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

Jeffrey Clemens†
Jonathan M. Leganza‡
Alex Masucci⁋

December 20, 2024

Abstract

We analyze the introduction of new Medicare billing codes for Chronic Care Management (CCM) and Transitional Care Management (TCM). We first show that new code take-up occurs gradually and varies across space and physician characteristics. Second, we study how the codes correlate with other services, focusing on two case studies. Illustrating code substitution, we show TCM services predict fewer traditional office visits following hospital discharges, suggesting crowd out. Illustrating code complementarity, we show TCM and CCM services predict increases in annual wellness visits. Take-up frictions and the relationship between new and existing codes are important for evaluating payment reforms.

Keywords: Health Care, Health Economics, Medicare, Payment Systems, Procurement

JEL Codes: H51, H57, I10

---

* We thank Kate Antonovics, Julian Betts, Colleen Carey, Mike Geruso, Todd Gilmer, Tim Layton, and Gaurav Khanna for helpful comments and conversations.
† University of California, San Diego. (Email: clemens.jeffrey@gmail.com)
‡ John E. Walker Department of Economics, Clemson University. (Email: jleganz@clemson.edu)
⁋ Independent Researcher. (Email: 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. Importantly, patterns of complementarity and substitutability can involve subtle mixes of changes in bill coding, on the one hand, and real provision of care, on the other.

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). Simple time series reveal that the adoption of the new codes is a gradual process, suggesting the existence of take-up frictions. We also document substantial variation in take-up across space, some of which is correlated with the prevalence of chronic conditions, but much of which is not. We then explore several dimensions of heterogeneity in new code adoption across physicians. We show that new code take-up is greater for mid-career physicians compared to early-career and late-career physicians, and we show 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.

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 relationship between new code billing and other services, and we conduct each of the regression analyses at two levels, the county level and the physician level. First, we use a fixed effects framework that exploits all panel variation in the intensity with which new codes are billed. Second, we use a descriptive event study framework that compares the evolution of outcomes for a high new code take-up group (county or individual physician) to that of a low new code take-up group, before and after the introduction of the new billing codes. The consistency of our estimates across estimation frameworks and levels of analysis contributes to the strength of the evidence, as our goal is to investigate empirically whether physicians tend to bill relevant existing codes less or more when they bill new codes, and to emphasize that the relationship between new and existing codes has implications for how reforms that introduce payments for new services play out in practice.

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, is associated with fewer standard office visits after hospital discharges, consistent with partial crowd out. Because this outcome variable is only available at the county level, this is the one outcome for which we report county-level analyses only. Our county-level fixed effects estimates imply roughly one less traditional office visit for every 26 additional Transitional Care Management visits, and our corresponding 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.

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. The event study and fixed effects estimators yield complementary estimates, and our findings are similar across levels of analysis as well. Overall, the results from both the county-level and physician-level analyses suggest a substantial complementarity between Annual Wellness Visits and Transitional Care Management billing and a more modest degree of complementarity with Chronic Care Management billing.

After presenting these two case studies, we use our fixed effects framework to provide additional suggestive evidence on the relationship between new code billing and broader billing behaviors. We find that Transitional Care Management billing predicts meaningful increases in total billing, whereas Chronic Care Management billing predicts more modest, if any, increase in total 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 complementarity could impact claims-dependent systems of quality measurement. 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. 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.

Our paper contributes to two literatures. First, our analysis of take-up extends an emerging medical literature that also documents adoption of the new codes (Agarwal et al., 2018; Marcotte et al., 2020; Reddy et al., 2020; Agarwal et al., 2020). Using Medicare claims data, Reddy et al. (2020) document time series on Chronic Care Management billing, Marcotte et al. (2020) document time series on Transitional Care Management billing, and Agarwal et al. (2018) document the fraction of eligible beneficiaries receiving both Transitional and Chronic Care Management. The paper most closely related to ours is Agarwal et al. (2020), who use Medicare claims data on 20% of beneficiaries to analyze take-up of the new codes by characteristics of primary care practices and to also point out that the new codes can substitute for or add to other services. Specifically, they were the first to document trends in means that show declines in office visits after hospital discharges among practices that adopt Transitional Care Management services compared to those that do not; they also show that the total number of visits increases for beneficiaries eligible for Chronic Care Management at practices that take up that new code.[1]

In contrast, our analysis of take-up uses data on the near-universe of Medicare-billing doctors to analyze how the likelihood of billing a new code varies with physician characteristics. A novel aspect of our take-up analysis is the analysis of career stage, which previous papers have been unable to investigate, but which may be important to a physician's assessment of the long-run financial returns to investing in the adoption of new codes. Our analysis of code complementarity and code substitution contributes further by using a pair of complementary regression frameworks to quantify associations between new code billing and the provision of other services. One of the margins we consider, namely the substitution of regular post-discharge office visits for Transitional Care Management services, has been considered by prior work (Agarwal et al., 2020). The remainder of the margins we consider are novel, namely the complementarity between annual wellness visits and both new codes, as well as the relationship between new codes and broader billing behaviors. Moreover, our county-level analyses are novel and, when contrasted with our physician-level analyses, allow us to assess the extent to which physician-level estimates might be attenuated by referral patterns. This would be the case, for instance, if new-code-intensive physicians refer patients to physicians who bill the new codes less intensively. Overall, we view our data and econometric methods as providing a more comprehensive analysis of how physician billing evolves following the introduction of these important new billing codes.

Our paper thus also contributes 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). For example, Cabral, Carey, and Miller (2021) analyze an Affordable Care Act reform that increased Medicaid payments for primary care services provided to low-income elderly and disabled people and find increases in primary care services. Others investigate margins including physicians' preferences over taking new patients (Chen, 2014; Clemens, Gottlieb, and Hicks, 2021; Garthwaite, 2012),

[1] To the best of our knowledge, this literature has not yet studied the question of whether these new codes have been integrated into fee schedules for non-Medicare patient populations or adopted by physicians in non-Medicare contexts. This may be an interesting area for future research.

prescription patterns (Carey et al., 2020), and choices over where to locate (Khoury et al., forthcoming). For example, Clemens, Gottlieb, and Hicks (2021) study changes to Medicare payment rules that affect physicians differentially based on their specialty and find that reductions in reimbursements led physicians to reduce investment activities and to be less willing to accept new patients. Taken together, relatively recent research in this broad literature and 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 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.[2] 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. 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 is likely to be beneficial for health outcomes and health care costs (Friedberg et al., 2010).

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

[2] 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).

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).[3]

[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.

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.

At first, the process of billing CCM involved some burdens and complexities. For instance, an initiating office visit and advanced patient consent was required. In an analysis of 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—while others reported that reimbursement rates were not sufficient to cover upfront investments in staffing and infrastructure required to provide CCM. Two year later, in 2017, CMS relaxed 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 the same year, 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).

2.4 New Billing Codes in Practice

The introduction of TCM and CCM billing codes creates financial incentives to provide these services. 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, which can require navigating the general administrative complexities associated with billing procedures (Gottlieb et al., 2018).[4]

The effectiveness of new codes could be limited by administrative burdens associated with their use. Adopting new codes may not be worthwhile if the codes represent a 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 geography. As take-up occurs, it is then important to evaluate empirically how the use of new codes affects other billing patterns and provision of care.

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, as well as one state-level dataset with information on a measure of vertical integration.

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 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

[4] For a recent paper on the effects of administrative burden and complexities in billing, see League (2023), who shows that claim denials lead to higher billing costs, more consolidation of practices, and no reduction in health care spending.

information on physician practice location.[5] 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 obtain information on physician medical school attendance and graduation dates.[6] We use these data to categorize physicians based on career stage. Guided by the humped-shaped physician age-earnings profiles documented in Gottlieb et al. (2020), we categorize physicians into three career stages that roughly correspond to (i) the early-career period during which earnings increase rapidly, (ii) peak earnings years, and (iii) the late-career period when earnings decline. Specifically, we define early-career PCPs as those who graduated from medical school 5 to 14 years prior (who are thus approximately under 40), mid-career PCPs as those who graduated 15 to 39 years prior (who are thus between 40 and 65), and late-career PCPs as those who graduated 40 or more years prior (who are thus over 65).[7] 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 conditions (arthritis, kidney disease, COPD, diabetes, heart failure, hyperlipidemia, hypertension, and ischemic heart disease). See Appendix A for details.

[5] 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.
[6] 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.
[7] Our definition of early-career PCPs is also 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.

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, the percent of beneficiaries who have a post-discharge office visit with a primary care physician, since this new billing code is for services directly used to provide managed care for patients after a hospital discharge. Because our measure of post-discharge visits with a primary care physician comes from this county-level dataset, we are unable to analyze it with our physician panel and must instead study it through county-level analyses.

3.3 State-Level Data

We use one state-level dataset as well. From the *Health Systems Dashboard* (Mathematica, 2024), we obtain the state-level fraction of physicians who are in health systems. Mathematica created the dashboard using data from the 2018 Compendium of U.S. Health Systems, CMS Hospital Compare, and CMS Hospital 2552-10 Cost Report. We use the information from the dashboard on the fraction of physicians in health systems when documenting the take-up of new billing codes by physician characteristics.

4 The Take-Up of New Medicare Billing Codes

We begin by documenting new code take-up. First, we document how adoption evolved over time. Second, we investigate geographic variation in new code usage. Third, we analyze how new code usage varies with physician characteristics.

4.1 New Code Billing Over Time

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. Panel A plots total billing in dollars for TCM (CCM), 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. By 2018, six years after the introduction of TCM and four years after the introduction of CCM, 12.3% of PCPs bill TCM and 4.5% of PCPs bill CCM.

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 makes up a greater share of total billing for those who do bill the code. This pattern is consistent with CCM-intensive billing practices emerging as a result of physicians undertaking investments in staffing and infrastructure to comply with CCM requirements (O'Malley et al., 2017).

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 2. 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 3 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. Figure 4 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.

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.

Finally, panel E breaks down billing rates for physicians practicing in states that have different medical system characteristics. Specifically, we report the fraction of PCPs billing the new codes who practice in states that are in the top tercile, the middle tercile, and the bottom tercile of the distribution of the percent of physicians in health systems. We use this measure to proxy for the extent of vertical integration, which increased during our time horizon throughout the U.S. (Kimmey et al., 2021) and for primary care physicians (Machta et al., 2020). TCM billing rates are higher in the bottom and top terciles compared to the middle tercile, and CCM billing rates are inversely related to the tercile measure. While this subsample analysis is coarse, it provides suggestive evidence that more vertically integrated areas are unlikely to be key drivers of more use of the new billing codes.

Overall, the results in Table 1 and Figure 4 indicate that there are meaningful variations in new code adoption rates across physician characteristics. One of the more striking patterns might be the higher billing rates of mid-career physicians. A natural question is whether this pattern is due to career stage itself, or perhaps some other factor correlated with career stage. To investigate this issue, we conduct a multivariate regression analysis that complements the raw means documented thus far. Specifically, we further investigate the association between career stage and new code billing by using data on PCPs from 2018 and estimating

$$Y_i = \alpha + \beta MidCareer_i + \gamma LateCareer_i + X_i\delta + \varepsilon_i, \qquad (1)$$

where y_i is an indicator for billing the new code of interest, $MidCareer_i$ and $LateCareer_i$ are indicator variables for mid-career and late-career physicians, respectively, X_i is a vector of other physician characteristics that we analyze in Table 1, and ε_i is an error term. The coefficients of interest are β and γ, which capture new code billing rates for mid-career and late-career PCPs compared to early-career PCPs, and we are interested in how these coefficients may change as we control for additional characteristics.

Table 2 presents the results. Panel A is for TCM and panel B is for CCM. Each column presents estimates of β and γ as we add additional control variables to the regressions. Column (1) includes no controls and thus replicates the patterns in Table 1. For example, mid-career PCPs are 7.5 percentage points more likely to bill TCM than their early-career counterparts, whereas late-career PCPs are 5.4 percentage points more likely to bill TCM than early-career PCPs. Column (2) adds indicator variables for the various group sizes. The key coefficients decrease modestly, but the “inverse-U” pattern remains. Columns (3) and (4) add controls for group type and for the percent of physicians in health systems, respectively. The key coefficients are essentially unchanged.

We conclude that the relationship between career stage and new code billing is mediated to a modest degree by the relationship between career stage and group size, but that career stage itself remains an important predictor of new code adoption. The “inverse U” shape 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 (as shown in Figure 4) 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.

5 Empirical Framework for Analyzing the Relationship between New Code Adoption and Other Billing Behaviors

Next, we investigate the substitutability and complementarity of new codes with existing codes, using two descriptive regression frameworks to estimate the relationship between new code billing and the billing or provision of other services. We conduct these regression analyses at both the physician (PCP) level and the county level. The county-level analyses are essential in part because, as noted in Section 3, one of our key outcomes of interest when studying TCM is obtained from the county-level files from the Dartmouth Atlas. The county-level analyses also have two potentially important advantages because they are conducted at a more aggregated level than physician-level analyses. First, they limit the extent to which our estimates are impacted by physician or group-level specialization, or by patient sorting across groups, to the extent to which counties capture the relevant markets. Second, the county-level analyses should allow us to capture changes in care due to referrals, which may be a key channel through which TCM alters care provision, as long as the referrals occur within counties. However, we also present results from physician-level analyses, which make fuller use of the available variations in new code billing.

First, we use a fixed effects regression framework that exploits all panel variation in the intensity with which new codes are billed. For our county-level analyses, 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 (1) 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 $\beta,$ which captures the correlation between the county-level outcome and the dollar value of new code billing per primary care physician.

For our PCP-level analyses, we similarly estimate regressions of the form:

$$Y_{i,c,t} \; = \beta New\ Code\ Billing\ _{i,,t} + X_{c,t}\,\gamma + \alpha_i + \delta_t + \varepsilon_{i,c,t}. \qquad (3)$$

Equation (2) controls for individual fixed effects (α_i), time fixed effects (δ_t), and the same time-varying county characteristics in equation (1). The primary coefficient of interest is again β, which captures the correlation between the physician-level outcome and the dollar value of physician new code billing.

We interpret these correlations captured by β as descriptive. They quantify the relationship between new code billing and other billing behaviors and provide evidence on whether the new codes appear to complement or substitute for existing codes. We note that we document these associations after controlling for (i) either county or physician-specific unobserved and time-invariant factors using the unit fixed effects, (ii) macroeconomic conditions using the time fixed effects, and (iii) time-varying county characteristics that may influence billing (the average age of beneficiaries, the percent of beneficiaries that are female, the percent of beneficiaries that are Medicaid-eligible, and a normalized index of chronic condition prevalence). When presenting the estimates, we investigate robustness to excluding the time-varying county-level characteristics and find that our estimates are insensitive to this choice.

Second, to provide additional descriptive evidence, we use an event study regression framework to categorize, quantify, and visualize the billing behaviors of high and low adopting counties or physicians. For our county-level analyses, we compare the evolution of outcomes in places with more new code take-up to that of places with less new code take-up. We treat high intensity adopters as our treatment group and low intensity adopters and non-adopters as a comparison 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 comparison group.

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

$$Y_{c,t} = \sum_{p(t)\neq -1} \beta_{p(t)} Treatment_c \times Event\ Time_{p(t)} + X_{c,t}\,\gamma + \alpha_c + \delta_t + \varepsilon_{c,t}. \qquad (4)$$

In equation (4), *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 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.

For our physician-level analyses, we compare the evolution of outcomes for PCPs who adopt the new codes to PCPs who do not adopt the new codes. Here, because new code adoption is rare, our "high take-up" PCPs are PCPs who ever billed the new code, and our "low take-up"

PCPs are PCPs who never billed the new code.[8] Using this grouping of PCPs, we estimate similar regressions of the form:

$$Y_{i,c,t} = \sum_{p(t)\neq -1} \beta_{p(t)} Treatment_i \times Event\ Time_{p(t)} + X_{c,t}\,\gamma + \alpha_i + \delta_t + \varepsilon_{i,c,t}, \qquad (5)$$

where the right-hand-side variables in equation (4) are the same as in equation (3), except the unit fixed effects are for individual physicians, denoted by the subscript i.

Overall, our two regression frameworks conducted at both the county and physician level work towards the same goal: providing empirical evidence on how the take-up of new billing codes relates to other billing behaviors. The fixed effects framework has the advantage of using all variation in new code billing to provide estimates of how a dollar of new code billing relates to other services. The advantage of the event study framework is that it provides relatively clear, graphical evidence that allows us to investigate pre-period trends in the outcomes.

The consistency of estimates across our two frameworks is thus important for assessing the strength of the evidence we present. While no pure quasi-experiment exists because the new codes were introduced to the entire country at the same time, our regression frameworks are able to establish patterns of complementarity and substitutability that are robust to controlling flexibly for unit (county or physician) effects and time effects, as well as time-varying county-level health and demographic characteristics. These patterns have implications for assessing the practicalities of policies that adapt payments systems to cover new services.

6 The Relationship Between New Code Adoption and Subsequent Coding and Care Provision

We next estimate our fixed effects and event study regression models with an emphasis on two case studies, one that illustrates billing code substitution and one that illustrates billing code complementarity.

Table 3 presents summary statistics for 2012 to 2018 that describe the samples underlying the bulk of our analyses. Panel A presents means for our county-level analysis sample. Total billing per PCP is about $100,000 on average, and we see that most of this billing is for evaluation and management services. Average billing of annual wellness visits is about $3,000 per PCP. The post-

[8] For each new code, the median physician in terms of average annual post-implementation new code billing did not bill the new code at all.

new-code-implementation averages for TCM and CCM billing amount to $520 and $626 per PCP, respectively. Finally, we see that about 64% of beneficiaries have a traditional office visit within 14 days of a hospital discharge. The observation counts for this outcome variable are lower because the variable is not available in 2018.

Panel B presents the corresponding means for our PCP-level analysis sample. Overall, the pattern of means is quite similar to that in the county-level data. Recall that we can only analyze the post-discharge office visits at the county level.

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?

Panel A of Table 4 presents county-level fixed effects estimates that show this type of code substitution in practice. It reports estimates of β from equation (2), where the outcome variable is the fraction of beneficiaries that have a traditional office visit within two weeks of discharge from the hospital.[9] 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.

Figure 5 presents corresponding event study results. Recall that the outcome variable 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 high take-up treatment group and low take-up comparison group. The right-hand side graph plots the event study coefficients from estimating equation (4).

[9] 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 graphs show that the fraction of beneficiaries receiving a traditional post-discharge office visit in the treatment group was trending in parallel with the comparison group before the introduction of TCM. Then, after the introduction of the new code, there is a clear and meaningful decline in post-discharge traditional office visits for the treatment group relative to the comparison group. By 2017, this decline amounts to 4.3 percentage points.

To help interpret this estimated decline and to compare it to our fixed effect estimate, we scale it by the estimated increase in new code billing for the high take-up counties compared to the low take-up counties. Panel A of Figure 6 shows that by 2017, the increase in TCM billing for the treatment group amounts to $1,373. Scaling the estimated decline in office visits by this "first stage" estimate implies a 3.13 percentage point decline in the fraction of beneficiaries receiving a traditional post-discharge visit for every $1,000 of TCM billing.

Taken together, our fixed effects and event study results 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.[10] 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.[11] 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

[10] 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.

[11] 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.

adapt to changes in coding systems. Note that this point connects to similar insights in the context of risk adjustment models.[12]

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.

Panel B of Table 4 presents results from the county-level 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.

Table 5 presents corresponding estimates from the fixed effects regressions at the physician level. These results also show a larger degree of complementarity between AWV billing and TCM compared to CCM. The magnitude of the estimate for CCM is quite similar to the magnitude from the county-level regression, whereas the PCP-level estimate for TCM is meaningfully smaller than its county-level counterpart, although it is still highly statistically significant. The difference in

[12] 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.

magnitudes across the levels of analysis could arise from the capacity of the county-level regressions to capture complementarities that arise through referrals. In the physician level analyses, referrals from more intensive new code adopters to less intensive new code adopters will tend to attenuate the estimated relationship between new code take-up and the provision of other services.

Next, we turn to the event study analyses. Here the scaling of the event study estimates by the corresponding first stage estimates is especially important as it facilitates both better comparisons to the fixed effects estimates as well as comparisons across levels of analysis.

We begin with the county-level results. Figure 6 shows how county-level TCM billing (panel A) and CCM billing (panel B) evolve for the treatment and comparison groups. In 2018, the estimated increase in TCM billing for the treatment counties is $1,430 and the estimated increase in CCM billing is $2,110. Panel A of Figure 7 shows the relationship between TCM take-up and 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 comparison counties after the introduction of TCM that amounts to $2,553 by 2018, which provides evidence pointing to complementarity. Scaling this estimate by the corresponding first stage estimate implies that each dollar of TCM billing predicts $1.79 of AWV billing.

Panel B of Figure 7 shows the relationship between CCM billing and AWV billing. Here we can investigate pre-period trends because the CCM billing codes were introduced in 2015. The pre-period estimates do indicate differential trends in AWV billing for the high and low take-up groups before the introduction of the new code, although the results also point to a more pronounced increase in AWV billing after 2015. Scaling the 2018 estimate by its corresponding first stage would imply that, at the county level, each dollar of CCM billing predicts a $0.38 increase in AWV billing.

Figures 8 and 9 present event study results when we conduct our analysis at the physician level. The first stage estimates in Figure 8 indicate that, by 2018, the average increase in TCM billing amounts to $4,880 and the increase in CCM billing amounts to $13,793. The event study estimates in panel A of Figure 9 reveal a $8,364 increase in AWV billing for the high TCM take-up PCPs compared to the low take-up PCPs, which scaled by its first stage implies that each dollar of TCM billing predicts $1.71 of AWV billing. This estimate is very similar to the analogous county-level estimate.

The event study estimates in panel B of Figure 9 reveal a $5,781 increase in AWV billing for high CCM take-up PCPs compared to low take-up PCPs. While there is still some evidence of differential pre-trends, we note that the physician-level increase in AWV billing in the post period is stark; there is a clear and sharp increase in AWV billing for the treatment group compared to the comparison group starting in 2015. Scaling the 2018 estimate by its corresponding first stage implies that each dollar of CCM billing predicts $0.42 of AWV billing. This estimate is also quite similar to its county-level equivalent.

Overall, we view the combination of our event study and fixed effects results on AWVs at both the county and physician level as suggesting 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.

6.3 Suggestive Evidence on Broader Patterns of Coding and Care Provision

Our two case studies highlight how the evaluation of payment reforms that introduce new billing codes can be complicated by both the substitutability and complementarity of new codes with existing codes. A more comprehensive analysis of the effects of adopting new codes on total service provision is beyond the goal of this paper, which is to illustrate the relevance and potential importance of several nuanced pieces of the puzzle. Yet we can provide some evidence on how new code billing relates to billing behaviors more broadly by using our fixed effects regression framework to analyze billing patterns across general categories of care. Table 6 reports county-level results, and Table 7 presents PCP-level results. TCM billing predicts increases in overall care, driven by evaluation and management services, whereas CCM billing predicts modest, if any, increase in overall billing. These findings could be interpreted as suggesting that the introduction of CCM codes may have rationalized the coding of services that had previously been delivered and billed using less lucrative codes. In contrast, the introduction of TCM codes appears to be correlated with meaningful increases in patient interactions with doctors.

7 Conclusion

Maintaining an efficient health care procurement system requires adapting to changes in the health care landscape. Procurement systems must accommodate the introduction of new procedures, for example, as analyzed by Dranove et al. (2022). The arrival of new tests or vaccines, as during the COVID-19 pandemic, and experimentation with new modalities like those used in the delivery of telehealth services also pose challenges for procurement and billing systems. In recent years, the U.S. health system has also confronted 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. We emphasize that the desirability of instances of complementarity and substitutability are context dependent. If the adoption of new codes leads physicians to shift away from less cost-effective alternatives, for example, then the associated patterns of substitution could be value increasing. Similarly, if the adoption of new codes enhances the delivery of complementary, high-value services, then associated patterns of complementarity could also be value increasing. However, if the adoption of new codes crowds in inefficiently delivered services (e.g., due to duplicative or otherwise excessive testing in connection with an increased number of referrals), then the associated patterns of complementarity could be value reducing.

Finally, we note that the Chronic and Transitional Care Management codes 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. One crucial question, for example, is whether the payment reforms that we analyze improve patient health outcomes. Another crucial question is how the reforms 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

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.

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?

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*.

Dranove, D., Garthwaite, C., Heard, C. and Wu, B., 2022. The economics of medical procedure innovation. *Journal of Health Economics*, *81*, p.102549.

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., Polyakova, M., Rinz, K., Shiplett, H. and Udalova, V., 2020. Who Values Human Capitalists' Human Capital? Healthcare Spending and Physician Earnings.

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.

Mathematica. 2024. "Health Systems Dashboard." https://health-system.mathematica.org/explore.

Kimmey, L., Furukawa, M.F., Jones, D.J., Machta, R.M., Guo, J. and Rich, E.C., 2021. Geographic Variation In The Consolidation Of Physicians Into Health Systems, 2016-18. *Health Affairs (Project Hope)*, *40*(1), pp.165-169.

Khoury, S., Leganza, J.M. and Masucci, A., forthcoming. Health Professional Shortage Areas and Physician Location Decisions. *American Journal of Health Economics.*

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.

League, R., 2022. Administrative Burden and Consolidation in Health Care: Evidence from Medicare Contractor Transitions.

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.

Machta, R.M., D Reschovsky, J., Jones, D.J., Kimmey, L., Furukawa, M.F. and Rich, E.C., 2020. Health system integration with physician specialties varies across markets and system types. *Health Services Research, 55*, pp.1062-1072.

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.

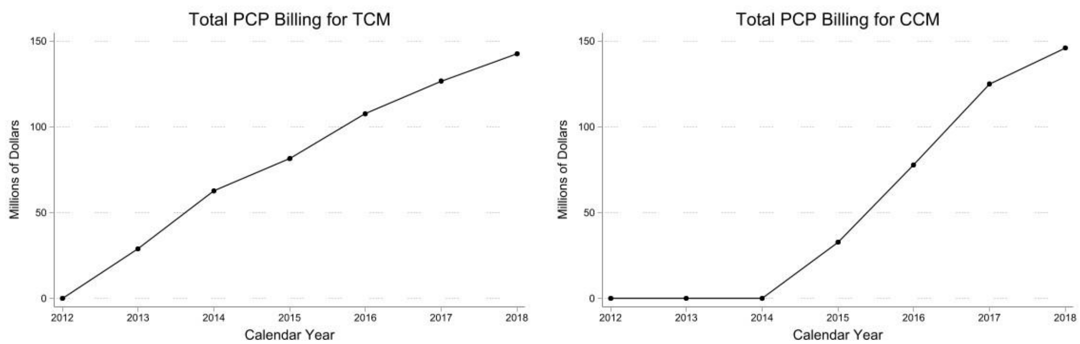
Schnell, M. and Currie, J., 2018. Addressing the Opioid Epidemic: Is there a Role for Physician Education?. *American Journal of Health Economics, 4(3),* pp.383-410.

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.

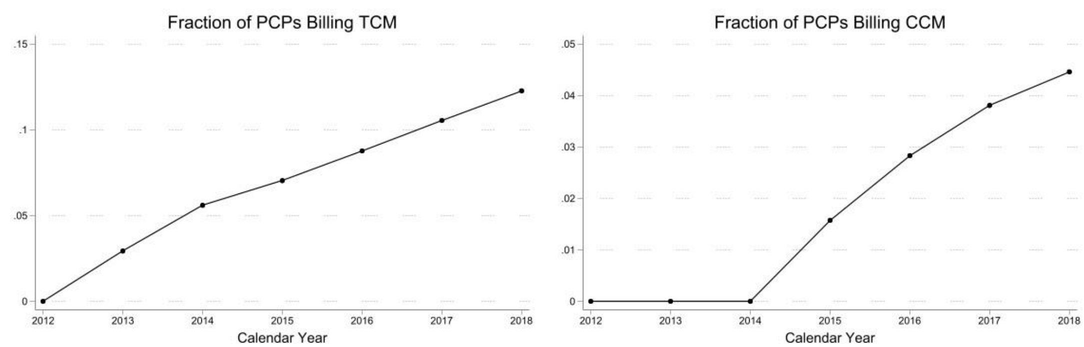
Figures and Tables

Figure 1: Take-Up of New Codes Over Time

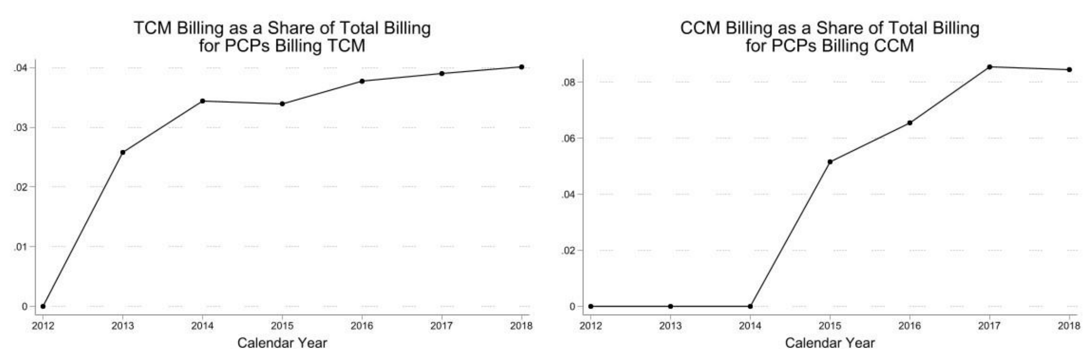
Panel A. Total New Code Billing



Panel B. Fraction of PCPs Billing New Codes



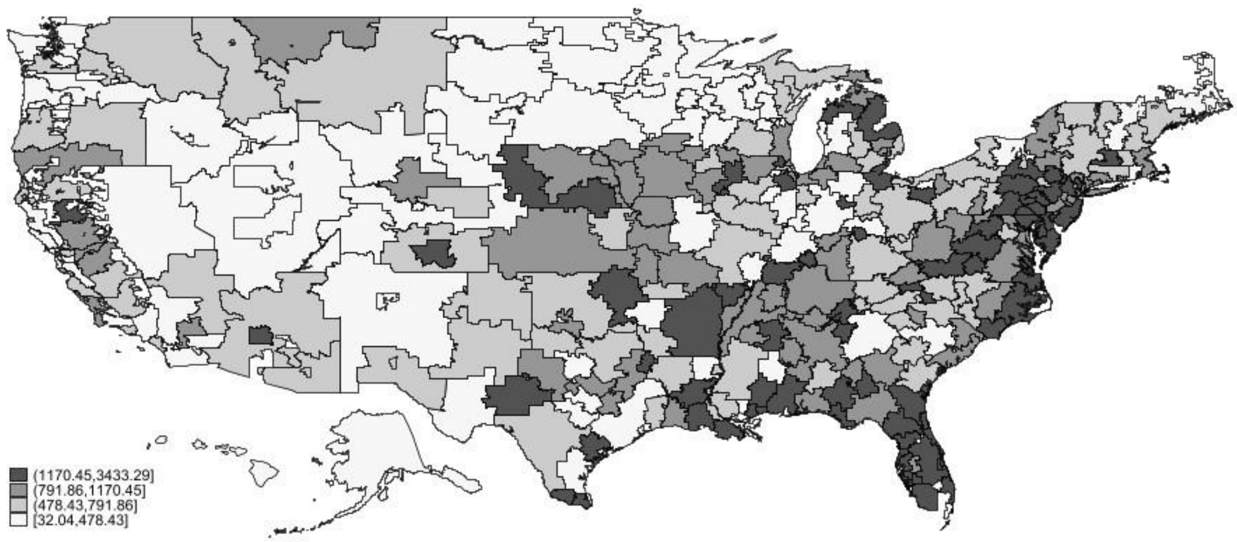
Panel C. New Code Billing as a Share of Total Billing



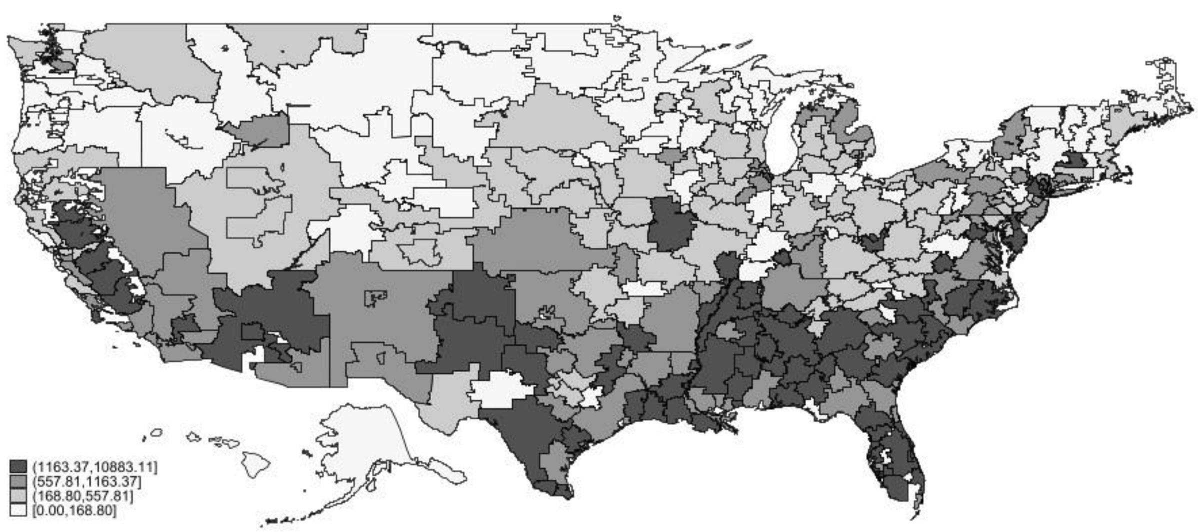
Notes: These graphs plot statistics related to the take-up of Transitional Care Management (TCM) and Chronic Chare Management (CCM) billing codes for primary care physicians (PCPs). We define PCPs to be physicians with a specialty of Internal Medicine, Family Practice, General Practice, or Geriatric 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



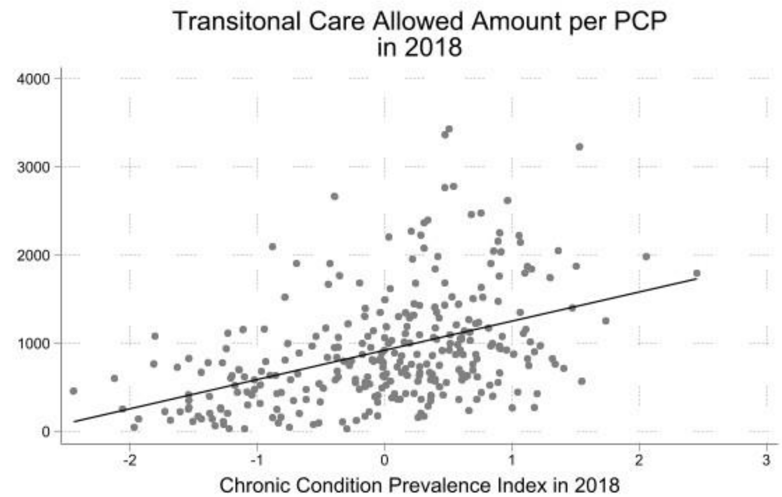
Panel B. CCM Hospital Referral Region Billing per PCP in 2018



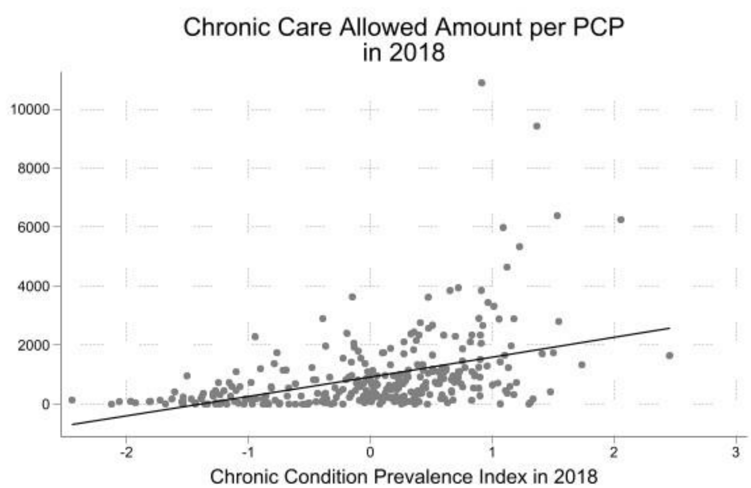
Notes: These heat maps illustrate regional variation in the take-up of Transitional Care Management (TCM) and Chronic Chare Management (CCM) billing codes. Each map plots new code billing per primary care physician (PCP) at the Hospital Referral Region (HRR) level in 2018, the final year of our sample.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

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

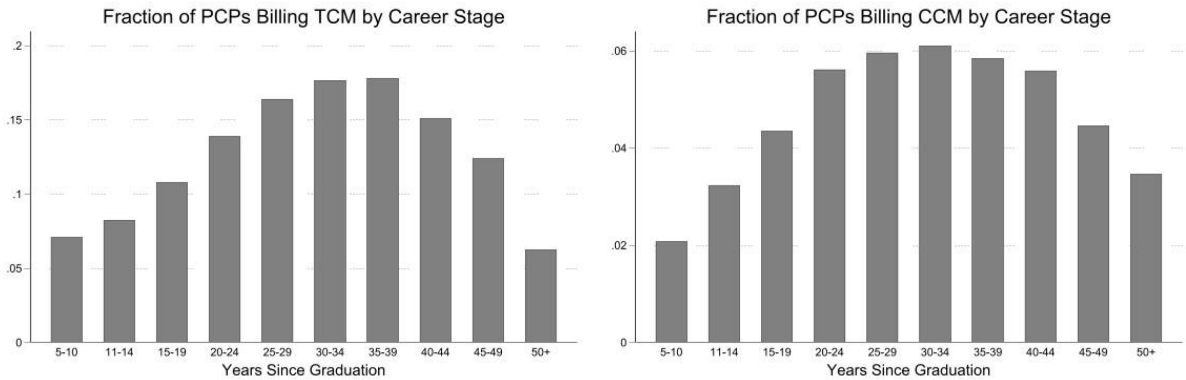


Panel B. CCM Hospital Referral Region Billing per PCP in 2018



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. 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 A for more details.

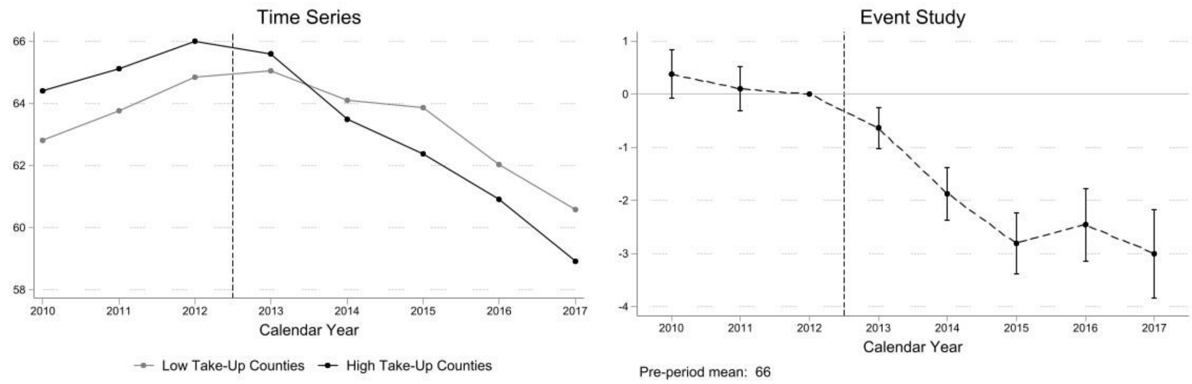
Figure 4: New Code Billing in 2018 by Career Stage



Notes: These bar graphs show how billing for Transitional Care Management (TCM) and Chronic Care Management (CCM) vary over career stages. Each graph plots the fraction of primary care physicians (PCPs) billing the new code for the various categories of career stage 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 5: An Example of Code Substitution

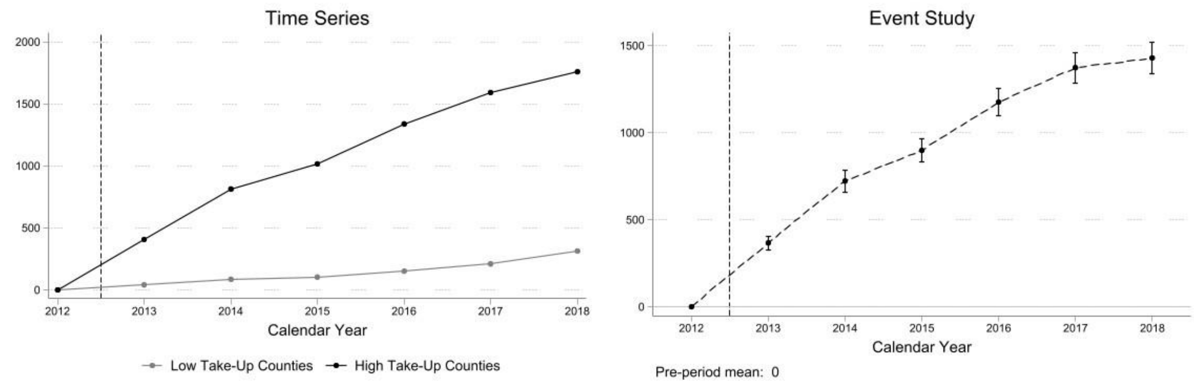
Fraction of Beneficiaries with a Traditional Post-Discharge Office Visit, by TCM Take-Up Group



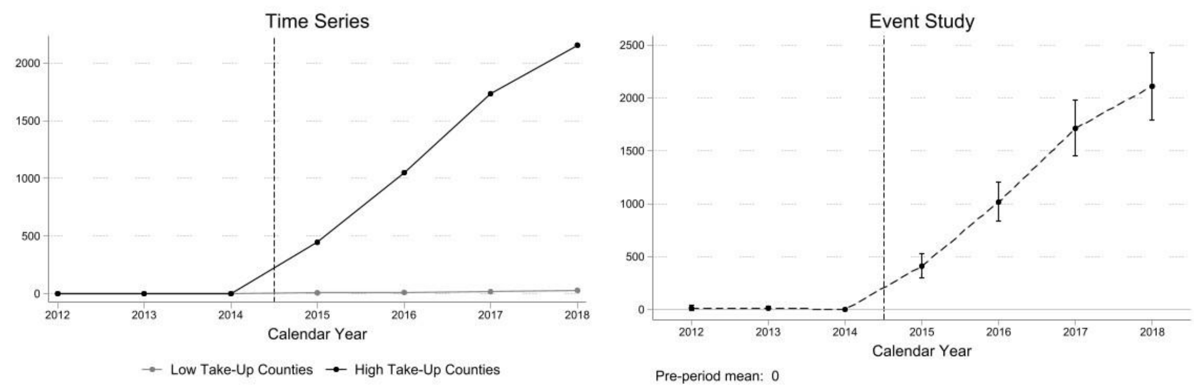
Notes: This figure shows how the fraction of beneficiaries with a traditional office visit after an inpatient discharge evolves around the time of the introduction of the Transitional Care Management (TCM) billing code. The left-hand side graph plots raw means for our treatment and comparison group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (4). 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 6: New Code Billing for High and Low Take-Up Counties

Panel A. TMC Billing per PCP, by TCM Take-Up Group



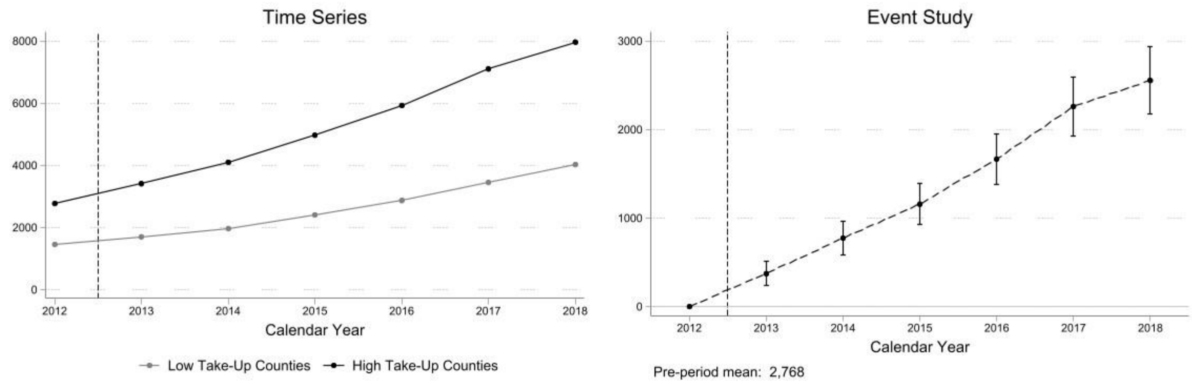
Panel B. CCM Billing per PCP, by CCM Take-Up Group



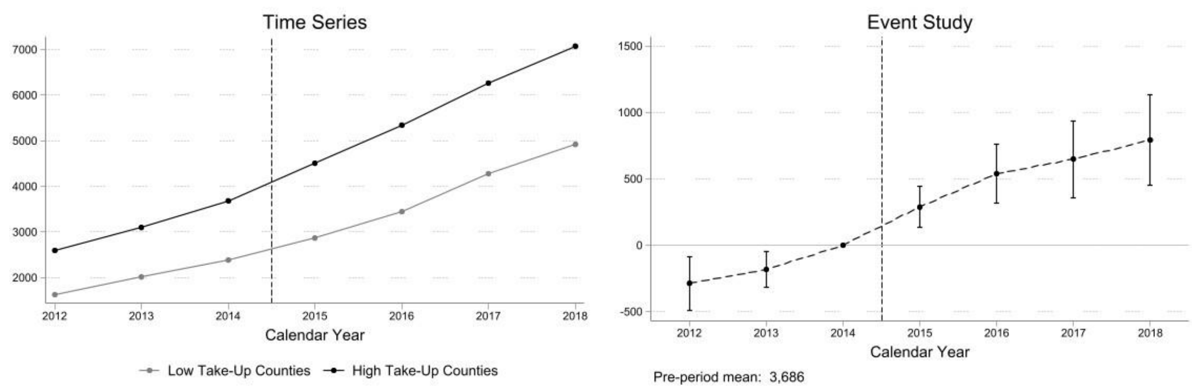
Notes: This figure shows how new code billing evolves around the time of the introduction of the new billing codes. Panel A corresponds to Transitional Care Management (TCM). Panel B corresponds to Chronic Care Management (CCM). In each panel, the left-hand side graphs raw means for the treatment and comparison group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (4). The dependent variable is the county-level allowed amount for the corresponding new code 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.

Figure 7: An Example of Code Complementarity: County-Level Analysis

Panel A. Annual Wellness Visit Billing per PCP, by TCM Take-Up Group



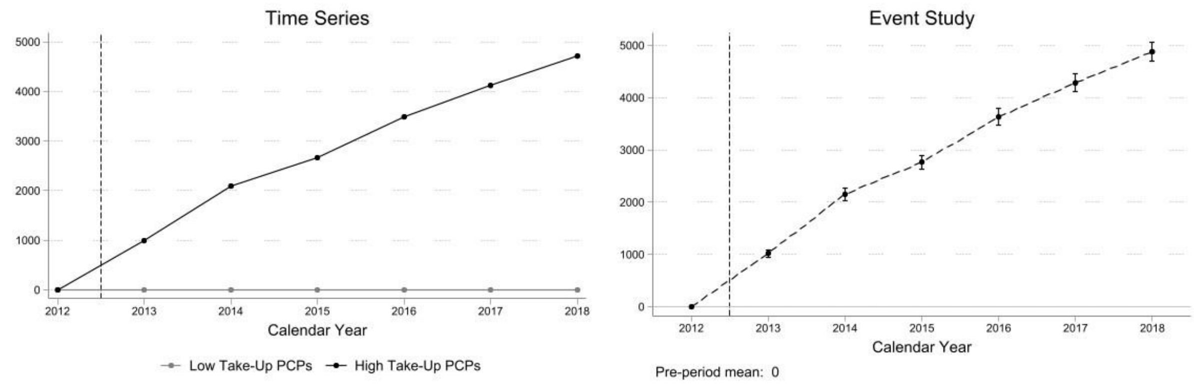
Panel B. Annual Wellness Visit Billing per PCP, by CCM Take-Up Group



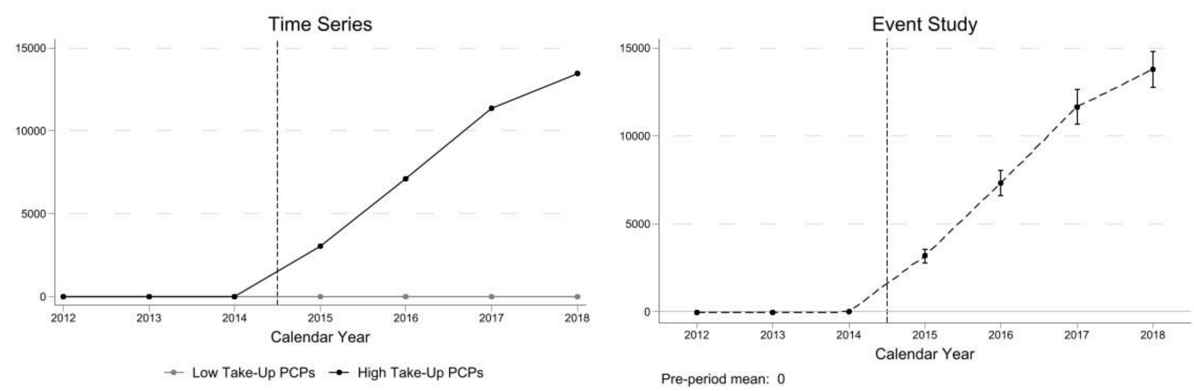
Notes: This figure shows how annual wellness visit billing evolves around the time of the introduction of the new billing codes. Panel A corresponds to Transitional Care Management (TCM). Panel B corresponds to Chronic Care Management (CCM). In each panel, the left-hand side graphs raw means for our treatment and comparison group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (4). 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.

Figure 8: New Code Billing for High and Low Take-Up Primary Care Physicians

Panel A. TMC Billing by TCM Take-Up Group



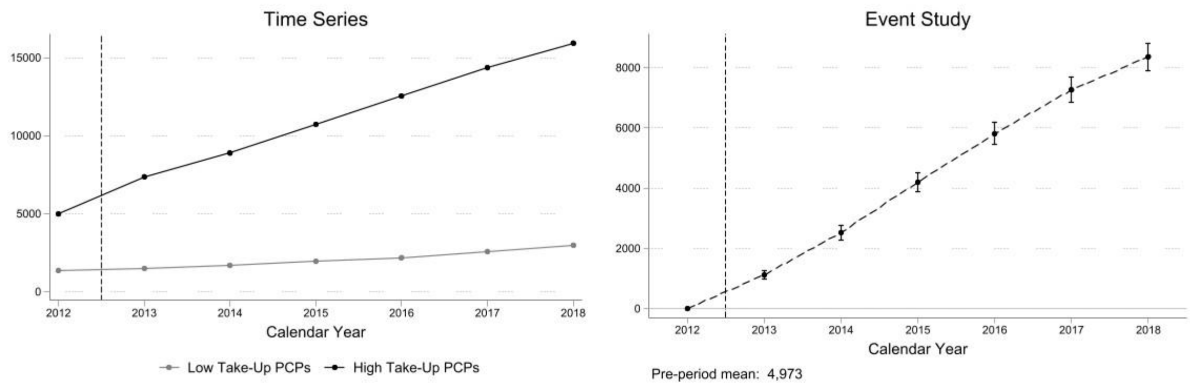
Panel B. CCM Billing by CCM Take-Up Group



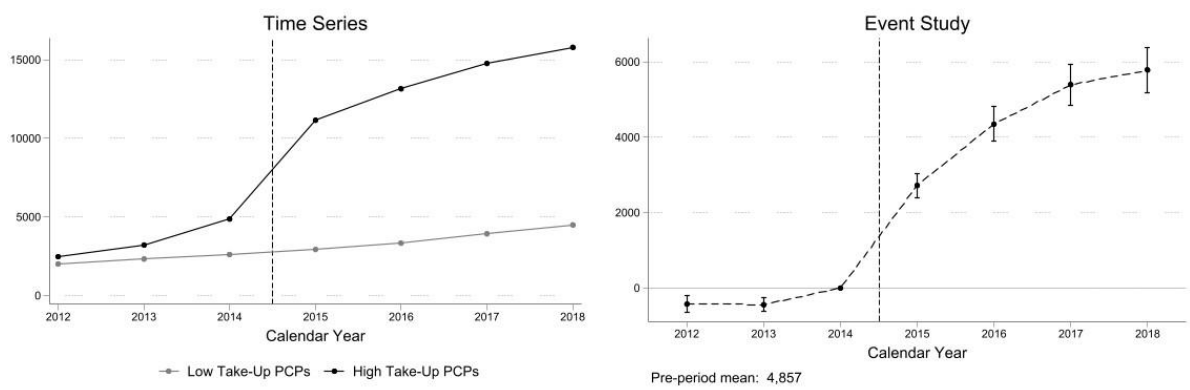
Notes: This figure shows how new code billing evolves around the time of the introduction of the new billing codes. Panel A corresponds to Transitional Care Management (TCM). Panel B corresponds to Chronic Care Management (CCM). In each panel, the left-hand side graphs raw means for the treatment and comparison group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (5). The dependent variable is the PCP-level allowed amount for the corresponding new code in dollars. The event study regressions include controls for county-level 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 Code Complementarity: Physician-Level Analysis

Panel A. Annual Wellness Visit Billing by TCM Take-Up Group



Panel B. Annual Wellness Visit Billing by CCM Take-Up 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 the treatment and comparison group, and the right-hand side graph plots the corresponding event study estimates for $\beta_{p(t)}$ from equation (5). The dependent variable is the PCP-level allowed amount for annual wellness visit in dollars. The event study regressions include controls for county-level 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	7.5%	2.5%	44,989
Mid-Career PCPs	15.0%	5.5%	104,825
Late-Career PCPs	12.9%	4.9%	17,731
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
Panel E. Percent of Physicians in Health Systems			
PCPs in Lowest Tercile States	13.7%	6.0%	53,467
PCPs in Middle Tercile States	11.0%	4.3%	80,592
PCPs in Highest Tercile States	12.9%	2.8%	42,617

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: Multivariate Regression Analyses for the Likelihood of Billing New Codes in 2018

Panel A. Transitional Care Management				
	Billed TCM (1)	Billed TCM (2)	Billed TCM (3)	Billed TCM (4)
Mid-Career	0.075***	0.067***	0.067***	0.067***
	(0.002)	(0.002)	(0.002)	(0.002)
Late-Career	0.054***	0.045***	0.046***	0.046***
	(0.003)	(0.003)	(0.003)	(0.003)
Controls for Group Size		x	x	x
Controls for Group Type			x	x
Controls for Vertical Integration				x
Observations	167,545	167,545	167,545	167,545
Panel B. Chronic Care Management				
	Billed CCM (1)	Billed CCM (2)	Billed CCM (3)	Billed CCM (4)
Mid-Career	0.030***	0.025***	0.025***	0.025***
	(0.001)	(0.001)	(0.001)	(0.001)
Late-Career	0.024***	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)	(0.002)
Controls for Group Size		x	x	x
Controls for Group Type			x	x
Controls for Vertical Integration				x
Observations	167,545	167,545	167,545	167,545

Notes: This table assesses the relationship between new code billing and career stage. Panel A corresponds to Transitional Care Management. Panel B corresponds to Chronic Care Management. Each panel reports estimates of β and γ from equation (1) as we add additional control variables to the regression.

Table 3: Summary Statistics for County-Level and Physician-Level Analysis Samples from 2012 to 2018

	Mean	Obs.
	(1)	(2)
Panel A. County-Level Analysis Sample		
Total Billing Per PCP ($)	100,076	20,262
Evaluation and Management Billing Per PCP ($)	82,214	20,262
Annual Wellness Visit Billing Per PCP ($)	3,052	20,262
Transitional Care Management Billing Per PCP after 2012 ($)	520	17,346
Chronic Care Management Billing Per PCP after 2014 ($)	626	11,534
Percent of Beneficiaries with a Post-Discharge Office Visit (%)	63.5	17,217
Panel B. PCP-Level Analysis Sample		
Total Billing ($)	99,009	1,258,727
Evaluation and Management Billing ($)	82,020	1,258,727
Annual Wellness Visit Billing ($)	3,505	1,258,727
Transitional Care Management Billing after 2012 ($)	506	1,083,630
Chronic Care Management Billing Per PCP after 2014 ($)	526	725,003

Notes: This table presents summary statistics for our analysis samples used to estimate the relationship between new code billing and the provision of other services. Panel A corresponds to our county-level analysis sample. The underlying data contain information on counties from 2012 to 2018. Observation counts are lower for the new code billing amounts because the means displayed in the table are calculated using only years after the implementation of the new code of interest. Observation counts are lower for the percent of beneficiaries with a post-discharge office visit because we have data for that variable only through 2017. Panel B corresponds to our PCP-level analysis sample. The underlying data contain information on primary care physicians from 2012 to 2018. Observation counts are lower for the new code billing amounts because the means displayed in the table are calculated using only years after the implementation of the new code of interest.

Table 4: County-Level Fixed Effects Estimates for the Two Case Studies

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). The underlying dataset is our county-level panel. Panel A shows the case of code substitutability. The 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 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.

Table 5: Physician-Level Fixed Effects Estimates for the Case of Code Complementarity

	Annual Wellness Visit Billing	Controls
Transitional Care Management ($)	0.72***	No
	(0.04)	
	0.71***	Yes
	(0.04)	
Chronic Care Management ($)	0.11***	No
	(0.01)	
	0.11***	Yes
	(0.01)	
Dependent Variable Mean	3,504.93	
Observations	1,258,727	

Notes: This table shows estimates for β from estimating equation (3) for the case of code complementarity. The underlying dataset is our PCP-level panel. The data span the years 2012-2018. The independent variable is either the amount for Transitional Care Management in dollars or the allowed amount for Chronic Care Management in dollars. The dependent variable is the allowed amount for Annual Wellness Visits. All regressions include year and physician fixed effects. Regressions with controls include county-level 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: County-Level Relationship Between New Code Billing and Broader Billing Categories

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***	0.18	-0.13	0.13	0.01	1.44***	No
	(1.20)	(0.82)	(0.12)	(0.21)	(0.11)	(0.03)	(0.16)	
	5.24***	3.62***	0.17	-0.11	0.13	0.01	1.42***	Yes
	(1.21)	(0.83)	(0.12)	(0.21)	(0.11)	(0.02)	(0.16)	
Chronic Care Management ($ per PCP)								
	0.27	0.21	-0.01	-0.09**	-0.03	0.002	0.19**	No
	(0.29)	(0.20)	(0.02)	(0.04)	(0.05)	(0.006)	(0.08)	
	0.27	0.21	-0.01	-0.09**	-0.03	0.003	0.19**	Yes
	(0.29)	(0.21)	(0.02)	(0.04)	(0.05)	(0.006)	(0.08)	
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 from equation (2). The underlying dataset is our county-level panel. The data span the years 2012-2018. The independent variables are the county-level allowed amount for the new codes in units of dollars billed by PCPs per PCP. Similarly, the dependent variables are the county-level allowed amounts 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 7: Physician-Level Relationship Between New Code Billing and Broader Billing Categories

New Code	Total Billing	Evaluation & Management Billing	Procedures Billing	Imaging Billing	Tests Billing	Durable Medical Equipment Billing	Other Billing	Controls
Transitional Care Management ($)								
	3.25***	2.30***	0.04***	-0.04**	0.15***	-0.002***	0.81***	No
	(0.24)	(0.19)	(0.01)	(0.02)	(0.03)	(0.001)	(0.05)	
	3.25***	2.30***	0.04***	-0.04**	0.15***	-0.002***	0.80***	Yes
	(0.24)	(0.19)	(0.01)	(0.02)	(0.03)	(0.001)	(0.05)	
Chronic Care Management ($)								
	0.60***	0.47***	0.01	-0.04	0.07***	0.004	0.08**	No
	(0.09)	(0.06)	(0.01)	(0.03)	(0.02)	(0.004)	(0.04)	
	0.60***	0.47***	0.01	-0.04	0.07***	0.004	0.08**	Yes
	(0.09)	(0.06)	(0.01)	(0.03)	(0.02)	(0.004)	(0.04)	
Dep. Mean	98,639.29	81,953.52	3,702.00	2,163.16	4,587.58	17.60	6,215.48	
N	1,258,727	1,258,727	1,258,727	1,258,727	1,258,727	1,258,727	1,258,727	

Notes: This table shows estimates for β from equation (3). The underlying dataset is our PCP-level panel. The data span the years 2012-2018. The independent variables are the allowed amounts for the new codes in dollars. Similarly, the dependent variables are the allowed amounts for the specified outcomes in dollars. All regressions include year-level and physician-level fixed effects. Regressions with controls include county-level 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 A Additional Data Details

A.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.

A.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.