***	.18	-.13	.13	.01	1.44***	No
	(1.20)	(.82)	(.12)	(.21)	(.11)	(.03)	(.16)	
	5.24***	3.62***	.17	-.11	.13	.01	1.42***	Yes
	(1.21)	(.83)	(.12)	(.21)	(.11)	(.02)	(.16)	
Chronic Care Management ($ per PCP)								
	.27	.21	-.01	-.09**	-.03	.002	.19**	No
	(.29)	(.20)	(.02)	(.04)	(.05)	(.006)	(.08)	
	.27	.21	-.01	-.09**	-.03	.003	.19**	Yes
	(.29)	(.21)	(.02)	(.04)	(.05)	(.006)	(.08)	
Dep. Mean	99,675.41	82,169.14	3,706.79	1,997.22	5,456.28	40.30	6,305.68	
N	20,262	20,262	20,262	20,262	20,262	20,262	20,262	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2018. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. Similarly, the dependent variable is the county-level allowed amount for the specified outcome billed by PCPs per PCP. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level. Transitional Care Management and Chronic Care Management belong to the Evaluation & Management category, but the new code of interest for each regression is excluded from this category as well as from Total billing. The dependent means for the first two columns are the average of the means that result from dropping each new code, which are approximately the same.

Table 8: Recommended Care

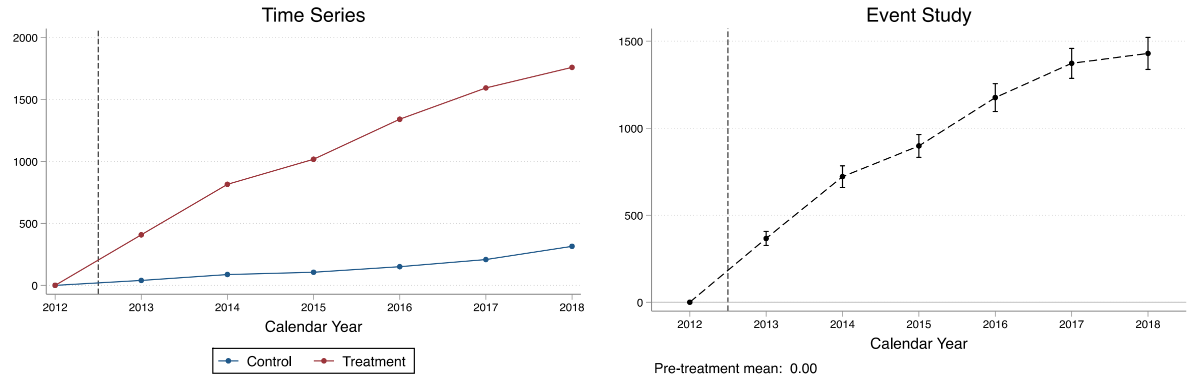
New Code	Influenza Vaccination Billing per PCP	Pneumonia Vaccination Billing per PCP	Mammogram Billing per PCP	Controls
Transitional Care Management ($ per PCP)				
	.18***	.43***	.02**	No
	(.03)	(.06)	(.008)	
	.18***	.43***	.02**	Yes
	(.03)	(.06)	(.008)	
Chronic Care Management ($ per PCP)				
	.01	.04***	-.003	No
	(.01)	(.01)	(.004)	
	.01	.03***	-.003	Yes
	(.01)	(.01)	(.004)	
Dep. Mean	1,810.14	1,544.92	83.22	
N	20,262	20,262	20,262	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2018. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. Similarly, the dependent variable is the county-level allowed amount for the specified outcome billed by PCPs per PCP. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

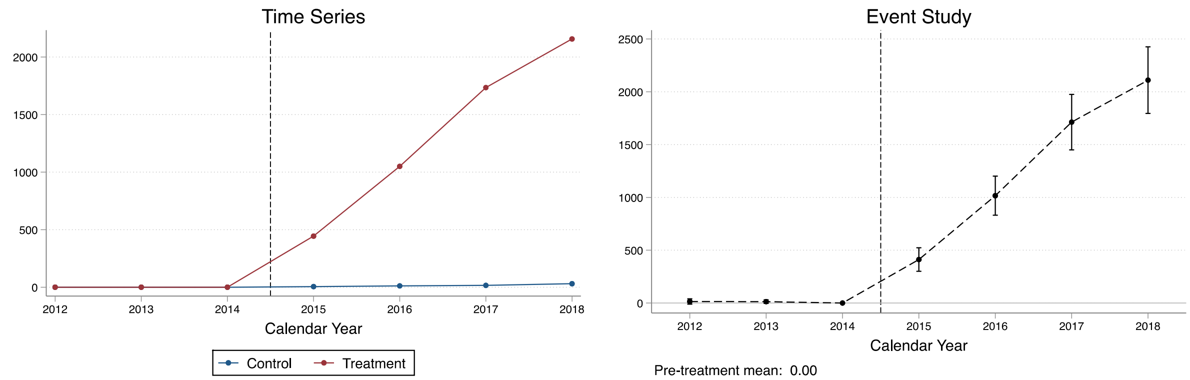
Appendix A: Additional Figures and Tables

Figure A1: New Code Allowed Amount by Treatment Status – Unmatched Sample

Panel A. Transitional Care Management Billing per PCP, by TCM Treatment Group



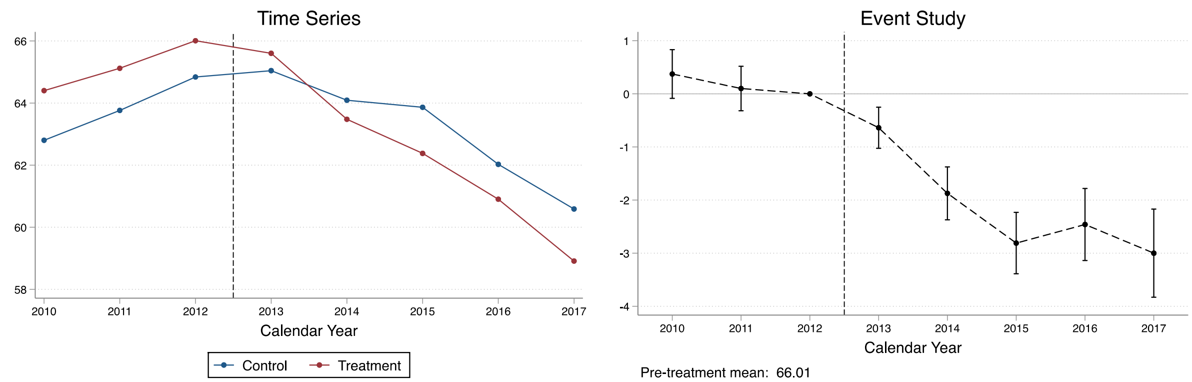
Panel B. Chronic Care Management Billing per PCP, by CCM Treatment Group



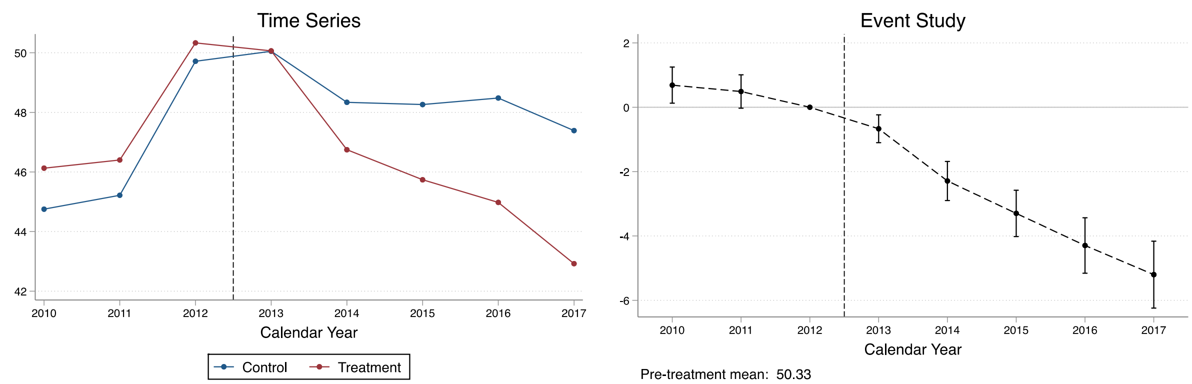
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable in panel A is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. The dependent variable in panel B is the county-level allowed amount for Chronic Care Management in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A2: An Example of Code Substitution – Unmatched Sample

Panel A. Fraction of Beneficiaries with a Traditional Post-Discharge Ambulatory Visit, by TCM Treatment Group



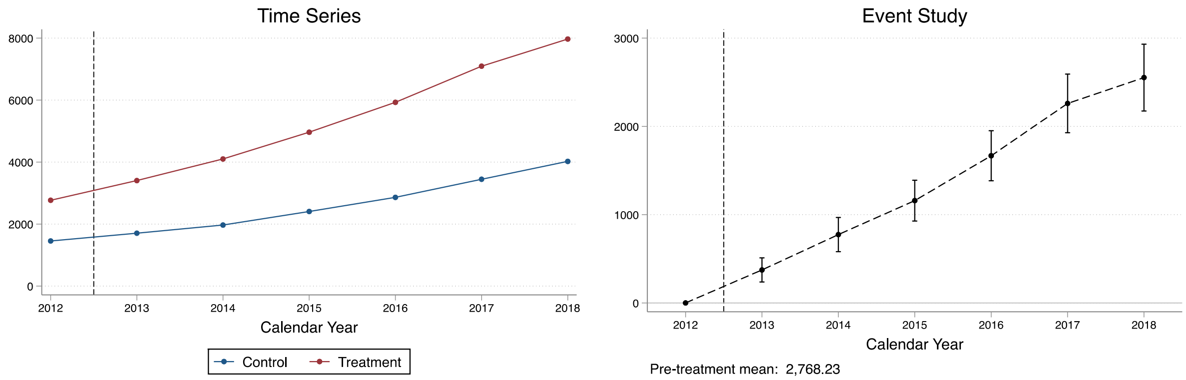
Panel B. Fraction of Beneficiaries with a Traditional Post-Discharge Visit with a PCP, by TCM Treatment Group



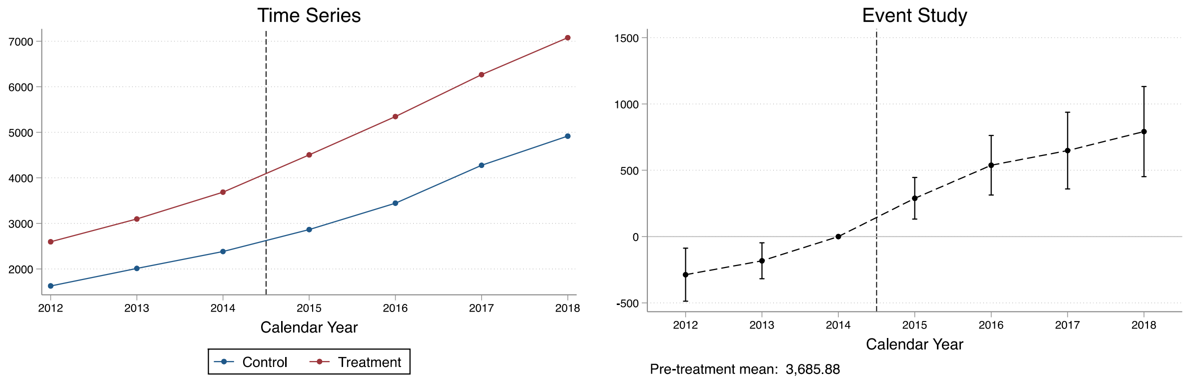
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2), estimated from our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable in panel A is the county-level fraction of beneficiaries with a traditional office visit within 14 days of a hospital discharge. The dependent variable in panel B is the county-level fraction of beneficiaries with a traditional office visit with a PCP within 14 days of a hospital discharge. Traditional office visits are defined in the data to include HCPCS codes 99201-99205, 99211-99215, 99381-99387, 99391-99397, 99241-99245, and 99271-99275. PCPs are defined in the data as any practitioners with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric Medicine. The denominator for both of these variables is the number of discharges in the given county-year. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A3: An Example of Complementarity with Another Recently Introduced Code – Unmatched Sample

Panel A. Annual Wellness Visit Billing per PCP, by TCM Treatment Group



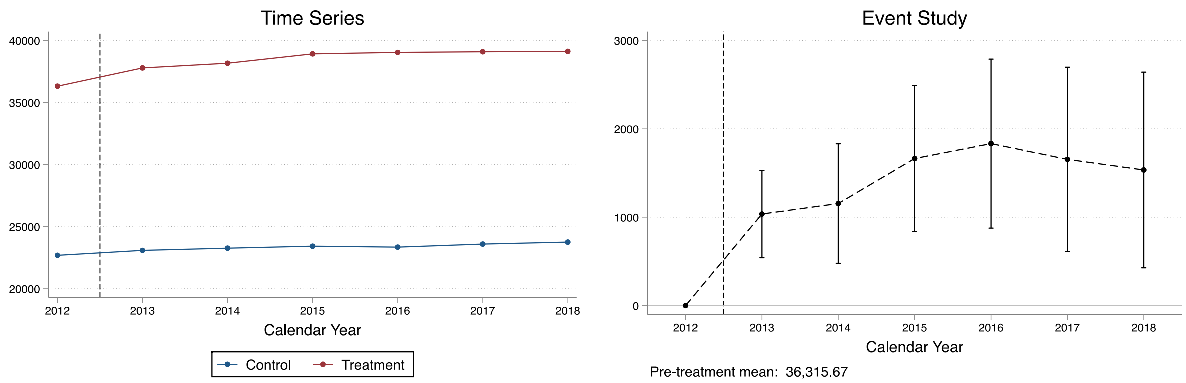
Panel B. Annual Wellness Visit Billing per PCP, by CCM Treatment Group



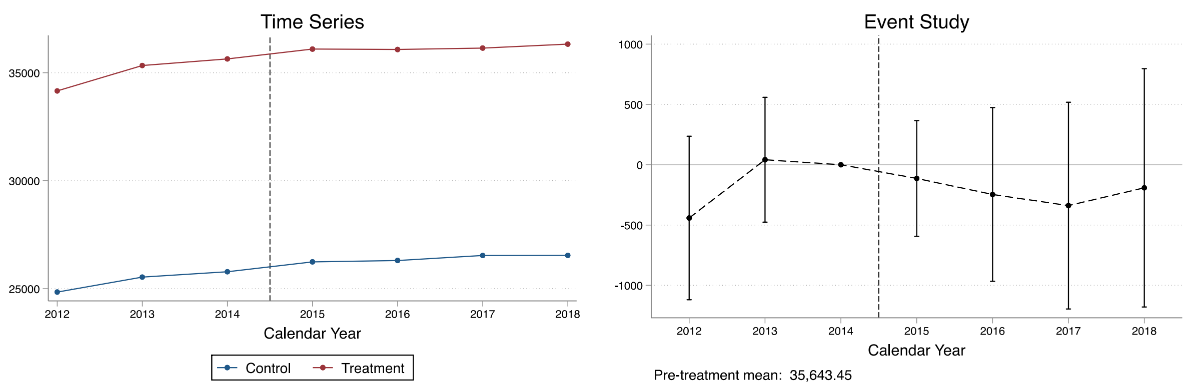
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for Annual Wellness Visits in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A4: An Example of Complementarity with a Traditional Primary Care Code – Unmatched Sample (Complexity Level 4 Office Visit Billing)

Complexity Level 4 Office Visit Billing per PCP, by TCM Treatment Group



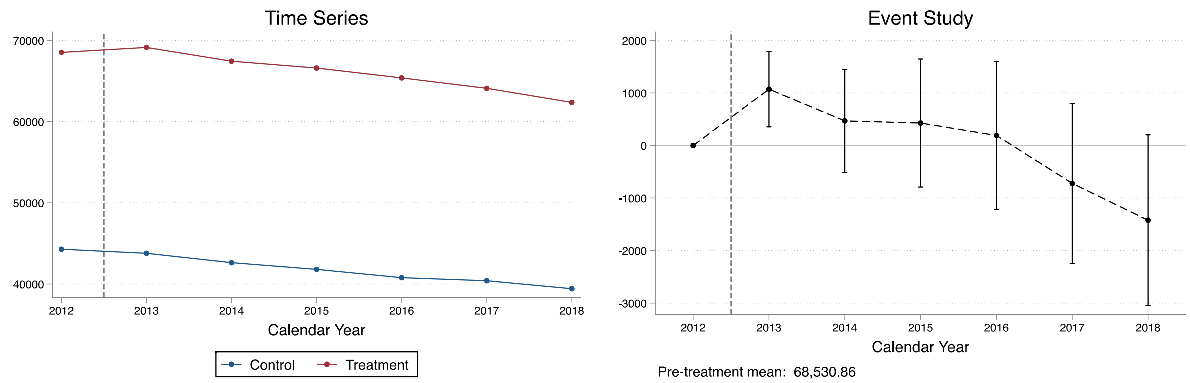
Complexity Level 4 Office Visit Billing per PCP, by CCM Treatment Group



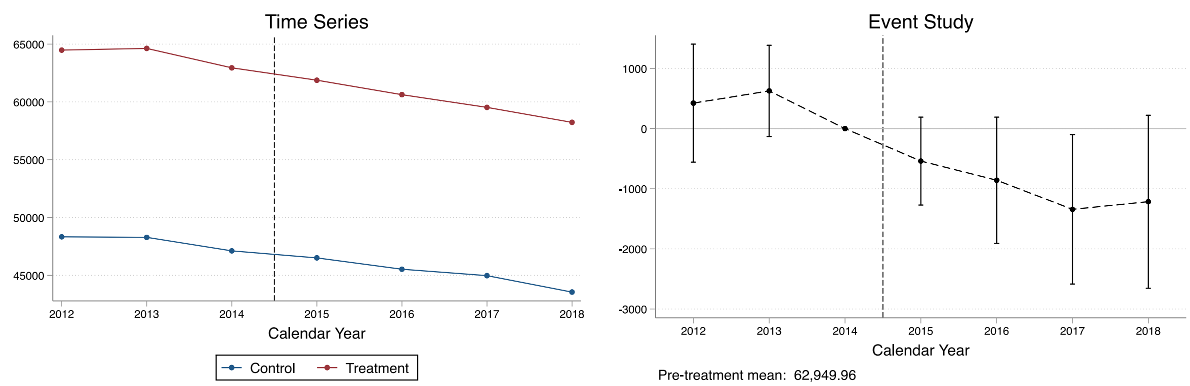
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for complexity level 4 office visits in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A5: An Example of Complementarity with a Traditional Primary Care Code – Unmatched Sample (Total Office Visit Billing)

Total Office Visit Billing per PCP, by TCM Treatment Group



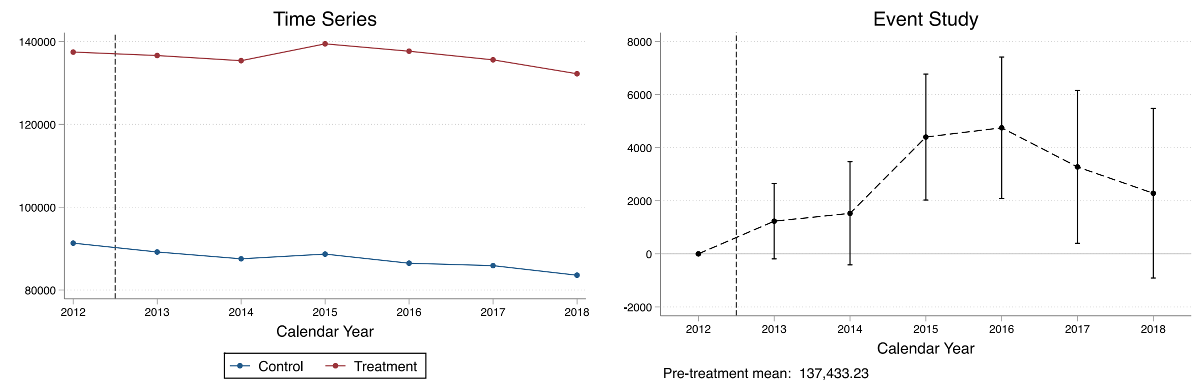
Total Office Visit Billing per PCP, by CCM Treatment Group



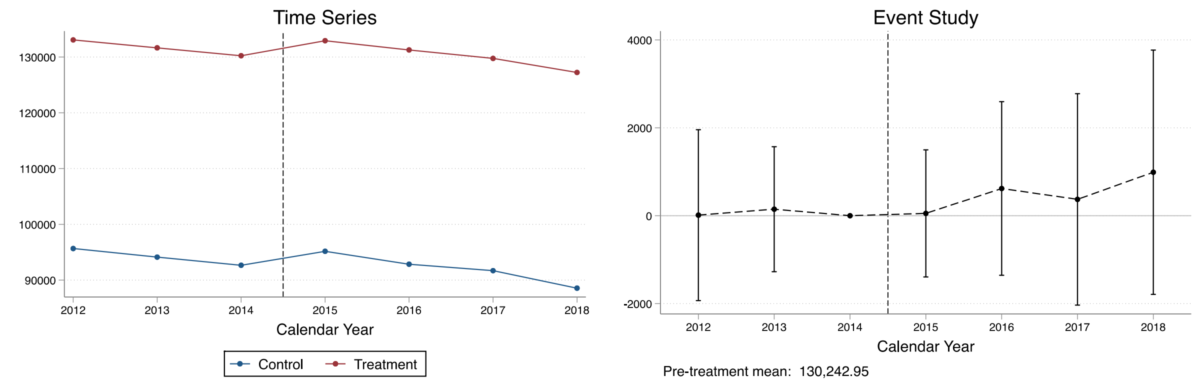
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for office visits in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A6: Total Billing – Unmatched Sample

Panel A. Total Billing per PCP, by TCM Treatment Group



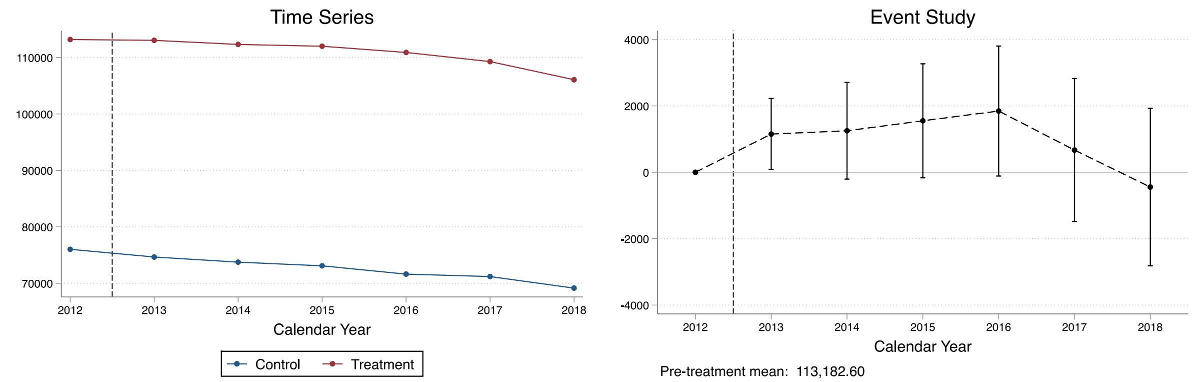
Panel B. Total Billing per PCP, by CCM Treatment Group



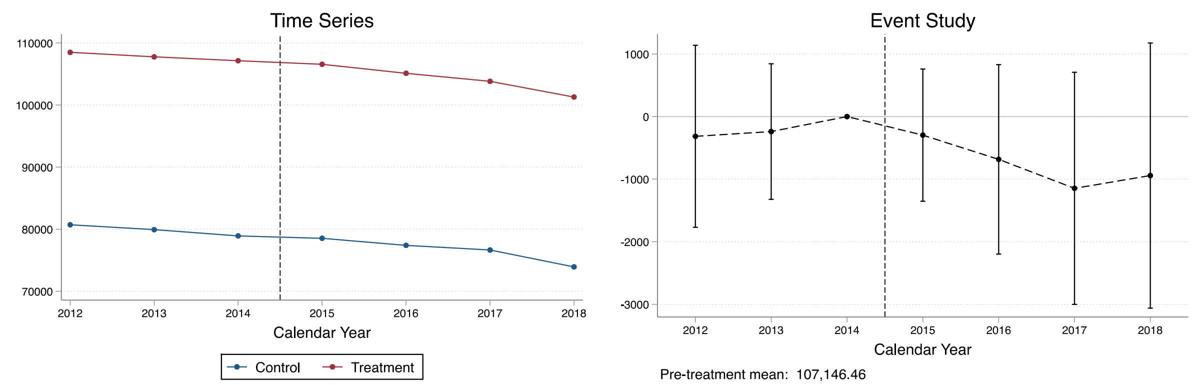
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level total allowed amount in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A7: Evaluation & Management Billing – Unmatched Sample

Panel A. Evaluation & Management Billing per PCP, by TCM Treatment Group



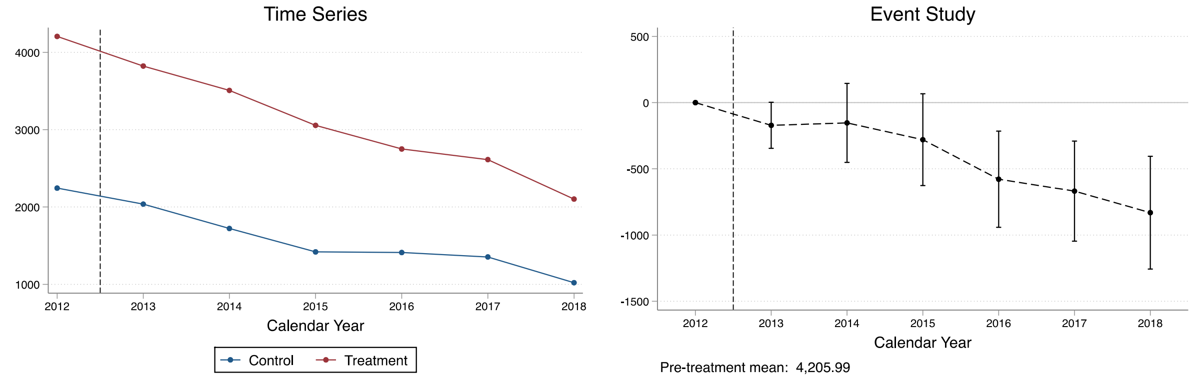
Panel B. Evaluation & Management Billing per PCP, by CCM Treatment Group



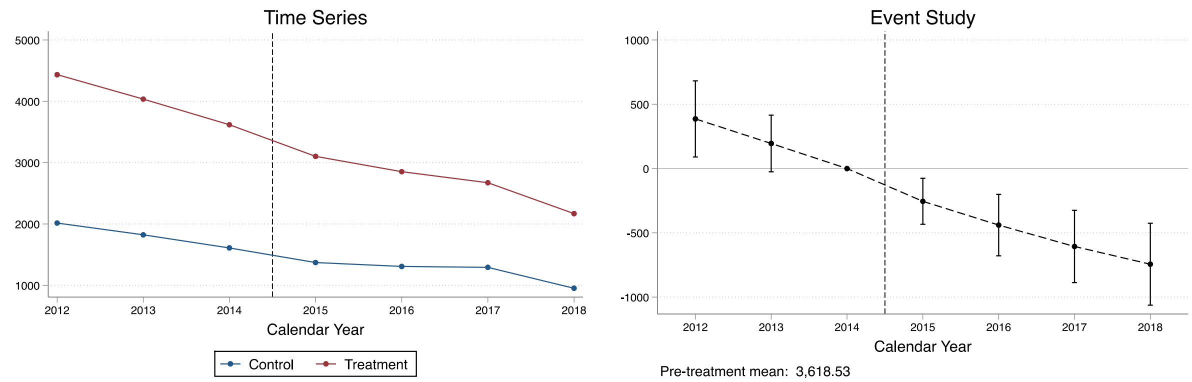
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for Evaluation & Management services in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A8: Imaging Billing – Unmatched Sample

Panel A. Imaging Billing per PCP, by TCM Treatment Group



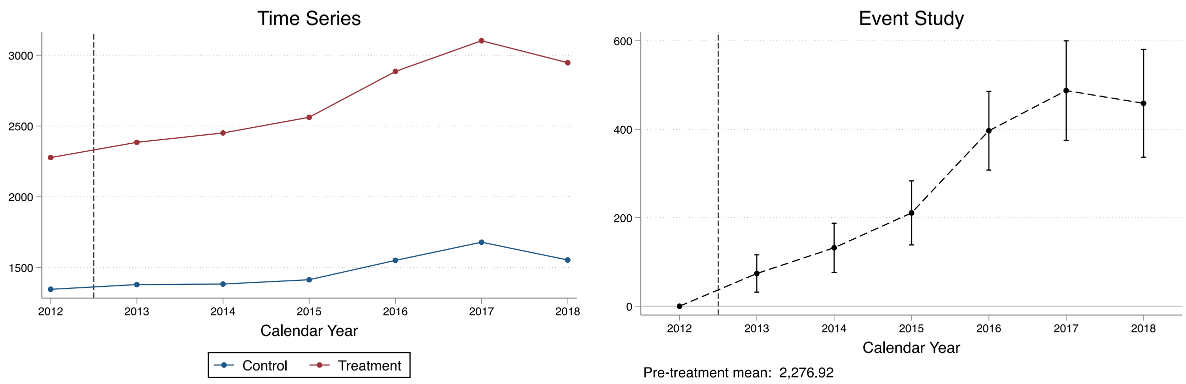
Panel B. Imaging Billing per PCP, by CCM Treatment Group



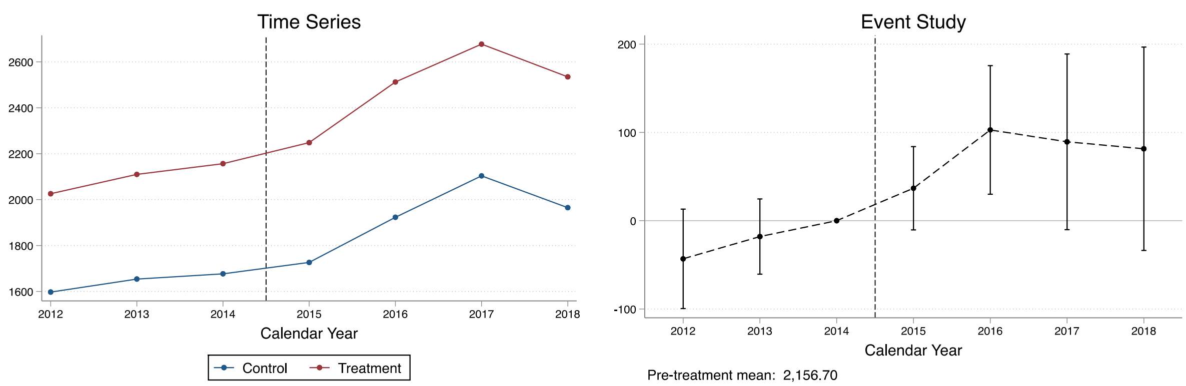
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for Imaging services in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A9: An Example of Complementarity with Recommended Primary Care Services: Influenza Vaccination – Unmatched Sample

Panel A. Influenza Vaccination Billing per PCP, by TCM Treatment Group



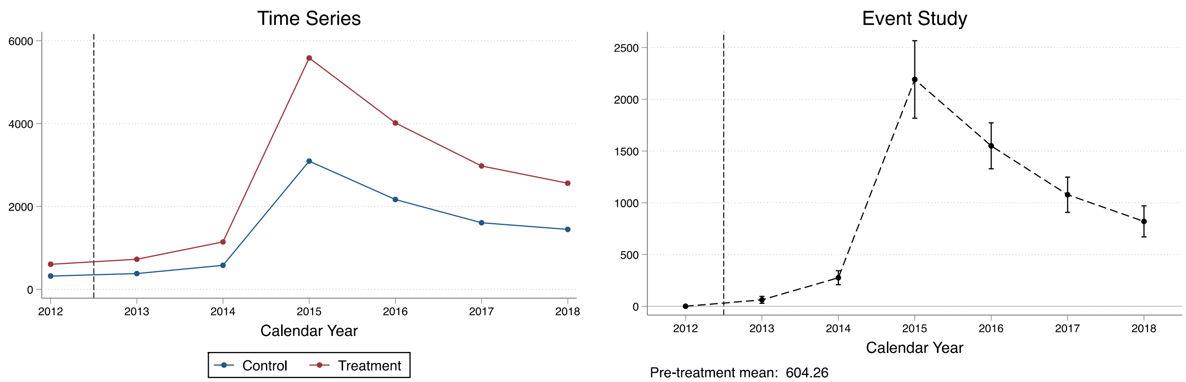
Panel B. Influenza Vaccination Billing per PCP, by CCM Treatment Group



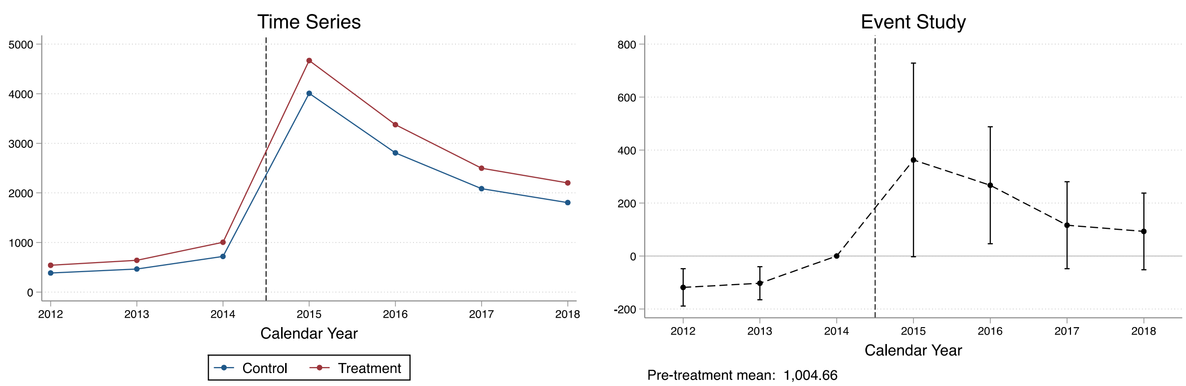
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for influenza vaccinations in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A10: An Example of Complementarity with Recommended Primary Care Services: Pneumonia Vaccination – Unmatched Sample

Panel A. Pneumonia Vaccination Billing per PCP, by TCM Treatment Group



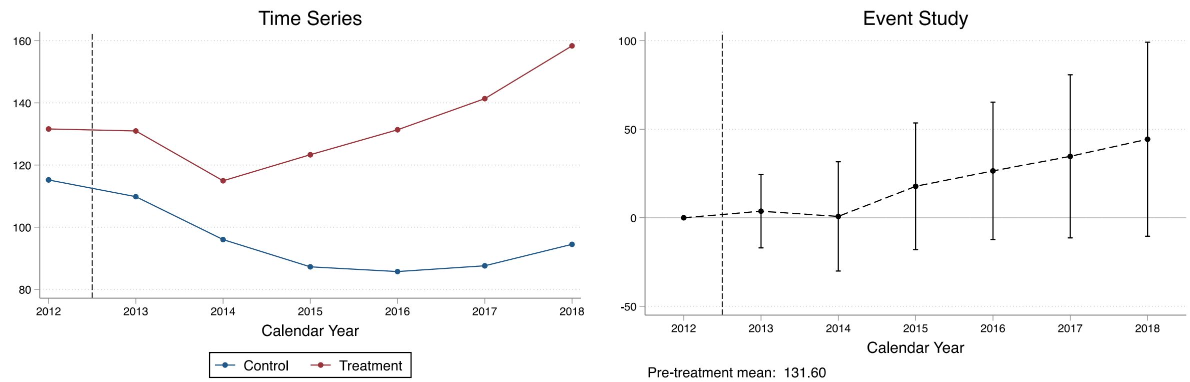
Panel B. Pneumonia Vaccination Billing per PCP, by CCM Treatment Group



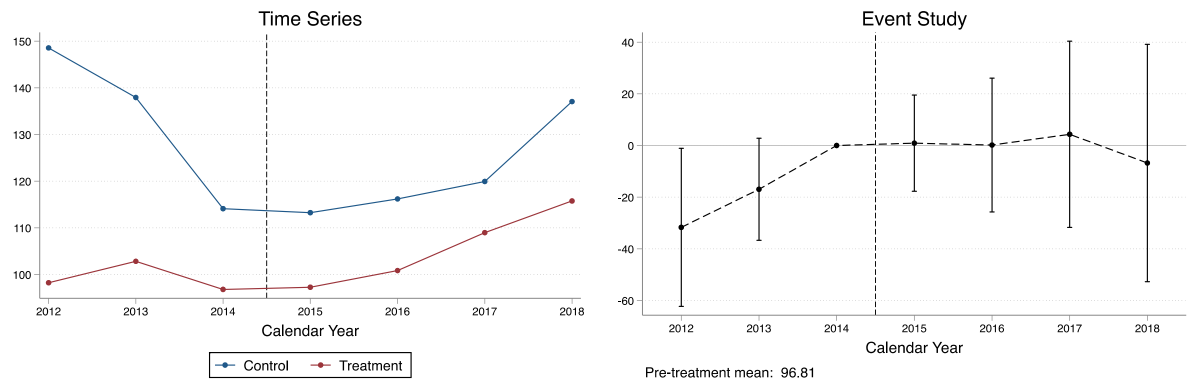
Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for pneumonia vaccinations in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Figure A11: An Example of Complementarity with Recommended Primary Care Services: Mammograms – Unmatched Sample

Panel A. Mammogram Billing per PCP, by TCM Treatment Group



Panel B. Mammogram Billing per PCP, by CCM Treatment Group



Notes: This figure shows estimates for $\beta_{p(t)}$ from equation (2). The sample in panel A is our unmatched sample of counties where treatment is defined by Transitional Care Management (TCM) take-up, and the sample in panel B is our unmatched sample of counties where treatment is defined by Chronic Care Management (CCM) take-up. In each panel, estimates of $\beta_{p(t)}$ are shown in the right-hand graph and the corresponding time series are shown in the left-hand graph. Data is at the county-year level. The dependent variable is the county-level allowed amount for mammograms in units of dollars billed by PCPs per PCP. All regressions include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level.

Table A1: Post-Discharge Outcomes – Annual Estimates

New Code	Year	Fraction of Beneficiaries with a Traditional Post-Discharge Visit	Fraction of Beneficiaries with a Traditional Post-Discharge Visit with a PCP	Controls
Transitional Care Management (Thousands of $ per PCP)				
	2013	-.33 (.29)	-.17 (.40)	Yes
	2014	-1.18*** (.15)	-1.08*** (.19)	Yes
	2015	-1.23*** (.17)	-1.02*** (.21)	Yes
	2016	-.90*** (.18)	-1.31*** (.23)	Yes
	2017	-1.06*** (.14)	-1.54*** (.17)	Yes

Notes: This table shows estimates for β_1 from a version of equation (1) that is estimated separately on each year of data. Data is at the county level and these data span the years 2012-2017. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. Dependent variables are county-level rates where the denominator is the annual number of discharged patients. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are heteroskedasticity-robust.

Table A2: Non-PCP Billing by Category – Outcomes Scaled per PCP

New Code	Total Billing per PCP	Evaluation & Management Billing per PCP	Procedures Billing per PCP	Imaging Billing per PCP	Tests Billing Per PCP	Durable Medical Equipment Billing per PCP	Other Billing per PCP	Controls
Transitional Care Management ($ per PCP)								
	7.31**	2.97***	.60	1.62	-.32	-.04**	2.47*	No
	(3.27)	(.73)	(.85)	(2.32)	(.22)	(.01)	(1.29)	
	7.03**	2.84***	.52	1.63	-.28	-.04***	2.36*	Yes
	(3.28)	(.73)	(.81)	(2.31)	(.22)	(.01)	(1.37)	
Chronic Care Management ($ per PCP)								
	-.23	.07	-.11	-.20**	-.06	-.003	.07	No
	(.69)	(.31)	(.22)	(.08)	(.05)	(.01)	(.30)	
	-.33	.03	-.13	-.19**	-.06	-.003	.004	Yes
	(.70)	(.31)	(.23)	(.08)	(.05)	(.01)	(.31)	
Dep. Mean	311,501.64	100,090.68	70,524.22	21,079.84	16,930.18	212.21	102,664.52	
N	20,262	20,262	20,262	20,262	20,262	20,262	20,262	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2018. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. The dependent variable is the county-level allowed amount for the specified outcome billed by non-PCPs per PCP. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level. Transitional Care Management and Chronic Care Management belong to the Evaluation & Management category, but the new code of interest for each regression is excluded from this category as well as from Total billing. The dependent means for the first two columns are the average of the means that result from dropping each new code, which are approximately the same.

Table A3: Non-PCP Billing by Category – Outcomes Scaled per PCP at Baseline

New Code	Total Billing per PCP	Evaluation & Management Billing per PCP	Procedures Billing per PCP	Imaging Billing per PCP	Tests Billing Per PCP	Durable Medical Equipment Billing per PCP	Other Billing per PCP	Controls
Transitional Care Management ($ per PCP)								
	5.47**	1.82***	.21	.94	-.28	-.04**	2.81***	No
	(2.34)	(.51)	(.50)	(1.68)	(.21)	(.01)	(1.04)	
	5.02**	1.63***	.09	.95	-.25	-.04***	2.65**	Yes
	(2.36)	(.52)	(.48)	(1.68)	(.21)	(.01)	(1.12)	
Chronic Care Management ($ per PCP)								
	.41	.26	-.0002	-.17**	-.03	-.003	.35	No
	(.49)	(.25)	(.20)	(.07)	(.04)	(.008)	(.27)	
	-.32	.22	-.01	-.16**	-.03	-.003	.30	Yes
	(.50)	(.25)	(.21)	(.07)	(.04)	(.009)	(.28)	
Dep. Mean	305,763.18	98,411.30	70,229.07	20,993.41	17,037.88	215.28	98,876.24	
N	20,262	20,262	20,262	20,262	20,262	20,262	20,262	

Notes: This table shows estimates for β_1 from equation (1). Data is at the county-year level and these data span the years 2012-2018. The independent variable is the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP. The dependent variable is the county-level allowed amount for the specified outcome billed by non-PCPs divided by the number of PCPs in the county in 2012. All regressions include year-level and county-level fixed effects. Regressions with controls include controls for average age, percent of beneficiaries that are female, percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence. Standard errors are clustered at the county level. Transitional Care Management and Chronic Care Management belong to the Evaluation & Management category, but the new code of interest for each regression is excluded from this category as well as from Total billing. The dependent means for the first two columns are the average of the means that result from dropping each new code, which are approximately the same.

Appendix B: Additional Data Details

B.1 MPUP, NPPES, and Physician Compare

The *Medicare Provider Utilization and Payment Data* (MPUP) has address data for the practice of each physician in the data set. CMS obtains this data from the *National Plan and Provider Enumeration System* (NPPES) data and merges it into the MPUP claims data before publishing it. However, each year of the raw MPUP data actually contains physicians' addresses from the end of the calendar year following the given year of claims data. The exception to this is the 2012 MPUP data, for which physicians' addresses were taken from the end of calendar year 2014. We download the NPPES files and overwrite the address variables in each year of the MPUP data with the address variables in the NPPES file from December of the year in which the claims in the MPUP data occurred. That is, we fix the raw input data so that the physician addresses reflect where they practiced during that year of claims data.

The main use of the address data in our paper is to define physician groups. We define a physician group as any physicians that practice at the same address in a given year. Before defining groups, we do some basic changes to the street address variables to align observations where the same address may have been typed in different ways. Namely, we remove all punctuation, and we convert all address suffixes recognized by the U.S. Postal Service to their standard abbreviations (e.g. "STREET" becomes "ST").

We also use data from the *Physician Compare* database to provide us with information on graduation year and medical school at the physician level. For any conflicts between the values of these variables for the same physician across different years of Physician Compare data, which are rare, we use the most recent non-missing value. Some physicians are missing data on these variables: 7.9% of physicians in our panel in 2018 are missing their graduation year, and the same fraction are missing their medical school. We do not define these physicians as belonging to any career stage or as having attended a ranked or unranked medical school.

B.2 Constructing the Chronic Care Index

We construct an index that reflects the overall prevalence of eight chronic conditions at the county level for each year. These are conditions that are often experienced by the elderly. We use this index as a control variable in our regressions and show that it is correlated with new code take-up in Figure 3. The data on the prevalence of these chronic conditions come from the *CMS Chronic Conditions Files*.

The eight conditions included in our baseline index are arthritis, kidney disease, COPD, diabetes, heart failure, hyperlipidemia, hypertension, and ischemic heart disease. For each year, we normalize the prevalence rate of each of these conditions by subtracting that year's mean of the prevalence rate and dividing this difference by that year's standard deviation of the prevalence rate. This gives us eight normalized values reflecting how many standard deviations above the mean each county is in terms of each of the eight conditions. The mean of these eight values for each county gives us our baseline normalized chronic condition prevalence index. Our findings are robust to chronic condition indices that include more chronic conditions than the eight included in our baseline index.

County-level chronic condition prevalence rates are sometimes missing in the CMS data. The number of counties in our unmatched sample that are missing data in 2018 (out of a total of 3,078 counties) is 2 for arthritis, 2 for kidney disease, 6 for COPD, 2 for diabetes, 4 for heart failure, 2 for hyperlipidemia, 2 for hypertension, and 2 for ischemic heart disease. Rates of missing data are lower for our matched sample. When data is missing for a condition in a given county, we impute the condition's prevalence rate using the beneficiary-weighted average of that condition's prevalence rate in the other counties in the same Hospital Referral Region with non-missing data for that condition.