NBER WORKING PAPER SERIES

PLUGGING GAPS IN PAYMENT SYSTEMS:
EVIDENCE FROM THE TAKE-UP OF NEW MEDICARE BILLING CODES

Jeffrey Clemens
Jonathan M. Leganza
Alex Masucci

Working Paper 31336
http://www.nber.org/papers/w31336

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2023

We thank Kate Antonovics, Julian Betts, Colleen Carey, Mike Geruso, Todd Gilmer, Tim Layton, and Gaurav Khanna for helpful comments and conversations. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Plugging Gaps in Payment Systems: Evidence from the Take-Up of New Medicare Billing Codes
Jeffrey Clemens, Jonathan M. Leganza, and Alex Masucci
NBER Working Paper No. 31336
June 2023
JEL No. H57,I11

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 analyze the effects of introducing these new billing codes. First, we provide evidence on the adoption of the new codes by primary care physicians. We show that take-up of the new billing codes occurs gradually and exhibits substantial variation across space and across physician characteristics. Second, we provide evidence on how the new billing codes can both complement and substitute for the billing or provision of other services. We focus on two case studies. As a case of code substitution, we show that Transitional Care Management services partially crowd out traditional office visits following hospital discharges. As a case of code complementarity, we show that both Transitional Care Management and Chronic Care Management services predict increases in annual wellness visits. Overall, our analysis highlights how both new code take-up frictions and the impact of new code billing on existing code billing can be important for assessing the total costs and benefits of payment reforms.

Jeffrey Clemens
Department of Economics
University of California, San Diego
9500 Gilman Drive #0508
La Jolla, CA 92093
and NBER
jeffclemens@ucsd.edu

Jonathan M. Leganza
John E. Walker Department of Economics
Wilbur O. and Ann Powers College of Business
Clemson University
Clemson, SC 29634
United States
jleganz@clemson.edu

Alex Masucci
Independent Researcher
abmasucci@gmail.com

1 Introduction

Health care payment models shape the financial incentives physicians and hospitals face while delivering care. Payment models can thus have implications for the efficiency of the health system. Importantly, the patterns of service provision that constitute cost-effective care are not static. 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.

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 care provision, they must be recognized and adopted by physician 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.

To provide evidence on code adoption, code substitution, and code complementarity, 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 codes played an important role in a broader effort by CMS to increase the financial rewards to providing primary care and improve incentives for managing the care of patients with high health care needs.

Our analysis proceeds in two steps. In the first step, we provide evidence on the adoption of the Transitional and Chronic Care Management codes by primary care physicians (PCPs). This evidence extends the work of an emerging medical literature that also documents the uptake of the new codes (Agarwal et al., 2018; Marcotte et al., 2020; Reddy et al., 2020; Agarwal et al., 2020).[1] We document take-up that occurs gradually over time and that varies across space and across physician characteristics. Overall, the patterns we document are consistent with the idea that the

[1] Reddy et al. (2020) document time series on Chronic Care Management billing, and Marcotte et al. (2020) document time series on Transitional Care Management billing. Agarwal et al. (2018, 2020) use data on a sample of beneficiaries to analyze take-up. They develop complementary findings by comparing characteristics of primary care practices that billed the new codes to those that did not. In contrast, we use data on the near-universe of Medicare-billing doctors to analyze the likelihood of billing a new code based on physician characteristics. One important physician characteristic that our data allow us to analyze is career stage, which previous papers have been unable to investigate.

adoption of new codes requires physicians to make investments in their practices' mastery of bill coding, a form of organizational or entrepreneurial capital.

In the second step, we analyze patterns of complementarity and substitutability between the billing of new codes and the billing or provision of other services. We use two regression frameworks to study the effects of new code take-up at the county level. We begin by using an event study framework that compares the evolution of outcomes for high take-up counties to that of a (matched) group of low take-up counties, before and after the introduction of the new billing codes. We then transition to using a fixed effects framework that exploits all panel variation in the intensity with which new codes are billed across counties.

We focus our analysis of patterns of care complementarity and substitutability on two case studies. First, we show a clear case of code substitution. We find that billing Transitional Care Management, which is for managing care after an inpatient discharge, partially crowds out the billing of standard office visits after hospital discharges. Our event study evidence reveals a sharp decline in traditional post-discharge office visits in high take-up counties compared to low take-up counties after the introduction of the new codes, and our fixed effects estimates imply roughly one less traditional office visit for every 26 additional Transitional Care Management visits.[2] Second, we show a case of code complementarity. We find that both Transitional and Chronic Care Management services predict increases in the provision of Annual Wellness Visits, another type of care management service. While our event study provides less striking evidence for this second case study, the event study and more basic fixed effects estimators yield complementary estimates. The results indicate a substantial complementarity between wellness visits and Transitional Care Management billing and a more modest degree of complementarity with Chronic Care Management billing.

Overall, our analysis shows that patterns of complementarity and substitutability in bill coding and service provision can play important roles in shaping a payment reform's effects. We find that new service codes can both complement and substitute for existing service codes. We emphasize two policy relevant aspects of these findings. First, code substitution and code

[2] By quantifying this partial crowd, our results complement and are consistent with the patterns of raw means first presented by Agarwal et al. (2018), who also show a decline in standard office visits after hospitalizations by individual practices that bill Transitional Care Management.

complementarity could impact claims-dependent systems of quality measurement.[3] Second, the existence of complementarities in real service provision can have straightforward effects on both the cost and health benefits of introducing new codes. A comprehensive analysis of the costs and benefits of introducing new codes must account for these spillovers.

Moreover, we contribute to the literature that analyzes the effects of financial incentives on the services physicians provide. One set of papers estimates standard impacts of reimbursement levels on the supply of services (e.g., Cabral, Carey, and Miller, 2021; Alexander and Schnell, 2019; Clemens and Gottlieb, 2014; Gruber, Kim, and Mayzlina, 1999). Others investigate 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 locate (Khoury et al., 2021). Relatively recent research on this rich variety of margins provides evidence that health care becomes more widely accessible when physicians are paid more generously to provide it. Still other research demonstrates important roles for additional factors including intrinsic motivation (Kolstad, 2013) and team environments (Chan, 2016). We contribute to this literature by emphasizing how the effects of incentives on the supply of services can depend on frictions such as physicians' awareness of those incentives and on the time horizons over which they adapt.[4] Our analysis points to a novel dimension of physicians' organizational or entrepreneurial capital: their mastery of the billing systems that shape their practices' profitability.

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 conditions that need to be regularly managed. Despite playing such an integral role, evidence highlights how PCPs often provide services that are left out of the Physician Fee Schedule (PFS).

[3] For instance, if traditional office visits after hospital discharges are included in quality measurement systems, and if these systems are not updated to account for the introduction of new billing codes, then physicians billing Transitional Care Management rather than traditional office visits after discharges might be negatively impacted.

[4] While frictions have received little attention in prior research on physicians' labor supply, they have received substantial attention other lines of work. Frictions play a role, for example, in research on the causes of incomplete take-up of public benefits (Aizer, 2007; Bhargava and Manoli, 2015; Manoli and Turner, 2014). The complexity of physicians' contracts and reimbursement procedures has also been examined elsewhere (Clemens and Gottlieb, 2017; Clemens, Gottlieb, and Molnar, 2017; Gottlieb, Shapiro, and Dunn, 2018; Dunn et al., 2021).

They are thus not paid in full for the services they deliver (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 this problem. In the final rule for the Medicare Physician Fee Schedule for 2018, CMS 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).

By adding these new billing codes, CMS adjusted the PFS by explicitly paying physicians for TCM and CCM services. The new codes can either compensate doctors more fully for services they were already providing or increase incentives for providing services for primary care needs that were previously going unmet. Overall, the new codes are the result of policy makers aiming to make the provision of primary care more financially attractive (Burton et al., 2017), and 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 for care management services provided 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 codes for 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-making 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 codes were introduced in 2013. Reimbursement rates were set by CMS, taking into consideration the input and feedback from committees and stakeholders 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).[5]

2.3 Chronic Care Management

The Chronic Care Management (CCM) codes are for care coordination and care management for patients with multiple chronic conditions, such as dementia, asthma, cancer, cardiovascular disease, or diabetes, among others. Chronic conditions are common among Medicare beneficiaries, and spending on patients with these afflictions is substantial (Anderson, 2010). A recent report found that 42% of adult Americans had multiple chronic conditions and that the prevalence was even higher (81%) for Americans 65 years and older (Buttorff et al., 2017).

Against this backdrop, CMS created the new CCM codes. Billing code 99490 pays for care management of at least 20 minutes of clinical staff time per month. Eligible patients are those with 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. CMS introduced this code in 2015. Payment rates were determined by CMS with input from stakeholders. Reimbursement was roughly $43. Two year later, in 2017, CMS 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 additional 30 minutes of CCM (no matter the complexity).

3 Data

To study the introduction of the new codes, we use several datasets, primarily from CMS. Using three physician-level datasets, we build a physician panel from 2012 to 2018 that contains information on physician characteristics and billing. We also use three 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 that covers health care professionals who bill services to Medicare Part B. It spans the years 2012 to 2018. The data are derived from

[5] 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.

administrative claims data from CMS and allow us to observe almost all Medicare-billing physicians. (Physicians who do not bill any 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. We focus mostly 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 NPIs. From the *National Plan and Provider Enumeration System* (NPPES), we obtain information on physician practice location.[6] This information allows us to study physician groups, which we define as physicians practicing at the same address. Then, from the *Physician Compare* dataset, we pull information on physician medical school attendance and graduation dates.[7] We use these data to categorize physicians based on 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.[8] 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 for our county-level analyses. From the *CMS Geographic Variation Public Use File*, we extract information on demographics. Specifically, we use 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 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

[6] 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.
[7] CMS began publishing Physician Compare 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, but we are missing information for physicians who appear in our data only before 2014.
[8] 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.

conditions (arthritis, kidney disease, COPD, diabetes, heart failure, hyperlipidemia, hypertension, and ischemic heart disease). See Appendix B for details.

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

4 The Take-Up of New Medicare Billing Codes

4.1 New Code Billing Over Time

Panel A of Figure 1 plots the time series on national billing for TCM and CCM and shows that the adoption of the new codes is a gradual process. Total billing for TCM (CCM) is defined as the sum of the billing for all new codes classified as TCM (CCM). The graphs show how billing for the new codes ramps up steadily over time. Neither type of new code billing seems to have leveled off over the time horizon of our data. Panel B shows a similar pattern for the fraction of PCPs billing the new codes over time.

4.2 Regional Variation in New Code Billing

There is also significant regional variation in the take-up of the new codes. We present maps of new code billing in Figure A1. The maps plot Hospital Referral Region (HRR) billing per PCP in 2018 for TCM (panel A) and CCM (panel B). TCM billing is more heavily concentrated in the Northeast and the Southeast. CCM billing appears concentrated in southern regions. Figure A2 assesses the extent to which underlying health conditions can contribute to this regional variation. The scatter plots show how the billing of TCM (panel A) and CCM (panel B) relate to the prevalence of chronic conditions in HRRs. New code billing is correlated with our constructed chronic condition index. The simple regression model shown in panel A explains 19.5% of the variation in HRR-level TCM billing, and the simple regression model shown in panel B explains 19.2% of the variation in HRR-level CCM billing.

4.3 New Code Billing by Physician Characteristics

Table 1 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. Panel A documents billing rates across specialties and shows that PCPs are much more likely to bill the new codes than non-PCPs.

Panel B breaks down billing rates by physician career stage. The likelihood of billing the new codes is higher for mid-career PCPs compared to early-career or late-career PCPs. Panel C of Figure 1 provides 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 might 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 to 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.

Finally, panels C and D of Table 1 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.

Overall, the evidence presented in this section provides insight into how physicians respond to the introduction of new billing codes. We find patterns consistent with the idea that adopting new codes requires ongoing learning and investments related to bill-coding proficiency.

5 Empirical Framework for Analyzing the Effects of New Code Adoption

Next, we investigate the substitutability and complementarity of new codes with existing codes, using two regression frameworks to estimate the effects of new code take-up on the billing or provision of other services. To prevent our analysis from being impacted by physician- or group-level specialization or by patient sorting across physician groups, we conduct it at the county level.

First, we use an event study regression framework that compares the evolution of outcomes in places with more new code take-up to that of places with less new code take-up. High intensity adopters are our "treatment" group, whereas low intensity adopters and non-adopters are our "control" group. 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. We define the top half of these counties as the treatment group, and we define the bottom half as the control group.

Using this grouping of counties, we then estimate regressions of the form:

$$Y_{c,t} = \sum_{p(t)\neq -1} \beta_{p(t)} Treatment_c \times Event\ Time_{p(t)} + X_{c,t}\,\gamma + \alpha_c + \delta_t + \varepsilon_{c,t}. \qquad (1)$$

In equation (1), *c* denotes counties and *t* denotes years, $Y_{c,t}$ is a billing or service provision outcome variable, $Treatment_c$ is an indicator for being a high intensity adopter of the new billing code being analyzed, $EventTime_{p(t)}$ are dummy variables coded to correspond to the numbers of years relative to the new code's introduction (which is 2015 for Chronic Care Management and 2013 for Transitional Care Management), $X_{c,t}$ is a vector of time-varying county characteristics, α_c are county fixed effects, δ_t are year fixed effects, and $\varepsilon_{c,t}$ is an error term. We omit the interaction between the treatment indicator and the event time indicator for the time period corresponding to the year immediately prior to the new code's introduction, which we define as year $p(t) = -1$. The coefficients of interest, $\beta_{p(t)}$ 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 provide evidence on whether divergent trends in the outcome occurred prior to the new code's introduction. Estimates for years following the new code's introduction track the dynamics with which the outcome subsequently evolved.

The event study approach informs on whether high take-up counties appear to have been on similar trajectories to low take-up counties before the introduction of the new codes. The absence of divergent pre-existing trends would provide evidence that outcomes of interest were on parallel paths. However, one might still worry that differential shocks may have occurred in later years in ways that correlate with high intensity take-up. This motivates us to augment our event study framework along one additional dimension. Specifically, we limit our leading event study analysis sample to high and low intensity take-up counties that look similar to one another at baseline. Specifically, we match high and low intensity counties on their overall health care utilization at baseline, defined using total allowed amounts.[9] Estimating equation (1) on the resulting matched sample provides a check for divergent pre-existing trends in high vs. low take-up counties with populations that had similar levels of overall utilization at baseline.

Second, we transition to a fixed effects regression framework. The fixed effects approach allows us to exploit all panel variation in the intensity with which new codes are billed at the county level. We estimate regressions of the form:

$$Y_{c,t} = \beta New\ Code\ Billing\ Per\ PCP_{c,t} + X_{c,t}\,\gamma + \alpha_c + \delta_t + \varepsilon_{c,t}. \qquad (2)$$

Equation (2) controls for county fixed effects (α_c), time fixed effects (δ_t), and time-varying county characteristics ($X_{c,t}$). The primary coefficient of interest is β, which describes the relationship between the outcome and the dollar value of new code billing per primary care physician.

For β to be an unbiased estimate of the effect of new code adoption, 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. The results from our event study analysis provide some reassuring evidence on this assumption. Moreover, we investigate the robustness of our fixed effects estimates to the exclusion of the time-varying county characteristics that describe the health of the Medicare population and find that they are not sensitive to this choice. Nonetheless, we acknowledge that there could still be other unobservable factors influencing both new code take-up and our outcomes of interest, and so we view the fixed effects regression approach as being less likely to capture causal estimates.

Overall, our two regression frameworks work towards the same goal: providing evidence on how the take-up of new billing codes influences other billing behaviors. The advantage of the event study framework is that it provides relatively clear, graphical evidence that we argue can be interpreted as causal. The disadvantage is that it takes all variation in new code billing and collapses it into comparisons of counties with high versus low take-up. The advantage of the fixed effects framework is that it allows us to use all variation in new code billing to provide estimates

[9] The treatment group using this matched strategy is identical to the treatment group using the unmatched strategy. To generate the 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 introduction of the new code of interest.

of how a dollar of new code billing relates to the billing of other services. The disadvantage in using all variation in take-up is that it reduces the plausibility of a strictly causal interpretation of the resulting estimate. The consistency of estimates across our two frameworks is thus important for assessing the strength of the evidence we present.

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

We next present estimates of equations (1) and (2) with an emphasis on two case studies.

6.1 A Case of Code Substitution

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 new codes were introduced to improve compensation for physicians 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. Here we investigate this possibility in the context of the introduction of TCM, which requires a face-to-face visit with a patient recently discharged from an inpatient setting. Does TCM thus substitute for standard office visits after a patient discharge?

Figure 2 presents event study results that illustrate this type of code substitution in practice. The figure depicts the impact of TCM adoption on the fraction of beneficiaries that have a traditional office visit within two weeks of discharge from the hospital.[10] Note that the outcome variable analyzed here comes from the Dartmouth Atlas of Health Care, which allows us to track the outcome from 2010 through 2017. The left-hand side graph shows the raw means for our treatment and matched control group. The right-hand side graph plots the corresponding event study coefficients of interest from estimating equation (1).

The graphs in Figure 2 show that, before the introduction of TCM, the fraction of beneficiaries receiving a traditional post-discharge office visit in the treatment group was trending in parallel with that of the control group. Then, after the introduction of TCM, there is a clear and meaningful decline in post-discharge traditional office visits for the treatment group, relative to

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

the control group. By 2017, this decline amounts to 4.3 percentage points. Note that Figure A3 presents results for the unmatched sample analysis, which are similar.

Table 2 shows the corresponding estimates of β from equation (2), where the outcome of interest is the same as in the event study analysis. We find that an additional thousand dollars of TCM billing per PCP is associated with a 1.21 percentage point reduction in the fraction of beneficiaries receiving a traditional post-discharge visit with any care provider. This estimate does not appear sensitive to the inclusion of additional control variables in the regression.

Taken together, Figure 2 and Table 2 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. First, the amount of code substitution appears to be modest, implying a non-trivial net increase in post-discharge visits. Our fixed effects estimates imply a reduction of one traditional post-discharge visit for every 26 additional TCM visits.[11] So, while TCM is substituting for some care that was previously being provided, the bulk of TCM visits represents an increase in real post-discharge care that is taking place because of the introduction of the codes.

Second, we highlight potential and subtle implications for claims-dependent measures of care quality. Metrics like post-discharge office visits are sometimes interpreted as measures of care quality.[12] 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 codes. This implication highlights that quality metrics using billing codes to assess compliance with recommended care delivery must adapt to changes in coding systems. Note that this point connects to similar insights in the context of risk adjustment models.[13]

---

[11] To arrive at this figure, 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 result by the average billed amount for a TCM visit ($190.08). This calculation tells us that $1,000 of additional new code billing per PCP amounts to 307.34 TCM visits on average. The average county level count of discharged patients in our sample is 965.67. Comparing the estimated 1.21 percentage point decline in this count to the total increase in TCM visits yields the figure above.

[12] See, e.g., Goodman et al. (2011), a Dartmouth Atlas Report that in the context of assessing how communities and hospitals care for the sickest patients, examines the frequency of clinician follow-up visits after a discharge.

[13] For instance, Carey (2017) 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 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.

6.2 A Case of Code Complementarity

We might also expect the new codes to serve as complements to other services. Complementarities could arise due to a blend of changes in real service provision with changes in coding practices. For instance, on the one hand, the TCM codes were 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.

Here we present an example of a service that acts as a complement to both TCM and CCM: the Annual Wellness Visit (AWV). AWVs are another type of care management service first introduced by the Affordable Care Act. They are office visits during which a patient receives a standard wellness check and works with a physician to plan for upcoming preventive care.

Figure 3 presents event study results. Panel A illustrates the impact of TCM take-up on AWV billing. Because this outcome comes from our physician panel, which starts in 2012, we do not have the data to check pre-existing trends as it relates to the introduction of the TCM codes in 2013. While we view it as encouraging that the previous case study on code substitution (which used data from the Dartmouth Atlas of Health Care that extended back to 2010) showed no differential trends between the TCM-based treatment and control groups for a different outcome, our inability to directly look at pre-trends for AWV billing limits the strength of the conclusions we can draw from this specific event study. Taking the post-period trends at face value though, we observe an increase in AWV billing for the treatment counties relative to the control counties after the introduction of TCM, which provides evidence pointing to complementarity.[14]

Panel B illustrates the impact of CCM billing on AWV billing. Here we can investigate pre-period trends, which do appear parallel, because the CCM billing codes were introduced in 2015. The post-period point estimates indicate a short-run increase in AWV billing in 2015 and 2016, although neither point estimate is statistically distinguishable from zero at the 95-percent confidence level. For 2017 and 2018, point estimates are close to zero. Panel B of Figure A4

[14] Panel A of Figure A5 shows similar results for the unmatched sample event study analysis.

presents results for the unmatched sample event study analysis. The results indicate a much more pronounced increase in AWV billing, but they also indicate more pronounced pre-period differential trends. The matching strategy seems to improve the comparability between CCM treatment and control groups here.

Table 2 presents results from the fixed effects regression framework. We estimate that one additional dollar of TCM billing per PCP is associated with a $1.28 increase in AWV billing per PCP. For CCM, we find a modest complementarity. We estimate that one additional dollar of CCM billing is associated with a 13-cent increase in AWV billing.

Overall, we view the combination of our event study and fixed effects results on AWVs as indicating that the new codes can be complementarity with the billing of an existing service. We acknowledge, however, that this evidence is less clear than that for the case of code substitution. That said, the complementarity with AWVs could be quite important when beginning to assess the potential health benefits of the new codes, as AWVs involve patient-physician interactions. Whether these AWV services represent a net increase in total interactions depends on the extent to which billing the new codes impact all other types of care provision, a topic beyond the goal of our paper, which is to illustrate the relevance and potential importance of several nuanced pieces of the puzzle.

7 Conclusion

Maintaining an efficient health care procurement 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 a reform to the U.S. Medicare program that introduced new billing codes for the provision of Chronic Care Management and Transitional Care Management. Our analysis of these new billing codes points to several economic margins that can complicate the jobs of policy makers designing and implementing such reforms. We highlight how 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 billing and care provision. Each of these factors can impact the total cost of new code implementation and the overall care received by patients, both of which would be important ingredients in a complete analysis of the costs and benefits of attempting to plug gaps in payment systems by introducing new billing codes.

References

Agarwal, S.D., Barnett, M.L., Souza, J., Landon, B.E., 2020. Medicare's Care Management Codes Might Not Support Primary Care As Expected: An Analysis of Rates of Adoption for Medicare's New Billing Codes for Transitional Care Management and Chronic Care Management. *Health Affairs* 39, 828-836.

Agarwal, S.D., Barnett, M.L., Souza, J., Landon, B.E., 2018. Adoption of Medicare's Transitional Care Management and Chronic Care Management Codes in Primary Care. *JAMA* 320, 2596.

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.

Cabral, Marika, Colleen Carey, and Sarah Miller. 2021. "The Impact of Provider Payments on Health Care Utilization: Evidence from Medicare and Medicaid." *NBER Working Paper No w29471*.

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., and 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.

Goodman, D.C., Fisher, E.S., Chang, C.H., 2011. After Hospitalization: A Dartmouth Atlas Report on Post-acute Care for Medicare Beneficiaries. *Hanover, NH: The Dartmouth Institute for Health Policy and Clinical Practice*, *28*.

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. *Working Paper.*

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*.

Marcotte, L.M., Reddy, A., Zhou, L., Miller, S.C., Hudelson, C., Liao, J.M., 2020. Trends in Utilization of Transitional Care Management in the United States. *JAMA Network Open* 3, e1919571.

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.

Reddy, A., Marcotte, L.M., Zhou, L., Fihn, S.D., Liao, J.M., 2020. Use of Chronic Care Management Among Primary Care Clinicians. *The Annals of Family Medicine* 18, 455-457.

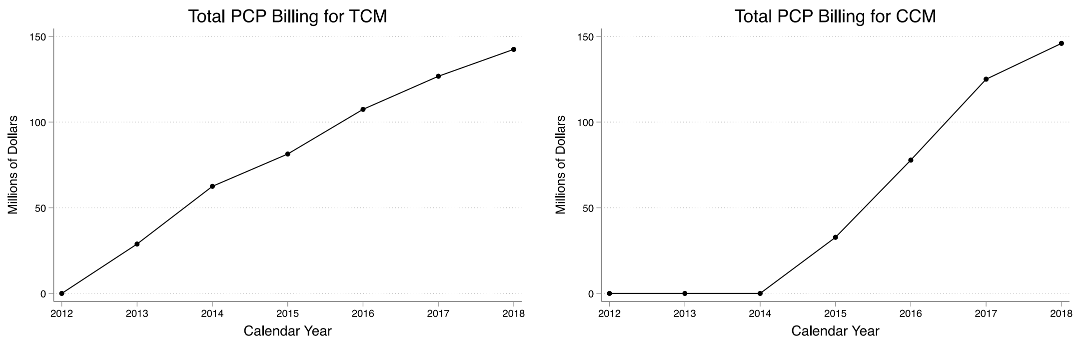
Schnell, M. and Currie, J., 2018. Addressing the Opioid Epidemic: Is there a Role for Physician Education?. *American Journal of Health Economics, 4(3),* pp.383-410.

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.

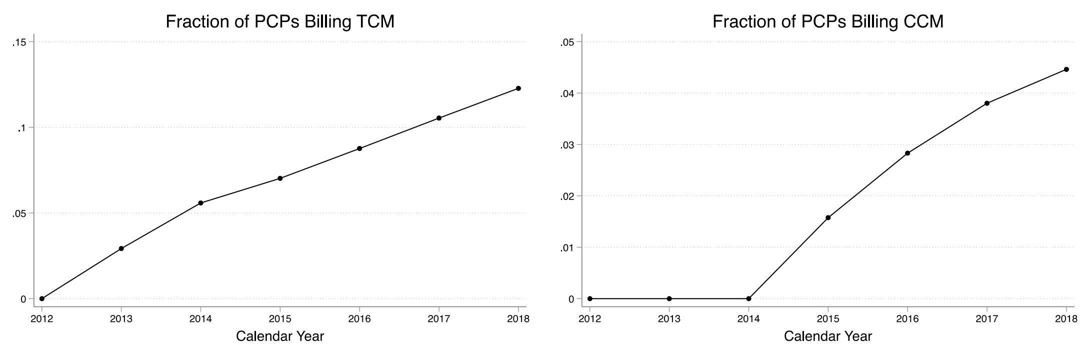
Figures and Tables

Figure 1: Evidence on New Code Take-up

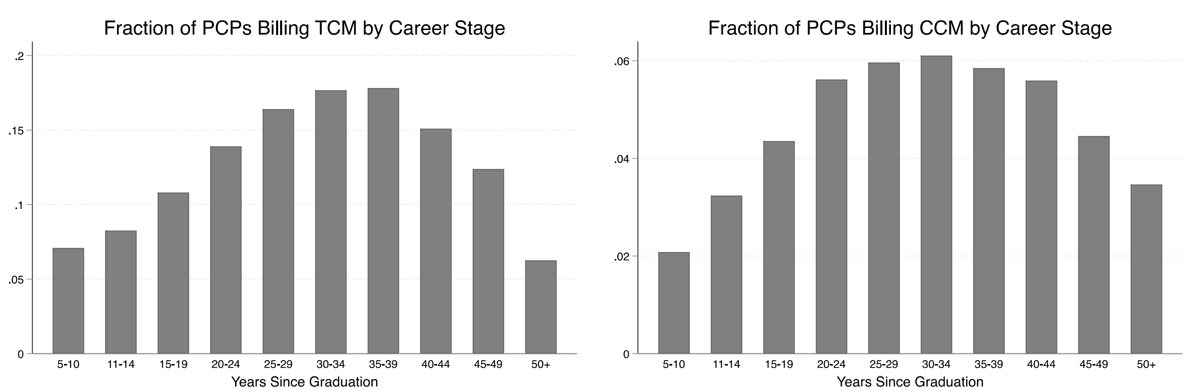
Panel A. Take-up Over Time: Total New Code Billing



Panel B. Take-up Over Time: Fraction of PCPs Billing New Codes



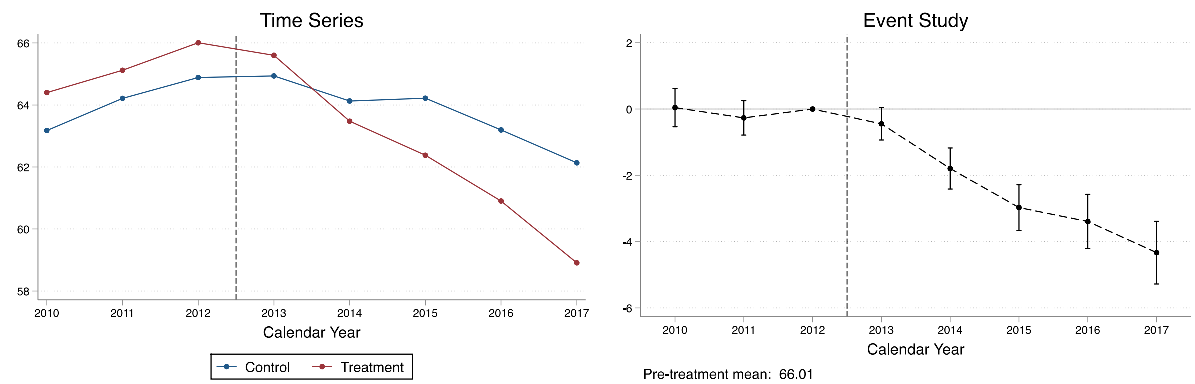
Panel C. Take-up by Career Stage



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). The underlying data source is our 2012–2018 panel of physicians. Panel A plots total new code billing over time for each of TCM and CCM. Panel B plots the fraction of PCPs billing each of the new codes over time. Panel C plots new code billing in 2018 against career stages.

Figure 2: An Example of Code Substitution

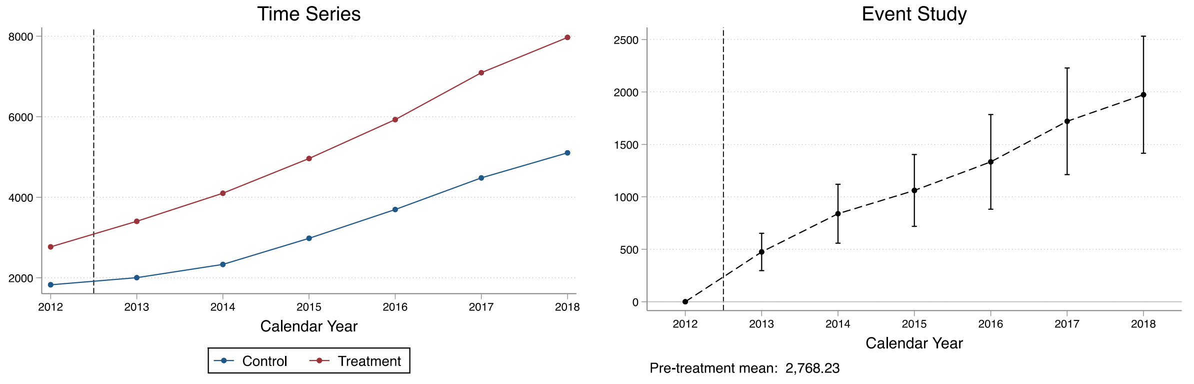
Fraction of Beneficiaries with a Traditional Post-Discharge Office Visit, by TCM Treatment Group



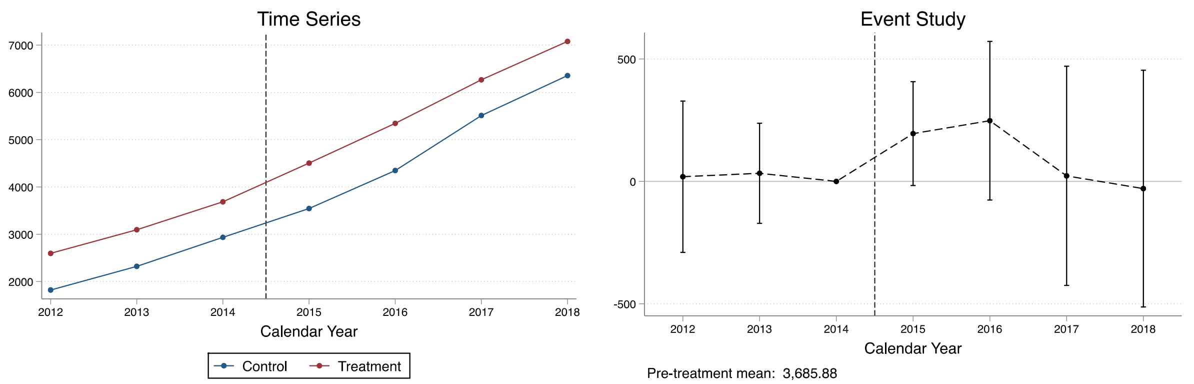
Notes: This figure shows how the fraction of beneficiaries with a traditional office visit after an inpatient discharge evolves around the time of the introduction of the Transitional Care Management (TCM) billing code. The left-hand side graph plots raw means for our treatment and matched control group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (1). The dependent variable is the county-level fraction of beneficiaries with a traditional office visit 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. The denominator is the number of discharges in the given county-year. The event study regression includes 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 3: An Example of Code Complementarity

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 how annual wellness visit billing evolves around the time of the introduction of the new billing codes. Panel A corresponds to Transitional Care Management (TCM). Panel B corresponds to Chronic Care Management (CCM). In each panel, the left-hand side graphs raw means for our treatment and matched control group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (1). The dependent variable is the county-level allowed amount for Annual Wellness Visits in units of dollars billed by PCPs per PCP. The event study 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: 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. 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 D. 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

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 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.

Table 2: Fixed Effects Estimates

Panel A: An Example of Code Substitution

	Fraction of Beneficiaries with a Traditional Post-Discharge Visit	Controls
Transitional Care Management (Thousands of $ per PCP)	-1.15***	No
	(0.15)	
	-1.21***	Yes
	(0.15)	
Dependent Variable Mean	63.50	
Observations	16,760	

Panel B: An Example of Code Complementarity

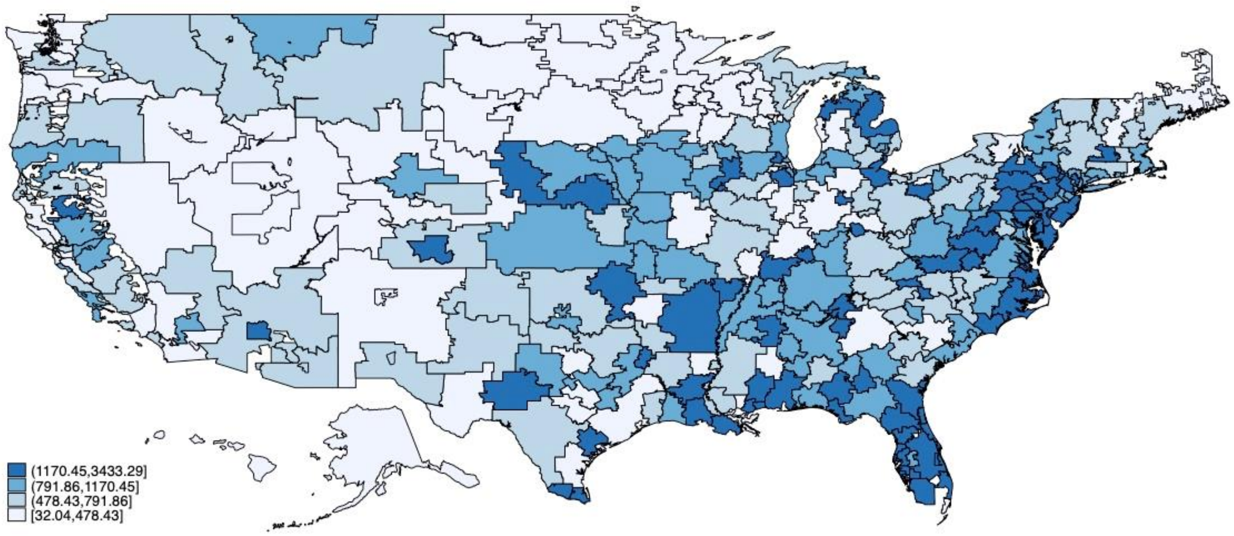
	Annual Wellness Visit Billing per PCP	Controls
Transitional Care Management ($ per PCP)	1.30***	No
	(0.11)	
	1.28***	Yes
	(0.11)	
Chronic Care Management ($ per PCP)	0.14**	No
	(0.06)	
	0.13**	Yes
	(0.06)	
Dependent Variable Mean	3,051.80	
Observations	20,262	

Notes: This table shows estimates for β from estimating equation (2). Panel A shows the case of code substitutability. The underlying 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. The dependent variable is the county-level rate of traditional office visits after an inpatient discharge. Panel B shows the case of code complementarity. The underlying data span the years 2012-2018. The independent variable is either the county-level allowed amount for Transitional Care Management in units of dollars billed by PCPs per PCP or the county-level allowed amount for Chronic Care Management in units of dollars billed by PCPs per PCP. The dependent variable is the county-level allowed amount for Annual Wellness Visits billed by PCPs per PCP. All regressions include year and county 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.

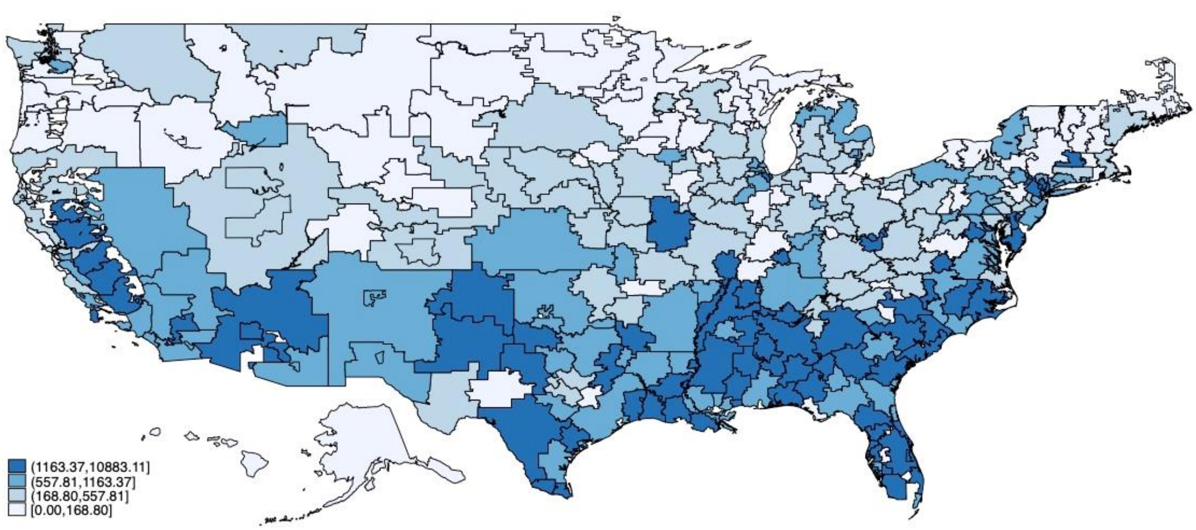
Appendix A Additional Figures and Tables

Figure A1: Regional Variation in the Take-Up of New Codes

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



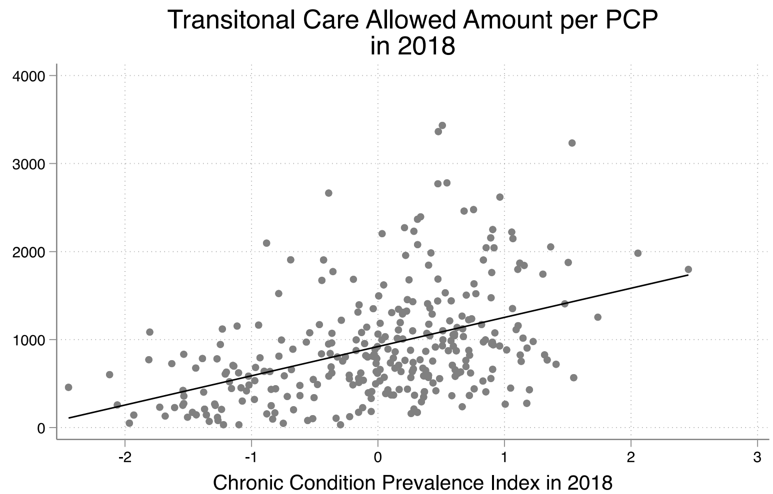
Panel B. CCM Hospital Referral Region Billing per PCP in 2018



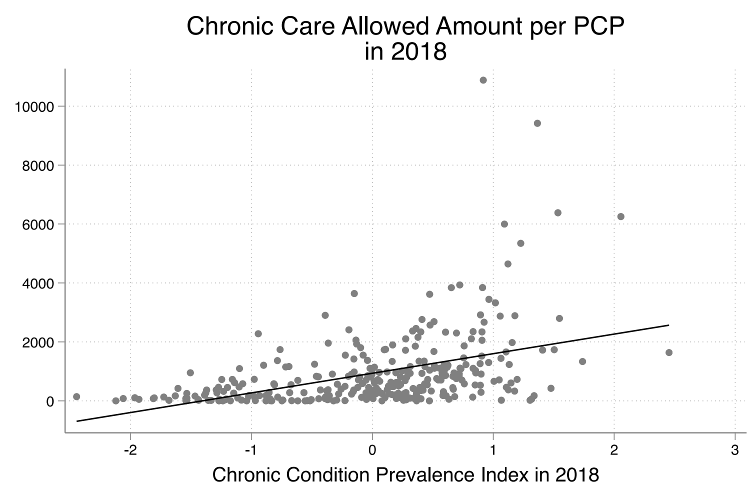
Notes: These heat maps illustrate regional variation in the take-up of Transitional Care Management (TCM) and Chronic Chare Management (CCM) billing codes. Each map plots new code billing per primary care physician (PCP) at the Hospital Referral Region (HRR) level in 2018, the final year of our sample. The underlying data source is our 2012–2018 panel of physicians.

Figure A2: Regional Variation in the Take-Up of New Codes by Chronic Condition Prevalence

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



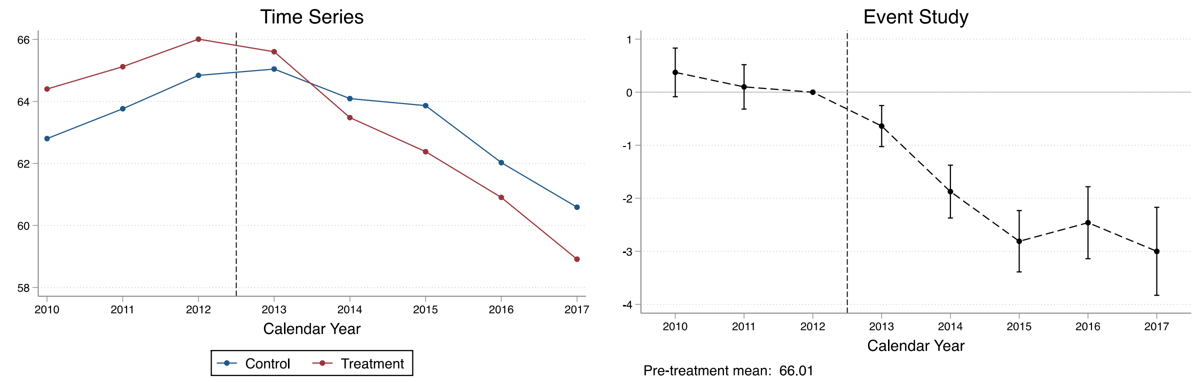
Panel B. CCM Hospital Referral Region Billing per PCP in 2018



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. 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 A3: An Example of Code Substitution – Unmatched Sample

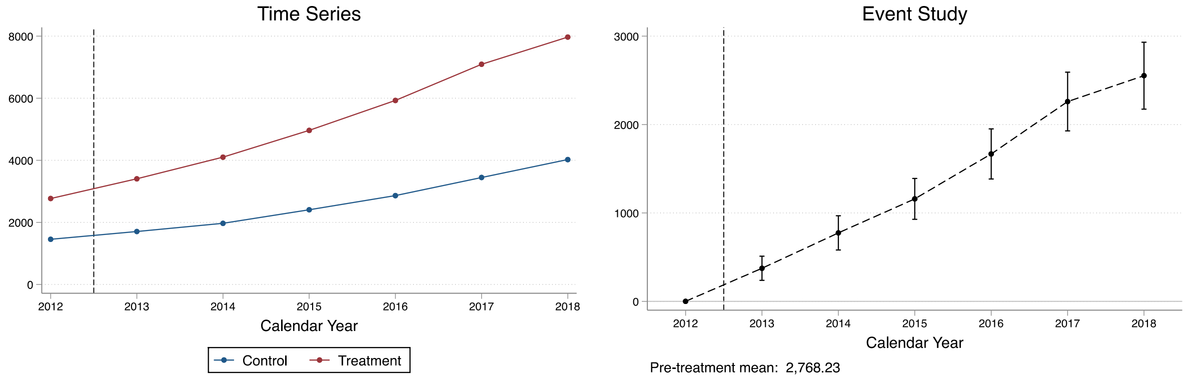
Fraction of Beneficiaries with a Traditional Post-Discharge Office Visit, by TCM Treatment Group



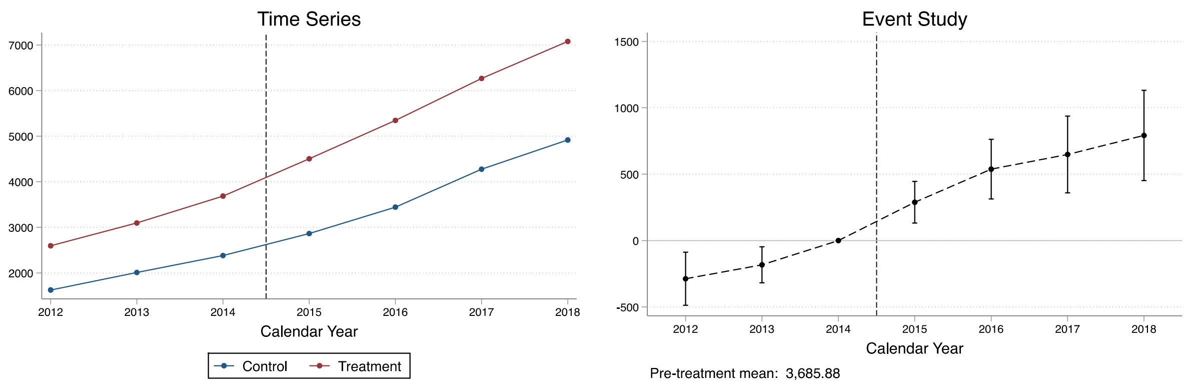
Notes: This figure shows how the fraction of beneficiaries with a traditional office visit after an inpatient discharge evolves around the time of the introduction of the Transitional Care Management (TCM) billing code. The left-hand side graph plots raw means for our treatment and unmatched control group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (2). The dependent variable is the county-level fraction of beneficiaries with a traditional office visit 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. The denominator is the number of discharges in the given county-year. The event study regression includes 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 Code Complementarity – 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 how annual wellness visit billing evolves around the time of the introduction of the new billing codes. Panel A corresponds to Transitional Care Management (TCM). Panel B corresponds to Chronic Care Management (CCM). In each panel, the left-hand side graphs raw means for out treatment and unmatched control group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (1). The dependent variable is the county-level allowed amount for Annual Wellness Visits in units of dollars billed by PCPs per PCP. The event study 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.

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 dataset. 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 A2. 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.