# The Effect of Doctor Interaction in Local Peer Networks on Prescription Behavior: Empirical Study on Peer Effects among Cardiologists

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| *Supervisor*: | *Co-supervisor*: |
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| Rita Ginja | Arild Aakvik |

# Abstract

The purpose of this thesis is to understand how doctors are affected by local network effects. By using a fixed effects model for panel data, I identify prescribing migrant cardiologists' and estimate spillovers from their interactions with new local peer networks. I use rich data provided by CMS on Medicare Part D Drug Coverage in the U.S. to identify and estimate these spillovers in the time-period 2013 to 2018.

From the migrant cardiologists' interactions with new peers, I find a statistically significant increase in per capita cost for cardiologists who are affected by peer effects. The results can likely not be interpreted as causal due to some data and model limitations, but the increase in per capita cost, which shows the change in prescription behavior, is likely affected by peer effects.

I have used a substitution-sample from Medicare Fee-For-Service Medical Insurance with specification-changes to the main model to assess their validity. The robustness analysis provides slightly lower, but related results, which leads me to support my main results. Prescribing behavior is therefore, likely increasing, with uncertainty about the true magnitude of the spillovers.

*The analysis was performed using the statistical software STATA/SE 16.0.*

# Contents

# 1 Motivation

Peers at work matter in differing ways. Anyone with work experience knows the importance of co-workers and their lasting effects, through social and work-related ties. Getting along with ones' coworkers can go a long way, setting the "bar" lower when asking for help, asking for advice, or discussing problems that may have differing solutions. Coworkers and their effects on their peers are highly important in the current business environment. Interdependent tasks make coordination and exchanging of information between coworkers highly important when analyzing a workers' output as well as growth (Kim & Yun, 2015, p. 575). A workers' experience or productivity when performing tasks may improve passively by working with their coworkers and sharing information, which could improve a focal workers' performance (Kim & Yun, 2015, p. 576). These effects can grow significantly when workers are introduced to coworkers with a higher productivity than themselves, as Mas & Moretti (2009, p. 143) find in their study of network effects among cashiers at supermarkets.

These network effects may exist regardless of occupation, based on the assumption that one has coworkers, and may differ based on the tasks the workers perform. In occupations where productivity is not necessarily the most important factor in a workers' output, network effects may affect a worker differently based on the output that is expected. One such occupation is medicine. A doctors' main tasks when performing their work is; (i) finding the reason for a patients' ailment, (ii) choosing the right treatment for an ailment and (iii) following up on each patient. As network effects among peers at work increase knowledge-sharing between coworkers, this is likely applicable to a physicians' practice, identification of illness, choice of treatment and therefore, follow-ups. This may have a positive (or negative) effect on costs and life expectancy related to the treatment physicians give beneficiaries. As different medicine can dramatically change the costs and life-improving benefits of a treatment, it can be important to identify the variation in prescribing behavior among physicians.

In this master thesis I analyze the effects of local network effects among peers on prescription behavior among cardiologists in the U.S. that take part in the Medicare Part D prescription medicine program from 2013 to 2018. I will estimate these local network effects by analyzing migrant cardiologists and their interactions with new colleagues in the city they move to. To perform my analysis, I make a well-defined sample from the Medicare Part D datasets and will only focus on cardiologists. Limiting the sample is important as different specialties likely react differently to interactions among their peers and including vastly different types of doctors may impede the analysis and skew the results. Even with the limited sample, the analysis will be performed with around 21 000 cardiologists each year, as the datasets consist of data from the entirety of the U.S. This is a satisfactory number of cardiologists to assure that interactions among cardiologists that migrate are not too few and being able to estimate city fixed effects and yearly fixed effects among non-migrant cardiologists. After identifying migrating cardiologists, I will use these migrants to identify spillovers among peers, with the purpose of analyzing per capita cost related to prescribing. The per capita cost will then be used to analyze prescribing behavior, as per capita cost is directly linked with how many drugs a cardiologist prescribes while also considering what type of drug that is being prescribed, through the costs of drugs. So, to summarize the purpose for this thesis, I ask the question:

*How does doctors react to local network effects?*

The remainder of my thesis will be structured in the following way: In section 1, I look at related literature on peer effects both outside and within the field of medicine. In section 2, I provide a brief historical summary on Medicare and Medicare Part D before briefly considering the transferability of the issue to the Norwegian context. In section 3, I will explain the choice of method and model for my analysis, then I formalize them. In section 4, I present the data I use and provide descriptive statistics on the samples I use. In section 5, I present the main results, alternative estimates and other complementary results that are used as a robustness analysis for the main estimates. In section 6, I discuss the implications of the results, choice of models, robustness analysis and data-limitations. Finally, I conclude my findings in section 7.

## 1.1 Related Literature

There is little research on the link between local networks and prescription medicine, and especially the association between them. Literature on the field of local network effects peers is, for the most part, focused on peer effects among co-workers in fields outside of medicine, or by local network effects through drug-company advertisement and "star-physicians". A small number of articles have been written on the contagion of new technology within medicine, where the contagion of new prescription drugs and the influence from local networks on said adoption has been analyzed. Molitor (2018) analyzed the link between practice variation and practice styles among cardiologists, by exploiting migrating cardiologists to identify local network effects among cardiologists and highlight variation in practice styles among similar cardiologists with similar patients. Molitor utilizes a difference-in-differences event study with longitudinal-data to observe cardiologists before and after a move. A different approach to locate peer effects among local peers could be a fixed effects-model that utilize fixed effects among workers to identify spillovers in workers of interest, like Mas & Moretti (2009) did in their analysis of peer effects among cashiers in a supermarket.

Practice variation can become a topic of interest in countries all over the world based solely on the scale of public health care expenditure of GDP. In the U.S., Duggan & Morton (2008) suggested the share of health expenditure would account for 20 percent in 2016 and 35 percent by 2035 (Duggan & Morton, 2008, p. 2). Figure 1.1 shows that the realized health expenditure by 2016 was 17 percent, which is 3 percent short of the estimated expenditure, but health expenditure has been steadily rising in the last two decades in the U.S. In the world, the rise in expenditure have been increasing steadily, but at a lower level compared to the U.S., and in 2016 health expenditure was 9.947 percent of GDP in the world. With increasing expenditure on health, the rise of public health systems also takes a toll, as increasing use of public health care is naturally followed by higher expenditure by the government. It is in this context physician practice variation will be a topic of interest for the countries in the world, especially European countries with a sizable public health system. For the purpose of this analysis two types of physician variation is regarded as applicable; the variation in prescribing behavior among cardiologists and variation in services provided to beneficiaries through fee-for-service by cardiologists.

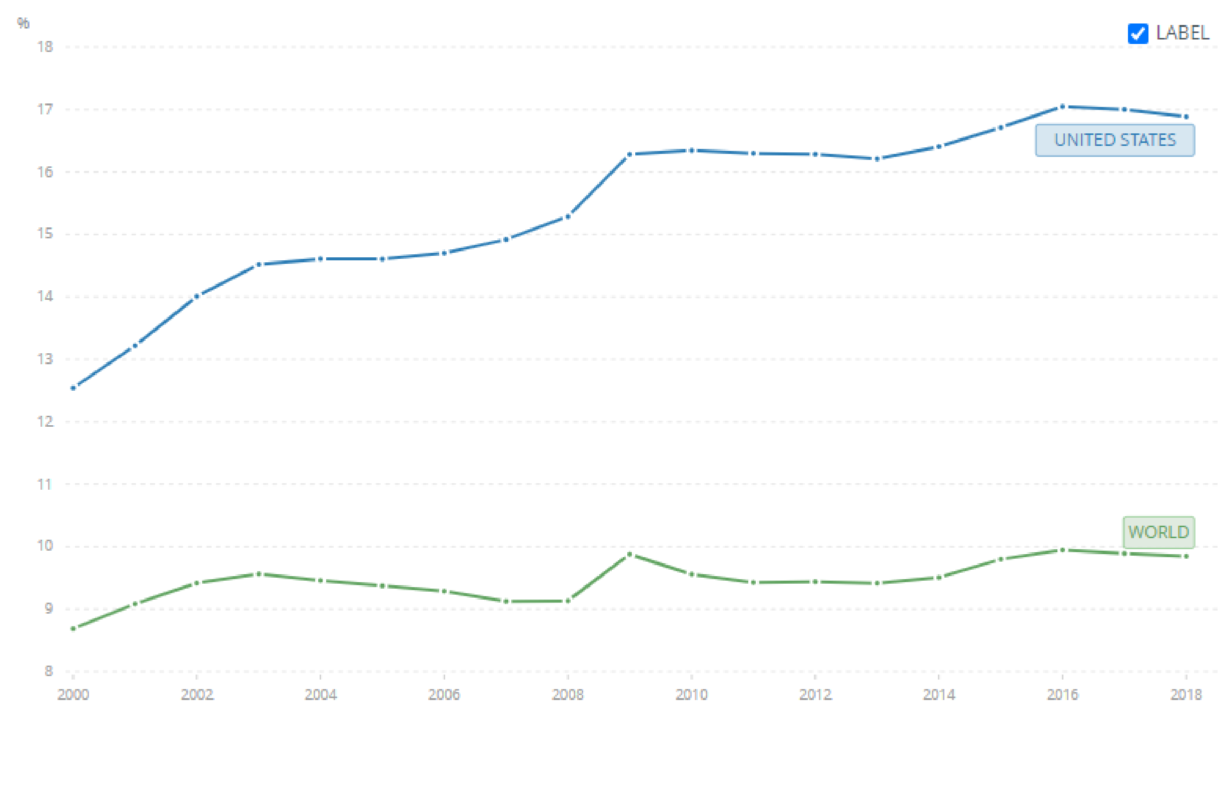


*Figure 1.1: Health Expenditure by GDP, U.S. & World. Extracted from the World Bank. The World Bank provides graphs based on data from the World Health Organization Global Health database. Website with the interactive graph in Figure 1.1: https://data.worldbank.org/indicator/SH.XPD.CHEX.GD.ZS?end=2018&locations=US-1W&start=2000&view=chart.*

## 1.2 Peer Effects

Economic literature has focused more intensely on peers at work and spillovers among co-workers the past two decades by analyzing whether co-workers affect each other, how they affect each other and what the results of peer effects are. Mas & Moretti (2009) performed such an analysis. They investigated how and why a workers' productivity varies not only with their own characteristics but also the productivity and characteristics of their coworkers (Mas & Moretti, 2009, p. 113). They find strong evidence of positive spillovers among peers, when a worker with high productivity is introduced to a work-shift, suggesting that positive spillovers may dominate free-riding effects that may arise among co-workers working on a joint project (Mas & Moretti, 2009, p. 114). They investigate positive spillovers and the environments they need to have an effect by looking into factors as possible explanations: social pressure and prosocial behavior. With these possible explanations in mind, they add controls to their analysis, by looking at frequency of interaction among the higher productivity worker and less-productive workers in a shift, and at the same time, taking into consideration if workers are in each other's line of sight.

They find higher positive spillovers on worker productivity when co-workers frequently interact in shifts, by having overlapping shifts over time. They also find that in an environment where a higher productivity worker and less productive worker can see each other, it will have a positive spillover effect on productivity (Mas & Moretti, 2009, p. 114). In a situation where a worker is not in the line of sight of the more productive workers, they adopt free riding into their productivity which has a negative effect on productivity. They conclude that the positive spillovers arise due to social pressure rather than prosocial behavior, on the less-productive workers' behalf. When combining the increased willingness to display cooperative behavior when observed and when future interactions are more frequent, they conclude that social pressure is the explanatory factor at play, as workers show selfish behavior when not observed (Mas & Moretti, 2009, p. 115).

Mas' & Moretti's analysis of peer effects at a workplace may more easily identify spillovers in a work-environment where productivity is both easily measured, while also being a major part of a workers' day and output. When it comes to occupations where productivity not necessarily is the best measurement of the quality of service, it becomes more complicated and complex to identify spillovers among peers. One such workplace exists in the field of medicine. When a patient visits a clinic, a doctor with high productivity may be good or bad, however, this depends on whether the treatment given to the patient is of good quality and the right choice. The most important factor when analyzing a doctors' performance then becomes a question of matching symptoms with treatment, rather than just being based on how productive he is when diagnosing a patient. The output from a doctor can have consequences not limited to just the patient getting the treatment. In the case of public healthcare, it is important that each beneficiary gets treatment of the best quality, while still being able to keep costs down to not exhaust the public health system.

In the case of services, this might mean making the right decision on which services need to be provided at which times, and in the case of medicine, whether general prescription medicine can provide treatment rather than a copyrighted prescription medicine with better health characteristics. Choosing a patented drug over a general drug will likely cause costs for the public health system to go up significantly if doctors on average choose to prescribe these drugs over general drugs (Duggan & Morton, 2008, p. 2). General drugs are subject to competition, as they used to be copyrighted drugs, but when a copyright comes of age, all pharmaceutical companies can produce them. Pharmaceutical companies that produce drugs are given a limited time as a “monopoly” after they have produced a new drug, which will likely be better in treating certain parts of an illness as compared to the older general drug. The decision to prescribe these patented drugs should therefore only be based on a patient’s illness, and if the copyrighted drug has positive effects that are beneficial for a patients’ health. Technology adoption can be an underlying factor in costs and health benefits rising in the U.S, where technology adoption can take the form of more prominent use of patented drugs (Agha & Molitor, 2015, p. 1).

Related literature has also focused their attention is peer networks in education where they analyze whether peers that partake in peer networks in education are subject to spillovers in academic results or education attainment. Calvó-Armengol et al. (2009) performed such an analysis using friendship-network data to analyze whether school performance is affected by peer effects and social networks (Calvó-Armengol et al., 2009, p. 1240). Education is a good way to estimate peer-effects if adequate datasets exist, as academic results is a clear-cut way of seeing increases in academic achievement based on peer-effects and spillovers that arise because of these networks. Calvó-Armengol et al. (2009) address existing problems in identification of endogenous social effect that make identifying and measuring these effects difficult (Calvó-Armengol et al., 2009, p. 1249-1250). These issues are mainly endogenous sorting of individuals into groups and the reflection problem.

When individuals sort into groups, they are likely affected by personal characteristics related to their own characteristics, family, and other sources of influence on a persons’ preferences. This can induce bias on the main regressor if some of these unobserved influence-variables are correlated with the sorting decision (Calvó-Armengol et al., 2009, p. 1250). They introduce network fixed effects to control for these individual unobserved variables and find that if conditioned on network-effects and extensive controls on individuals, the linking-decision is uncorrelated with observable variables. This alone will not guarantee that estimates isolate the causal effects of peer influence, as individuals interact in groups and with no other individuals. This means that every individual’s behavior affects all members in a group, which makes identifying if an individual’s actions is the cause of peer influence or effect of peer influence difficult (Calvó-Armengol et al., 2009, p. 1250). This is known as the reflection problem. However, as not every individual is not only part of one group, so the number of network-links is individually different as some are part of more than one group by interacting with individuals from different groups, which means that the reflection problem is eluded based on the network-data composition. With these added controls, Calvó-Armengol et al. (2009, p. 1261) show that an individual's position within networks does have a significant and positive effect on academic performance. These effects amount to more than 7% higher school performance for a standard deviation increase in the number of direct and indirect links an individual holds within their friendship-networks with other individuals. These links are captured by each individual being represented in the friendship networks as nodes, where direct links are two individuals who identify each other as friends, and indirect links are friends of a friend that belong to the same network.

In contrast to some of the above studies, Dahl et al. (2014) use a regression discontinuity design to analyze whether peer effects can affect the utilization of paid maternity leave for fathers in Norway. The program gave fathers 1 month paid maternity leave after the social program was issued, where fathers who were not eligible right before could not partake. They divided the channels where peer effects may arise and focus on whether social interactions happen either in the workplace, so the peers are coworkers, or in family networks, so the peers are brothers. Their results show that coworkers are 3.5 percent more likely to partake in maternity leave if their colleague was eligible around the cut-off point (Dahl et al., 2014, p. 2050). When peers are brothers, they find that brothers of fathers who were eligible for the program are 4.7 percent more likely to partake after the birth of their first child. They find reason to believe these increases to be stemming from knowledge-sharing among peers, as information about costs, benefits, and experiences, which reduce uncertainty for eligible fathers (Dahl et al., 2014, p. 2050-2051).

In addition to the direct effects in social interaction, there exist indirect effects that stem from the initial interaction within firms. Dahl et al. (2014) call it the snowball-effect, where one father talks to another, that talks to another, etc. This leads to an increase in participation within a firm that increases in size. They find the indirect effects to "take over" the first initial direct effect from the first two peers' interaction, where 50 percent of total peer effect stem from the snowball effect (Dah et al., 2014, p.1251). These results are not only important in the context of social program participation, like Dahl et al. (2014) described, but also for workplace analysis' in general. Their results show significant results that social networks among workers can be an important channel where knowledge spillovers may arise, represented in the interactions among coworkers leading to more information about maternity leave for men. These knowledge spillovers likely affect the decisions coworkers take, based on their peer's information, and could in-turn induce change a worker's way of behaving when working. The next paragraphs will focus more sharply on the field of medicine, where knowledge spillovers among peers may be a contributing factor.

## Technology Diffusion: Star Physicians / Highly Influential Physicians

Much of the research in spillovers among physicians and doctors in the field of medicine, analyze spillovers among local networks of doctors and their effects on new technology diffusion. Agha & Molitor (2015) studied technology diffusion when pioneer physicians were a part of the team that performed clinical tests of 21 new cancer drugs. Their main objective is to analyze whether "star-physicians" have a knowledge spillover-effect in their own organization and region regarding technology diffusion for the drugs they performed clinical tests on. The new technology being introduced are the 21 new cancer drugs (Agha & Molitor, 2015, p. 2). They then observe the authors that take part in clinical tests for these drugs and categorize them into two groups: first authors and "other" authors, which is an important distinction to make. First authors in their dataset are all practicing physicians and typically senior physicians that take charge of the clinical tests and their structure (Agha & Molitor, 2015, p. 7). Their results indicate that certain geographic areas are being affected by information frictions that limit technology diffusion among organizations and physicians (Agha & Molitor, 2015, p. 31). Prominent physicians, described as "star-physicians", who are connected to large local networks and well informed about new technology can play a key role in untangling frictions in knowledge-sharing about new technology. When a prominent physician is the first author in clinical trials for a new cancer drug, the adoption of the drug I increased by 36% in the first two years following approval in the regions the prominent physician operates (Agha & Molitor, 2015, p. 31). Other authors in clinical trials also increase the adoption-rate of new drugs, but not to the same degree as first authors. The local networks have a larger proximity for prominent physicians, which in turn leads to higher usage over a larger geographic area. Adding to this, they find that adoption of the new technology is more prominent in regions that had a slower adoption-rate before the first author took part in the clinical trials (Agha & Molitor, 2015, p. 32). These results indicate that local information-networks among physicians can be a key factor in managing costs in health systems, but also health benefits, as newer drugs are likely better in certain aspects at a higher price, when compared to general drugs. The effects these star-physicians have on their respective geographic regions were found to converge within four years after their FDA approval (Agha & Molitor, 2015, p. 3). The initial increase in usage for the first years after drug approval is still substantial enough to make a difference regarding both costs and health benefits for patients.

Barrenho et al. (2019) also explored peer effects and local network effects relating to technology diffusion among prominent surgeons in the English NHS. They focused on the uptake of laparoscopic surgery which would be cost-reducing, time-reducing and provide less possible negative health effects for patients compared to older methods (Barrenho et al., 2019, p. 18). They find that uptake of new technology, in the form of laparoscopic surgery, operate through multiple peer- and network-effects, however, they could not untangle and identify which channel it operates through. They point to peer effects among colleagues that is based around colleagues' current behavior at work (Barrenho et al., 2019, p. 18). Similarly, to Agha & Molitor (2015), they use prominent physicians to identify local network effects and find different channels these network effects may operate. They find that distance to where a pioneer physician operates can determine the extent of technology adoption, the number of connections they hold in common can affect technology adoption and lastly, the direct effect of one leader on the field (Barrenho et al., 2019, p. 18). If governments want to change these physician variations in practice styles, Barrenho et al. (2019) suggests focusing on opinion leaders and pioneers, as their networks lead to large spillover-effects on the surrounding networks of physicians, rather than targeting on outlying physicians that are not a part of the forementioned local networks who would generate less substantial spillover-effects.

## Industry payment: Pharmaceutical Advertising

As the previously mentioned literature on peer effects have showed, local networks and star-physicians can dictate the speed of technology diffusion for practicing physicians. Agha & Molitor (2015) and Barrenho et al. (2019) used prominent physicians with large peer networks to analyze how local networks and peer effects can affect technology diffusion among practicing physicians. As the two former articles have shown, star-physicians with large networks can influence their own peers and local networks with the information they hold, as well as the treatments they choose to use in practice. Drug companies are likely aware of these effects that star-physicians extrude onto their peers, as drug companies spend large amounts on advertisement toward physicians. From August to December in 2013, drug companies spent 3.5

billion dollars on advertisement, in the form of 4.4 million payments to more than half a million health care physicians and health care organizations (Thomas et al., 2014). The total industry payments are on small on average, but not evenly distributed. Most of the industry payments are targeted at a select few individual physicians of interest (Agha & Zeltzer, 2019, p. 1). These "select few" are reported to be key-opinion-leaders, or as Agha & Molitor (2015) and Barrenho et al. (2019) referred to them, "star-physicians".

Payment takes two forms according to Agha & Zeltzer (2019). "Food payments" that are on average under $40 and usually comes in the form of transfers towards food and beverages in exchange for detailing with a salesperson (Agha & Zeltzer, 2019, p. 2). "Compensation payment" is the other form and is linked with bigger payments in exchange for consulting, speaking and other services (Agha & Zeltzer, 2019, p. 2). Compensation payments have a median value of $2000, but only 1% of physicians receive these payments, and they tend to receive compensation-payment more than once for the same drug (Agha & Zeltzer, 2019, p. 2). The "select few" physicians that are being targeted by industry payments are disproportionately "star-physicians", in that they have larger peer-networks and are more highly specialized. Their results indicate that payments have substantial effects on prescribing behavior on the star-physician, while also having substantial spillover effects on their peers (Agha & Zeltzer, 2019, p. 25). Spillovers influence prescribing behavior by increasing prescription-rates on the paying company's drug, which in the case of Agha's & Zeitzer's (2019) analysis, is oral anticoagulants. As payments are targeting physicians with a large network of peers, the amassed effect of peer spillovers is significantly larger than the effect of the direct payment. These results show similarities to that of Carey et al. (2021) who find that industry payments increase expenditure by 7.6% as prescription of the advertised drug increases after a payment has been received (Carey et al., 2021, p. 13). With Agha's & Zeltzer's (2019) results showing significant and positive effects on prescription volumes of the drug companies advertised drug, they come to a similar conclusion to that of previous work related to technology diffusion: peer networks can be important factors regarding technology adoption in the field of medicine (Agha & Zeltzer, 2019, p. 25). These results mirrors Fleischman et al. (2016) results. Fleischman et al. (2016) found that physicians that take part in Medicare Part D and who received compensation payments were disproportionately associated with higher regional prescription volumes of the advertised drug (Fleischman et al., 2016, p. 7). These prescription volumes were higher compared to industry payments in the food compensation form as Agha & Zeltzer (2019) found. Fleischman et al. (2016) found no causal effect due to the nature of their study method, but the results mirrors Agha & Zeltzer (2019) who used patient-sharing between peer networks, which makes the estimated peer effects believable.

## Physician Variation

Grytten & Sørensen (2002) performed a study of physician variation among general practitioners in Norway. They wanted to expand on the previous studies on the subject by using individual physicians as a unit of measure rather than hospitals or geographic areas, as variation in costs can be attributed to variation in clinical practice between individual physicians (Grytten & Sørensen, 2002, p. 404). They estimated the physician variation by using the individual physician data to obtain total physician variation which they believe holds two advantages; they can find the upper limit of physician variation and identify treatment/diseases that induce more physician variation based on difficulty to diagnose and treat (Grytten & Sørensen, 2002, p. 406). They identify three channels from where they estimate variation based on individual physicians and health related variation. Firstly, they use expenditure for lab-tests per consultation as the dependent variable, then expenditure per 20-minute consultation and finally, expenditure for specific procedure per consultation as the dependent variable (Grytten & Sørensen, 2002, p. 410-414). With these channels as dependent variables, they produce estimates of variance in the two forementioned factors. Their results show that around 60% of variance in total expenditure is due to health-related factors, like differing patient needs (Grytten & Sørensen, 2002, p. 415). The remaining 40% of variation cannot be explained by other factors than differing practice styles, i.e., differences in clinical practice between individual physicians. This reaffirms significant expenditure variation due to physician practice style which could potentially be managed by implementing policy or better guidelines, if the variation is deemed neither cost-effective nor health-benefitting to the patients (Grytten & Sørensen, 2002, p. 415-417).

# 2 Medicare: Brief Summary of Institutional Background

Medicare is a health insurance program designed specifically for a given demographic in the U.S. The program is designed for individuals who are:

i) The age of 65 or older.

ii) Individuals that are under the age of 65 but with certain disabilities.

iii) Individuals of ALL ages with "End-Stage Renal Disease", which is an illness where permanent kidney failure makes dialysis or a kidney transplant necessary.

Medicare consists of three parts that covers different services (CMS, 2021, Medicare Program – General Information). Medicare Part A is the first part and provides beneficiaries with hospital insurance. It offers coverage for hospital stays, which includes critical access hospitals, and short-term care at skilled nursing facilities. In addition, it offers coverage in some home care cases and hospice care. Medicare Part A coverage is, for most beneficiaries, paid for through payroll taxes while working (CMS, 2021, Medicare Program – General Information). Medicare Part B is the second part of Medicare and provides beneficiaries with medical insurance. It offers coverage for services provided by doctors, services provided by physical therapists and some home care services. Part B helps pay for these services when they are needed and most beneficiaries pay monthly premiums to be covered by Part B (CMS, 2021, Medicare Program – General Information). Medicare Part D is the third part and provides beneficiaries with drug coverage. Beneficiaries are covered by Medicare Part D when they have joined a drug-plan that is approved by Medicare and suits their medical needs. Most beneficiaries pay a monthly premium for coverage by Medicare Part D (CMS, 2021, Medicare Program – General Information).

## 2.1 History of Medicare

Former President Lyndon Johnson signed Medicare into law July 30th, 1965, and declared:

> *No longer will older Americans be denied the healing miracle of modern medicine. No longer will illness crush and destroy the savings that they have so carefully put away over a lifetime so that they might enjoy dignity in their later years. No longer will young families see their own incomes, and their own hopes, eaten away simply because they are carrying out their deep moral obligations to their parents, and to their uncles, and their aunts.* (Lyndon Johnson, 1965).

This declaration was a promise to the elders in the U.S., a promise that have delivered financial stability and access to health services to tens of millions of Americans in the last 56 years of implementation (Oberlander, 2015, p. 119). From 1972, this coverage expanded to individuals with certain, permanent disabilities and end-stage renal disease.

### 2.1.1 Origins

Medicare was not enacted from nothing but came from several failed attempts at implementing health insurance. In 1915 a model health insurance bill was submitted but shut down as it gathered little support. In 1935, the Social Security bill contained a line that authorized a study of health insurance, but this was followed by protests from the American Medical Association (AMA), which the current President Franklin Delano Roosevelt thought could hinder the Social Security bill, and therefore removed the authorization for a study of governmental health care (Oberlander, 2015, p. 119). Harry Truman was the first president that endorsed a governmental health care plan, even if he could not pass a bill containing health care plans. These failed attempts fell through due to different factors; the American Medical Associations' protests, an opposing majority in Congress made up of Republicans and Southern Democrats, and reluctance to push for reform (Oberlander, 2015, p. 120).

Truman's failed attempt spurred advocates of health insurance to implement a new strategy. In June 1951, Oscar Ewing proposed sixty days of hospital insurance for 7 million retirees that were receiving Social Security, their new strategy was to narrow their scope for health insurance to the elderly (Oberlander, 2015, p. 120). Their narrowed strategy had roots in sound arguments, in 1962, as 47 percent of elderly families had incomes below the poverty line (Oberlander, 2015, p. 120). Medicare's composition was built along the lines of the Social Security bill, where one had to work to take part in the health insurance, however this did not pass into legislation in 1964. A year later, in 1965, Medicare was passed as a three-part-plan containing Medicare Part A, would cover hospitalization costs through payroll taxes, Medicare Part B, would cover physician and outpatient services through premiums and other general revenues (Oberlander, 2015, p. 121). The final part was Medicaid, which would provide coverage to the poor and would be financed and supervised jointly by the Federal Government and State Governments.

Following these two parts of Medicare, came Medicare Part C that aimed to contract private companies that could provide private plans that beneficiaries of Medicare could take part in, which around 30 percent of all Medicare beneficiaries took part in (Oberlander, 2015, p. 123). With the inclusion of Medicare Part C, private companies have gotten more political influence in Medicare affairs, and Medicare have changed significantly since its' implementation in 1965. From its' start as a federal government program, it has become a hybrid of private and public insurance with contrasting philosophies within (Oberlander, 2015, p. 123). It never became the public health insurance it was envisioned to be in the 1960s by Truman and his associates. However, Medicare has eroded the political power the medical industry once had, and beneficiaries now pay according to their income-levels based on differentiated premiums and Medicare has provided benefits to many (Oberlander, 2015, p. 124).

## 2.2 Medicare Part D: History, Structure, and Incentives

The final part of Medicare was implemented through the Medicare Modernization Act (2003) and revolves around the self-administration of prescription drugs for elders, Medicare Part D. Medicare Part D was introduced due to a relatively large share of elderly that did not take part in insurance which provided prescription drug coverage and the growing financial burden this had on them (Kaestner & Khan, 2010, p.1). Approximately one third of seniors did not have insurance with prescription drug coverage, which resulted in large out-of-pocket spending, where approximately 50 percent of them had annual costs related to out-of-pocket spending, on drugs alone, of $1200 or higher in 2003 (Kaestner & Khan, 2010, p.1). In the same year, the median income for the elderly was $16.000, which shows that the out-of-pocket spending on drugs was a burden on a large portion of the seniors, especially on low-income seniors and seniors with chronic diseases who need prescription drugs to maintain their health (Kaestner & Khan, 2010, p.1).

## 2.3 Transferability of the Issue: Norwegian context

Norway is a small country but is still one of the richest countries in the world. This is mainly due to the vast oil wealth they discovered in the 70s that they have used it sparsely and in clever ways to avoid the “resource curse” (Folkehelseinstituttet, 2013, 2013, p. 1). Norway’s economy is described as a mixed economy that consists of a capitalistic markets while being heavily controlled by the state (Folkehelseinstituttet, 2013, p. 4). The Norwegian health systems’ organizational structure is built on the principle of equality for all citizens. Every individual has equal access to services regardless of economic, social status, and geographic location (Folkehelseinstituttet, 2013, p. 12). The Norwegian health system is partly decentralized, where specialist-care has been in the states’ care since 2002, while primary-care from general practitioners is run and controlled by the different municipalities in Norway. The counties power to regulate is restricted to dental care and preventive health services (Folkehelseinstituttet, 2013, p. 12). The system is regulated through a significant number of laws and regulations. The main responsibility for the national health-sector is held by Helse og Omsorgsdepartementet. They decide the national health-politics, prepare, and overlook lawmaking, assign funds within the health-sector, and carries out national health politics through subordinate institutions (Folkehelseinstituttet, 2013, p. 14).

### 2.3.1 Prescription Drugs in Norway

Prescription medicine is highly regulated in Norway, where advertisement is only allowed for non-prescription medicine and not prescription medicine. For a new medicine to be approved for the Norwegian market, in the form of either prescription or non-prescription medicine, the companies that want to sell to the Norwegian market must get approved by Legemiddelverket. An application for a permit to sell must include details about the medicines' quality, safety, and medical effect of the drug (Folkehelseinstituttet, 2013, p. 29). It is then approved if and only if, the benefits outweigh negative side-effects a drug hold. Prescription drugs are followed by certain guidelines for doctors, pharmacists, and patients (Folkehelseinstituttet, 2013, p. 30). To keep prescribing as cost-effective as possible, doctors and pharmacists are guided to prescribe the cheapest alternative, in the form of a general drug rather than patented drug, unless a patented drug is required for severe health related reasons. The first-choice prescription is meant to be a general drug, even though doctors prescribe patented drugs more frequently than general as they are not required to prescribe general drugs over patented drugs. However, pharmacists are required to inform a patient if there exists a cheaper alternative unless health reasons are specified. Pharmacists and pharmacies are not only compelled to do so, but also motivated to do so, as general drugs have a higher profit margin compared to prescription drugs (Folkehelseinstituttet, 2013, p. 31).

Prices in the market for prescription medicine is not regulated which allows wholesales to negotiate with producers about margins, "Legemiddelverket" are however responsible for determining the pharmacies maximum purchase-price (Folkehelseinstituttet, 2013, p. 31-32). Suppliers of prescription medicine are required to apply for a maximum price, that becomes its' maximum price (price can be lowered). Pharmacies' profit margins on these medicines are regulated based on their attributes, price, and a VAT (value added tax).

### 2.3.2 KUHR-dataset: Obstacles to Analysis of Norwegian Context

In order to identify peer effects among doctors, one needs aggregated data on both costs related to the service, data on the amounts of services provided by each physician, and their location. In the publicly available data for Medicare in the U.S., all these variables are present. In Norway however, the KUHR-dataset shows the location of physicians and include variables on treatment during consultations like the U.S. data. The problem arises when trying to obtain access to these datasets. As I cannot access the Norwegian data, an analysis based on the Norwegian context is not possible at this moment.

If KUHR-data were available for use, they would be ideal for performing the analysis I will perform but in the Norwegian context. The KUHR-data includes variables on a beneficiary's specific age, which could make these data better suited for the analysis on prescription behavior. As I will explain under the section 4 – Dataset, a possible limitation to the Medicare data is the lack of beneficiary information that is provided, like age and gender. The KUHR-data contain information not only on the age and gender of beneficiaries of services, but also the specific illness they are receiving treatment for. An analysis on local network effects would be able to put in place narrower control on the estimations of "benchmarks" in a local network, as well as for the migrating physicians, as age is linked with higher propensity to suffer from certain ailments. As my analysis will be on cardiologists, it could be helpful to control for a beneficiaries' age, as likelihood of obtaining a heart disease increases with age.

# 3 Empirical Method: Basic Model

Social networks in the field of medicine seems to have an impact on individual prescribing when individual physicians interact with their peers. I want to perform an analysis within Medicare Part D to analyze whether spillovers among physicians may alter their prescribing behavior and which directions these spillovers change the prescribing behavior. To perform this analysis, I need data on prescription behavior among a specific practice in the field of medicine to keep prescription behavior among individuals similar, while also being able to identify local networks where social interactions among peers may happen. These are very demanding requirements for individuals in the field of medicine which likely does not exist. I therefore need to use manipulation on data that contains one of these requirements to obtain both. To obtain both preferences for data, I use Medicare Part D data which will be described in section 4. I will now motivate and further explain how I use models and key ideas from related literature to manipulate the Medicare Part D data on prescription behavior to obtain estimates of spillovers among cardiologists in different local networks in the U.S.

I will use an empirical framework that borrows extensively from Mas & Moretti (2009). I will use Medicare Part D data on cardiologists to identify the change in prescription behavior between local networks of peers in different cities in the U.S. To control for unobserved time invariant characteristics of cities that influence prescription behavior over time, I control for city fixed effects (FE) that control for time invariant characteristics specific to each city. I also use cardiologist FE to control for individual unobserved time invariant characteristics, like doctor practice-style, and year FE to control for yearly shocks that affect all physicians. This means that the change in average exposure to local networks will be the driving factor in the model.

Before presenting the model that I will use for my analysis, we need to consider assumptions and implications of using a FE model for panel data. Angrist & Pischke (2008) present a general FE model for panel data (Angrist & Pischke, 2008, p. 221-227). In a FE model for panel data, the following equation must hold (Angrist & Pischke, 2008, p. 222-223):

$$E[Y_{0it}|A_i, X_{it}, t, D_{it}] = E[Y_{0it}|A_i, X_{it}, t]$$

Let $Y_{it}$ be what we want to estimate for individual $i$ at time $t$. $D_{it}$ is the treatment variable, $A_i$ are unobserved confounders that are fixed and $X_{it}$ are observed covariates that vary with time. The confounders in $A_i$ can affect both the dependent and independent variables in the model. This shows that treatment is close to randomly assigned, while conditioned on $A_i$ and the other observed covariates. We further assume that the unobserved $A_i$ does not vary with time in a linear model, shown by:

$$E[Y_{0it}|A_i, X_{it}, t] = \alpha + \lambda_t + A_i'\gamma + X_{it}'\beta \tag{1}$$

We also assume that the causal effect of treatment is constant and additive:

$$E[Y_{1it}|A_i, X_{it}, t] = E[Y_{0it}|A_i, X_{it}, t] + \rho \tag{1.1}$$

When you combine (1) and (1.1) to consider both cases of treatment, you get:

$$E[Y_{it}|A_i, X_{it}, t, D_{it}] = \alpha + \lambda_t + \rho D_{it} + A_i'\gamma + X_{it}'\beta \tag{1.2}$$

Equation (1.2) holds the causal effect of interest $\rho$, and the equation can be further altered to become:

$$Y_{it} = \alpha_i + \lambda_t + \rho D_{it} + X'_{it}\beta + \epsilon_{it} \quad (1.3)$$

Where $\alpha_i \equiv \alpha + A_i\gamma$. This is a fixed effects model, if we then use panel data the causal effect of treatment on $Y_{it}$ can be estimated by treating $\alpha_i$ and $\lambda_t$ as parameters to be estimated. For the unobserved individual effects, you hold coefficients on dummies for every $i$, and for time effects, you hold coefficients on dummies for every $t$. Angrist & Pischke (2008, p. 223) show that treating individual effects as parameters to be estimated is the same as estimations for deviations from the means. First, we find individual averages: $\overline{Y_i} = \alpha_i + \bar{\lambda} + \rho\overline{D_i} + \overline{X_i'}\beta + \overline{\epsilon_i}$

Then take equation (1.3), and subtract the individual averages, you then get:

$$Y_{it} - \overline{Y_i} = \lambda_t - \bar{\lambda} + \rho(D_{it} - \overline{D_i}) + \beta(X_{it}' - \overline{X_i'}) + (\epsilon_{it} - \overline{\epsilon_i}) \quad (1.4)$$

Which shows that deviations from the means, take away the unobserved individual fixed effect. There is also an alternative to deviations from the mean which is called first differencing. In such case, you estimate:

$$\Delta Y_{it} = \Delta\lambda_t + \rho\Delta D_{it} + \Delta X'_{it} + \Delta\epsilon_{it} \quad (1.5)$$

Where instead of taking every year from a total mean over all time-periods, you estimate difference on a year-to-year basis. This shows the use and method of a FE model with panel data and is the baseline for the model I specify.

To apply this general model to my analysis, I start by specifying a FE model that describes cost and prescription factors in an environment where spillovers can occur. In the model for social interaction, two cardiologists can interact, spillovers may arise, and the cardiologists can influence each other. Since the data I utilize consist of information on total drug costs and prescriptions, the city they prescribe in, drug-type, and ties these variables directly to a national prescribing identifier (NPI), I can use these data to find means among cardiologists, in different cities and years, and compare these means to cardiologists that migrate to a given city each year. Migration may take two forms: Within a given region or across regions.

To identify spillovers among cardiologists, I specify a model used by Mas & Moretti (2009, p. 118-119):

$$y_{ict} = \alpha + \beta\bar{y}_{ct} + x_{ict} + c + t + e_{ict} \quad (2^*)$$

Where $y_{ict}$ is the prescription behavior of cardiologist $i$, in city $c$ at time (year) $t$. $\alpha$ is a constant. $\bar{y}_{ct}$ is the mean prescription behavior in city $c$ and year $t$ and it is the leave-out city-mean of a given city. The leave-out is individual $i$ and is left out to not include their own behavior when estimating spillovers for a given individual $i$. Then the means in cities are not skewed by finding means that contain individual $i$ when we analyze this exact individual. $x_{ict}$ are individual characteristics for individual $i$, in city $c$ at time $t$. $c$ is city, $t$ is time and $e_{ict}$ is the error-term of the estimation. I will first and foremost aggregate every observation per cardiologist, so that each variable of interest becomes yearly aggregates, before I calculate means of prescription behavior among different cities in the U.S. When these means have been calculated, I can calculate the means in each city. These means will likely be different across different regions, while states within regions will likely have similarities in their means based on the distance they are away from other states within the same region. This assumption is based on the idea of "star"-physicians that have extensive networks that may have spillover effects on choice of treatment in different parts of the U.S. covered in section 1.

Equation (2*) needs to be transformed into a FE model which requires changing of the $\alpha$ constant. As my main entity used in all the models is the NPI, i.e., the individual cardiologist, we need to include cardiologist FEs as cities consist of numerous observations of individual cardiologists. From (2*) we re-define $\alpha$ as (Angrist & Pischke, 2008):

$$\alpha_i \equiv \alpha + A_i\gamma$$

Where $\alpha$ is still a constant term, $A_i$ are unobserved and fixed entity confounders, i.e., they affect both the dependent and independent variable, and $\gamma$ is a constant (Angrist & Pischke, 2008, p. 222-223). In the case of cardiologists, $A_i$ might be ability, preferences, experience, where they received their training or other hidden characteristics that varies across entities but are assumed to be fixed over time. Equation (2*) can now be expressed as:

$$y_{ict} = \alpha_i + \beta\bar{y}_{ct} + x_{ict} + c + t + e_{ict} \tag{2}$$

Next, I will proceed with the same model as Mas & Moretti (2009) and specify a model that will find the lagged-leave-out city-mean. By lagging the leave-out mean, we remove contemporaneous correlated behaviors:

$$y_{ict} = \alpha_i + \beta\bar{y}_{ct-1} + x_{ict} + c + t + e_{ict} \tag{3}$$

This differs from (2) in that this leave-out-mean is lagged by one year when estimating, which is important. It is reasonable to believe that a migrant cardiologists' prescribing behavior will change with a lag when being exposed to new peers. A possible deciding factor is that it takes time to get to know new colleagues when starting in a new job. It may therefore take time for migrating cardiologists to take part in the existing medical networks in cities they migrate to. For example, a cardiologist that migrates and does not take part in a network will likely keep their preferences from prior to migrating. A migrant cardiologist that does interact with their new peers, will likely start adapting to the network after some time, when they have become acquainted to the peer- and network- "culture". Therefore, it can be important to lag by one year when estimating the leave-out-mean.

$\beta$ is the coefficient of importance in this equation, and I assume the spillovers from peers may operate in three different ways:

I) Spillovers among peers exist and affect the migrant cardiologist positively, by changing their prescription behavior. Expressed through changes in costs and/or prescribing amount and prescribing composition.

II) Spillovers exist but has a negative effect on the migrant cardiologist. Expressed by lowering costs and/or prescription costs and prescribing composition.

III) Spillovers have no effect on the migrant cardiologist. Expressed by no change in the forementioned factors.

Prescribing composition relates to the type of drug the cardiologists prefer for treatment of different ailments, where costs change drastically solely on the choice of drug-type. A general drug has lower costs per prescription compared to a newer patented drug that only the developing company can produce and sell. It essentially acts as a monopoly for the duration of the patent-period, which corresponds to a higher price until the patent expires and becomes a general drug, and thereafter is exposed to market competition, driving the price down. Patented drugs do come with certain benefits when compared to older general drugs. Newer medicine can be compared to new technology in the sense that it likely has better attributes for specific uses or ailments. The use of patented medicine is then not just a discussion of costs related to the use of the medicine, but also the health-benefitting factor for the patient. The problem arises if prescription of a certain drug increases for all types of patients, regardless of the necessity for the pricier drug.

## 3.1 Empirical Method: Key Idea

The key idea I follow in my empirical strategy is also similar to the key idea Molitor (2018) proposes in his empirical analysis of migrating cardiologists. However, the CMS data I use will not have nearly as long a timeline as the data he uses, but contain every prescription, both unique and renewed prescriptions, for every beneficiary a cardiologist provides to during a year. The difference in data longitude will set my analysis apart from Molitor (2018), as I cannot study "long" trends in cities and among migrants, but the frequent observations provided during a year allows me to observe changes in prescribing behavior from year to year and even within years. The key identifying assumption is the same as Molitor (2018), I assume that the only change a migrant experience after migrating is the change in environment in the form of interactions with new peers in a new local network.

I will be performing a linear regression that controls for FE, but since I have several key variables that are connected to each NPI and with a high number of observations connected to each NPI every year, I will be using a linear regression that will allow me to absorb these numerous observations, per NPI, to obtain my regression results. I will estimate equations (2) and (3) for the time-period of 2013-2018 by subtracting prescription behavior for migrants from prescription behavior city-means. With equation (2) and (3), I will perform deviations from the mean, shown in equation (1.4), to estimate the spillovers that originate from local peer networks.

With the main motivation and model formulated, it is important to consider the assumptions associated with FE regression models for panel data. All assumptions have been fitted to the model shown in equation (2) [1]. The assumptions for a least squares FE model with panel data are:

<u>ASSUMPTION 1:</u> $E(e_{ict} | \bar{y}_{c1}, \dots, \bar{y}_{cT}, \alpha_i, c, t) = 0$

[1] The assumptions are gathered from a lecture held by John C. Chao, Professor of Economics at the University of Maryland. Chao used Stock & Watson (2008) "Heteroskedasticity-Robust Standard Errors for Fixed Effects Panel Data Regression" as their source. Monique de Haan's lecture from the University of Oslo has also been used to complement Chao's lecture notes. See for example:

http://econweb.umd.edu/~chao/Teaching/Econ423/Econ423_Panel_Data.pdf

The expected value of the error term with respect to the lagged-leave-out mean, unobserved time invariant fixed confounders, city- and year-FE is equal to 0. This means that there are no omitted lagged effects, i.e., all lagged effects from $\bar{y}_{ct}$ must enter explicitly. This also implies that there is no effect from $e_{ict}$ to a future $\bar{y}_{ct}$.

ASSUMPTION 2: $(\bar{y}_{c1}, \dots \bar{y}_{cT}, y_{i1}, \dots, y_{iT})$ are independent and identical distributed over the cross-section, i.e., all individuals are normally distributed. This does not apply over time for a given individual, as prescription behavior is likely highly related to the leave-out city-mean from one year to another.

ASSUMPTION 3: $(y_{ict}, \bar{y}_{ct})$ large outliers are unlikely. This ties in with assumption 2, as the observations of prescription behavior and lagged-leave-out city-means are distributed normally and outliers that have so high, or low values that the estimated effects are altered significantly are unlikely.

ASSUMPTION 4: No perfect multicollinearity. This assumption states that two independent variables should not be highly correlated.

ASSUMPTION 5: $corr(e_{ict}, e_{ics} | \bar{y}_{ct}, \bar{y}_{cs}, \alpha_i, c, t) = 0$ for $t \neq s$. This states that given $\bar{y}_{ct}$, the error terms for two different time-points, $t$ and $s$, are uncorrelated over time for a given individual, $i$.

If all the assumptions above hold, this means that the estimated $\hat{\beta}$ is an unbiased and consistent estimator for $\beta$ (Haan, Econ4150 – Panel Data, p. 30). Assumption 5 states that the error terms, for two different times in the panel data, t, and s, where $t \neq s$, need to be uncorrelated within a group for a given X, which is NPI. In other words, for a given cardiologist, and two different times in the panel data, 2013 and 2014 for example, the omitted factors are uncorrelated within a city. We then must ask ourselves if this is plausible, and what goes in $e_{ict}$. In the case of Medicare Part D data, what omitted factors can have an impact on individual $i$? If a time varying factor affects prescription behavior and is not correlated with the independent variable[2]. If these

[2]

Underlying unobserved mental illness that might influence prescribing behavior in unknown ways, grow apathic, feel less motivated for a given year, which can affect cardiologist behavior. The same line of logic can be applied to stress – i.e. – overworking a given year leads to a more relaxed year, then year $t$ and $s$ are correlated for some years while not necessarily every year. Would likely return to normal workloads following a restitution-period.

situations arise, the error terms are correlated for years within the time-period. Assumption 5 does not hold any more. This means that: $cov\ (e_{ict}, e_{ics}|\bar{y}_{ct}, \bar{y}_{cs}, \alpha_i) \neq 0$ (Chao, Econ423 – Lecture Notes, p. 50). This can be shown using general SE notation:

Standard error for $\widehat{\beta}$ (ordinary least squares FE estimator): $SE(\hat{\beta}) = \sqrt{\frac{1}{nT} * \frac{\hat{\sigma}_\eta^2}{\widehat{Q_{\bar{y}}^4}}}$

From the SE of $\hat{\beta}$, what is $\hat{\sigma}_\eta^2$? There are two outcomes: when $u_{it}$ and $u_{is}$ are uncorrelated or correlated. If they are uncorrelated, then:

$$\hat{\sigma}_\eta^2 = var\left(\sqrt{\frac{1}{T}}\sum_{i}^{T}\widehat{v_{\iota t}}\right) = var\left(\frac{(\widehat{v_{\iota 1}} + \widehat{v_{\iota 2}} + \cdots + \widehat{v_{\iota T}})}{\sqrt{T}}\right)$$

Mathematical notation shows that: $var(X+Y) = var(X) + var(Y) + 2cov(X,Y)$.

When $u_{ict}$ and $u_{ics}$ are uncorrelated, then $2cov(X,Y) = 0$. Then it follows that:

$$\hat{\sigma}_\eta^2 = \frac{1}{T}T * var(\widehat{v_{\iota t}}) = var(\widehat{v_{\iota t}})$$

And you can use standard heteroskedasticity robust standard errors, as $u_{it}$ and $u_{is}$ are uncorrelated.

If $u_{it}$ and $u_{is}$ are correlated, then:

$$\hat{\sigma}_\eta^2 = var\left(\sqrt{\frac{1}{T}}\sum_{i}^{T}\widehat{v_{\iota t}}\right) = var\left(\frac{(\widehat{v_{\iota 1}} + \widehat{v_{\iota 2}} + \cdots + \widehat{v_{\iota T}})}{\sqrt{T}}\right) \neq var(\widehat{v_{\iota t}})$$

From the same mathematical notation as above:

$$var(X+Y) = var(X) + var(Y) + 2cov(X,Y)$$

This notation shows that if $u_{it}$ and $u_{is}$ are correlated, the $cov(X,Y)$ will not be non-zero and assumption 5 does not hold. This does not change the panel data estimators of the $\beta$ of interest, they stay consistent. When ASS 5 fails, it leads to wrong SEs – and usually understates the true

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In essence, any time varying factor that affects prescription behavior while not being correlated with the independent variable, which in the case of my analysis is the lagged-leave-out mean.

uncertainty of the estimates of $\beta$. So, if $e_{ict}$ is correlated over time, we do not have as much information as you would if $e_{ict}$ were uncorrelated. The solution to this problem is to use clustered standard errors, i.e., heteroskedasticity and autocorrelation-consistent standard errors. They are called clustered standard errors because there is a grouping (cluster) within the error term that is possibly correlated, while it is not across groups. The clustering does not have to be on time, but can also be over different groupings like city, state, region, etc. Based on the leave-out means and lagged-leave-out means and the entities of importance, I cluster standard errors at city-level for city-means, and zip-codes in zip-means. It is natural to believe that there is certain variation between different cities when it comes to treatment or other characteristics of the cardiologist that practice medicine. This can be difference in practice-culture from one city to another, difference in budgets or difference of politics that may affect cardiologists. Clustering could also be done on state-level, but this would likely not pick up all city-variation, for example when a migrant migrates within a state rather than between states. The same logic is used when clustering for the alternative models where I use zip-codes rather than cities to estimate leave-out means and lagged-leave-out means. In these alternative models, which will be discussed in section 3.3, we cluster SE on zip-codes to control for possible correlation between the error term $e_{izt}$ and $\bar{y}_{z1}, \ldots, \bar{y}_{zT}, \alpha_i, z, t$ in given times within the time-period.

Then, given that the assumptions 1 through 4 holds, and control-variables explain other variation in prescription behavior, then $\beta$ will estimate the causal effects of spillovers on prescription behavior from local networks.

## 3.2 Limitations and Advantages to the Model and Method

Fixed-effects model (FE) are generally the preferred models compared to OLS models (Collischon, M. & Eberl, A., 2020, p. 297-298). Even if this may be the case, any model chosen will include certain pitfalls and problems that may arise based on the data and method used. This section will present possible limitations in the models and discuss the likelihood of their existence. Estimation-results will be presented in section 5, and pitfalls regarding the model and method will be discussed in more detail in section 6.

## Unobserved Heterogeneity

A possible limitation in a FE model is unobserved time-varying heterogeneity (Collischon & Eberl, 2020, p. 292-293). This will occur if omitted variables that are partly time-varying affects the models' main specifications without being accounted for. This could arise if one omitted variable affects both the leave-out city-mean and the lagged-leave-out city-means in equation (2) and (3) and therefore skew the estimations. The model would not identify the relationship between a migrant and spillovers among new peers, as the estimates would not find estimated causal effects, but skewed results which could either be over- or under-stating the $\beta$ of interest, i.e., spillovers among cardiologists. One could make the case for an omitted variable to be industry payments, as it can be directly linked with prescription behavior and effect drug costs and propensity to prescribe certain drugs. In the case of industry payments towards peers that already operate in a city that a migrant cardiologist moves to, this would not be a problem. If a migrant cardiologist receives industry payments after conducting their move to a new city, the change in prescription behavior will then not only depend on the migration and their interactions with a new local peer network, but then instead be affected by the industry payments. If certain pharmaceutical companies advertise their prescription medicine based on geographic locations first and foremost, like focusing on certain regions of the U.S., then this could occur and skew the estimates of increases in per capita cost due to spillovers.

## Classical Measurement Error

Classical measurement error is an error concerning the data provided and will be in the form of mispresenting of values, either over-stated or under-stated (Collischon & Eberl, 2020, p. 293-294). Collischon & Eberl (2020) uses the example of two waves, where the true value of each wave is equal (£2550) but is reported to be (£2500) in wave 1 and (£2600) in the second wave. If one were to perform analysis on this, the reported numbers would indicate a rise from wave 1 to wave 2 because of the measurement error, when the true value is equal. This could skew the estimations by a lot if measurement errors occur several times in datasets. Panel data is vulnerable to this type of classical measurement error, and if it occurs, then measurement error can lead to conservative coefficient estimates because of attenuation bias (Angrist & Pischke, 2008, p.225). Attenuation bias leads to coefficients biased toward zero, i.e., an understatement in the estimates (Collischon & Eberl, 2020, p. 292-293; Hsiao, 2007, p. 5). CMS have provided data on Medicare D & B for the years 2013-2018, and they recently (in 2021) published the data for 2018. This gives an indication that the datasets take a long time to produce, which is likely based on their size and their efforts at controlling reported values and limiting measurement errors. Even so, measurement error can possibly affect both datasets, as I have only used a small sample of the entire datasets in each year and would likely affect the estimates by understating their true value. As each dataset over all specializations each year in Medicare Part D consists of around 23.5 million lines of data for all beneficiaries in just one year, some misrepresentation in prescriptions by either a doctor or data-manager is likely to happen. As Angrist & Piscke (2008, p. 226) mentions, deviations from the mean might remove omitted bias, but can also remove variation in the variable of interest which leads to understatement of the results. Measurement error will be considered when presenting the estimates in section 5.

## 3.3 Alternative approaches

### Sensitivity Analysis

I will now formalize the methods and models used to assess the robustness of the main method and model. We check the robustness on findings by subjecting equation (2) and (3) to different specifications. The first major change is the utilization of a substitute-sample, by using Medicare Fee-For-Service cardiologists instead of Medicare Part D cardiologists. This means that instead of estimating prescribing behavior, we will not estimate service-providing behavior. As neither prescribing or service-providing is not the entire practice of a cardiologist, they have the same specialization and operate within Medicare, service-providers are assumed to be a well-suited substitute-sample. In addition to the different sample, the alternative models will be estimated in different ways. Firstly, NPI FE are excluded, and individual characteristics-variables are added in steps to see the change in service-providing behavior. Zip-codes are added as a narrower geographical control to see whether spillovers are stronger in narrower local networks or whether spillovers operate across cities. A mirrored estimate of equation (2) and (3) with the substitute-sample being the only change. Lastly, we will look at an interaction-term between cardiologists who see higher number of elderly beneficiaries and a change in method where difference from the means is substituted by first-difference estimates. With the addition of these specifications to the model, we will see if small changes in the structure of method or model will change the outcome of the estimates. I will now formalize the alternative models.

Cities, Zip-codes and Added Controls

| Table 3.3: Nb of cities and zip-codes in dataset | Total unique observations |
|---|---|
| Number of cities | 2514 |
| Number of zip-codes | 13299 |

There exist alternatives to model (3) both in estimating interactions among cardiologists and which fixed effects are being considered when estimating interactions and spillovers. The first alternative approach is similar in many regards to the main specified model, as it follows the same principles, procedures, and specifications besides a few notable differences. The main difference between the former model, and the alternative approach, is the use of a new dataset: Medicare Fee-For-Service. It uses data for Medicare Fee-For-Service which include costs related to a service that cardiologists provide to a beneficiary while taking the number of services provided into consideration. Figure 3.3 show the difference between the number of unique cities and the number of unique zip-codes in the new dataset, where interactions can occur in a much smaller geographic area compared to cities. There are around five times more zip-codes compared to cities, which allows for much narrower controls and interaction not across cities, but within smaller parts of the cities. For completion, I will include models for cities that utilize Medicare Fee-For-Service data as well. The model for cities can formally be expressed as:

$$y_{ict} = \alpha_i + \beta\bar{y}_{ct} + x_{ict} + n_{ict} + c + t + e_{ict} \tag{4}$$

Which holds similar variables as equation (2) except for the addition of $n_{ict}$ which is the number of unique services provided by individual $i$ in city $c$ at time $t$. Adding individual-specific variables can increase a model's precision. By adding individual-specific variables like gender, type of treatment or other individual-specific variables that can explain parts of prescription behavior among cardiologists by reducing residual variance (Angrist & Pischke, 2008, p. 23-24). This can affect the size of SE as they are reduced when a model explains more of the residual variance in $y_{ict}$. This is the reason for including the new individual-specific variable on number of unique services provided, $n_{ict}$. As neither of the datasets, Medicare part B or D, represents the entire practice of a cardiologist, it can be important to control for how many unique prescriptions each cardiologist prescribe each year. This is likely due to natural differences in practice composition between cardiologists, as some likely prescribe more than others, and others provide more services than others. The variables have the same structure as equation (2) but with a different purpose. $y_{ict}$ is no longer prescription behavior but is now changed to service behavior for individual $i$ in city $c$ at time $t$. $\alpha_i$ is the same as in (2), where it holds unobserved individual fixed effects. $\bar{y}_{ct}$ is the leave-out city-mean that holds the leave-out mean for per capita costs related to the average service cost and unique service-amount provided. $c$ and $t$ are city FE and time FE respectively and $e_{ict}$ is the error term for individual $i$, in city $c$ and at time $t$. From (4) I can express the model in the lagged form to account for contemporaneous service behaviors:

$$y_{ict} = \alpha_i + \beta\bar{y}_{ct-1} + x_{ict} + n_{ict} + c + t + e_{ict} \tag{5}$$

Which is the same as equation (3), where $n_{ict}$ is included and $\bar{y}_{ct-1}$ is the lagged-leave-out city-mean for service providing. The coefficient of interest is still $\beta$. These two models are the baseline estimates for the alternative approach. As some cities in the U.S. can be quite large, it could be advantageous to use a narrower entity than city to perform the estimates on the Medicare Fee-For-Service data. The Fee-For-Service does include zip-codes, which is much narrower when compared to cities, as cities contain many zip-codes. The next step from equations (4) and (5) is to change all the forementioned variables on service behavior from city to zip-codes. As I use a model that is intended for an environment where social interaction happens in an environment where spillovers can operate, I need to drop all zip-codes that are only connected to one cardiologist in a year, as social interaction can only happen between two or more individuals. From (4) and (5), I utilize the inclusion of zip-codes to provide narrower controls in the leave-out means and lagged leave-out means. With the inclusion of zip-codes, model (4) changes to:

$$y_{izt} = \alpha_i + \beta\bar{y}_{zt} + x_{izt} + n_{izt} + z + t + g + e_{izt} \tag{6}$$

Where a new variable has been included: $g$. $g$ is a variable that controls for FE related to HCPCS-codes that the Fee-For-Service data hold. These codes are unique identifiers that are used to track which type of service a cardiologist provides to every beneficiary in a year. Every service a cardiologist can provide is linked with a HCPCS-code. This allows me to track the exact services a cardiologist provide in a year. HCPCS-codes can affect how much a service will cost as some services are likely much more expensive and difficult than others. It is therefore important to control for these service-types, as they likely will have some explanatory power on $y_{izt}$. $y_{izt}$ is service-providing behavior of cardiologist $i$, in zip-code $z$ at time $t$. $\alpha_i$ is the same as previously, $\bar{y}_{zt}$ is the leave-out zip-mean for a given zip-code and $x_{izt}$ is cardiologist characteristics. $z$ are zip-code fixed effects, $t$ is yearly fixed effects, $g$ is HCPCS-code fixed effects and $e_{izt}$ is an error term. These are the zip-code leave-out zip-means, and can now formalize the lagged version:

$$y_{izt} = \alpha_i + \beta\bar{y}_{zt-1} + x_{izt} + n_{izt} + z + t + g + e_{izt} \tag{7}$$

This is the simplest form of the alternative model with Fee-For-Service data and holds many parallels to model (3) in the main specification. As with (6), everything is the same except for $\bar{y}_{zt-1}$ which is the lagged leave-out mean for zip-codes, as we expect cardiologist behavior change to be lagged by one year when being exposed to new peers, i.e., a cardiologist needs time to adapt to a new workplace and new peers. As with (3), the coefficient of interest is $\beta$ and we assume spillovers among cardiologist interaction may operate in three ways:

i) Spillovers among cardiologists exist and affect the migrant cardiologist positively, by changing their service-providing behavior. Expressed through positive changes in total costs or total services provided.

ii) Spillovers among cardiologists exist and affect the migrant cardiologist negatively. Expressed through negative changes in total costs or total services provided.

iii) Spillovers among cardiologists have no effect on the migrant cardiologist of interest. Expressed by no changes in total costs or total services provided.

With the addition of HCPCS-codes, the formalized model will have narrower controls when estimating the leave-out and lagged leave-out means while also explaining more of the residual variance in the model. There are some characteristics that are not accounted for in the alternative model, however. We take equation (6) and (7) and add a variable that controls for the gender of the focal cardiologist, the mean of average service costs and a variable that controls for whether the place of service providing is a facility or not a facility. Equation (6) can now formally be expressed as:

$$y_{izt} = \alpha_i + \beta\bar{y}_{zt} + x_{izt} + n_{izt} + m_i + p_{it} + \bar{c}_{it} + z + t + g + e_{izt} \tag{8}$$

Equation (7) can now formally be expressed as:

$$y_{izt} = \alpha_i + \beta\bar{y}_{zt-1} + x_{izt} + n_{izt} + m_i + p_{it} + \bar{c}_{it} + z + t + g + e_{izt} \tag{9}$$

Now, service behavior for individual $i$, in zip-code $z$ at time $t$ can be expressed by the individual unobserved fixed effects $\alpha_i$, with the lagged leave-out zip-mean $\bar{y}_{zt-1}$ for a given zip-code at time $t-1$. Cardiologist characteristics are the same as before, $x_{izt}$, with the new variable $m_i$ that controls for whether individual $i$ is male, $p_{it}$ controls for place of service for individual $i$ at time $t$, $\bar{c}_{it}$ controls for mean of average cost for individual $i$ at time $t$. Place of service relates to if the cardiologist works in a facility or not, where non-facility usually relates to an office-setting. The rest are the same as for (6) and (7). With the addition of even more individual-specific variables, the residual variance in the model will likely fall as the model explains more of the "noise" as it is addressed. Adding a variable for gender can help explain the forementioned variance if there is a clear mean-difference in service-behavior between male and female cardiologists. It is better to include it than not at all, since if there is no difference between male and female cardiologists the added variable will not change the estimations and coefficients. Place of service is likely important to add as there is likely a difference between cardiologists who provide a service in a facility or not, as these likely affect the service-behavior and the costs in the model. The final added variable, $\bar{c}_{it}$, holds the mean average costs for cardiologist $i$ at time $t$, and can be important to add to the model by the same logic as when number of unique services were added to equation (5), it can be important to control for how big a part services are of a cardiologists practice. It can also be important to relate the scale of mean average costs to spillovers to see if cardiologists with a lower mean gets more affected by spillovers than cardiologists with a larger mean. With these variables added, the baseline alternative models are finalized. With the new models (8) and (9) I will not assess the sensitivity of estimates of $\beta$ in model (6) and (7).

## New Treatment Definition: First Differences ($\Delta y$)

A final alternative approach is the use of first difference between origin city and destination city to estimate spillovers that arise between cardiologists in different time-periods within the Medicare Part D prescription dataset. The model uses leave-out city-means with the composition in equation (2) as destination and takes the first difference with respect to the lagged-leave-out city-means in equation (3). These are not specific to two given timeframes, i.e., not just if origin is year = 2013 and destination is year = 2014 but generates first differences for the whole time-period of 2013-2018 (year = 2013 cannot be a destination timeframe, just as 2018 cannot be an origin destination based on the aggregated data for prescription medicine, as specified in section 4). It differs from the main model by differencing yearly prescription behavior from the lagged prescription behavior. In the main model, every year is de-meaned, where each prescription behavior is differenced with the total mean prescription behavior. The model can be formally expressed through the equation of change:

$$\Delta y = y_{ict} - y_{ict-1} = (\alpha_i + \beta\bar{y}_{ct} + x_{ict} + c + t + e_{ict}) - (\alpha_i + \beta\bar{y}_{ct-1} + x_{ict-1} + c + (t-1) + e_{ict-1}) \quad (10)$$

The key idea behind utilizing first-differences as an alternative model is the same as for the main model by following Molitor's (2018) key idea. The only change a migrant experience after migrating, is the change in environment represented by new interactions with new peers.

The first difference can then be used in two different ways:

i) Construct $\Delta y$ and use this difference directly with the leave-out city-mean to estimate a linear regression model with the same specifications and FEs as the lead estimates. The estimates will then be estimated with the $\Delta y$ term instead of the lagged-leave-out city-mean as in equation (3).
ii) Construct an indicator variable, $[\Delta\bar{y} > 0] = 1, [\Delta\bar{y} \leq 0] = 0$ and perform equation (3) with the addition of the indicator variable added to the other FE variables and controls.

Both methods of estimating the first difference will be used with the main model. This means that first differences will be based on cardiologists from the Medicare Part D data and will estimate spillovers that affect prescribing. The first method uses mean per capita cost and the leave-out city-mean after performing first differences on the model, as shown in equation (10), then perform regular ordinary least squares regression with city FE and year FE. NPI FE are excluded due to computational difficulties, as the number of NPI are too large to include a dummy for each individual cardiologist, and absorbing NPI is not feasible for this type of regression. In the second method, I perform the ordinary main model but include dummy-variables as shown in method ii). Thereafter, I will perform regular OLS with the main model, indicator variable, city FE and year FE. NPI FE are excluded again due to computational difficulties.

# 4 Data for Medicare Part D & B: Prescription Medicine & Fee-For-Service

The datasets for both Medicare Part B & D contain observations from the timeline: 2013 to 2018. Medicare Part B had the year 2012 available, but since Part D only contained data from 2013 to 2018, I limited Part B to the same timeline for completeness and to keep yearly effects similar. All data that are being utilized in this thesis, was collected from the Centers of Medicare & Medicaid Services' website. The data is publicly available from CMS' website. CMS is a governmental website which provides information on Medicare & Medicaid services, and is a part of the Department of Health and Human Services (HHS).

The datasets contain information connected to the public health care coverage in the U.S, and is further focused on two sub-parts of Medicare: Medicare Part B and Medicare Part D. Every dataset contains information on doctors that take part in Medicare, and each doctor can be distinguished by finding the national provider identification – code (NPI), which each observation in a year is connected to. NPI will then be used as an identifier for every other variable each dataset contains, so that everything can be connected to each individual doctor. All observations in both datasets can be connected to the forementioned NPI. To answer my research question, if local peer effects affect physicians' prescribing behavior, I need to divide the data into groups based on variables that are connected to NPI's, which there are several of.

## 4.1 Medicare Part D

Firstly, in the dataset for Medicare Part D, the natural dividers for NPI's and their corresponding variables is to group data either as NPI-city-year or NPI-state-year. The analysis could be performed both on state-level or city-level, but I decided to perform the analysis on the city-level to ensure narrow controls to pick up peer effects in large local networks. There are likely few local networks that span over an entire state, and some cities are already quite large with many cardiologists per city, it will not be necessary to group data based on state-level to ensure interaction among cardiologists. As some cities are large, the states that contain these large cities are likely very large as well. This could pose certain problems when identifying migrating cardiologists, as grouping on state-level would not identify within-state migration, but only between-state migration. Going down the state-route would also entail a higher possibility of not estimating the local effects that I want to analyze, as the scope is so large that the estimations could become skewed. Besides these concerns, using state-level grouping would have been an option to be considered if long-distance migration were a motivating factor in the analysis.

Grouping will therefore be on the city-level for Medicare Part D, as this is the narrowest control that is readily available. All data for the years 2013 to 2018 have been collapsed, so that the numerous observations each year will summarize to a single observation, this collapse will be on both year and city, so that I can capture observations in the case of a cardiologist that migrates to a different city each year.

## 4.2 Medicare Part B

Secondly, in the dataset for Medicare Part B, the natural dividers are the same two as in Part D, but CMS have included another observation-divider; zip-code. With the inclusion of zip-codes in the dataset, I will be able to control for local effects in a narrower way than on the city-level. As it includes the city-level as well, it is natural to include an analysis of Part B on the city-level, to keep estimations and analysis similar across datasets, while using zip-codes as a narrower control-tool to test with different specifications in regressions and the analysis. This could be important when it comes to cities that are large, like New York for instance, as they are big in size and contain many zip-codes. When a migrant doctor migrates from one zip-code, rather than city, two things can occur: Firstly, if the local networks span across the zip-code but no further, so not across cities, then zip-codes can be a better control when estimating spillovers. Secondly, if local networks span across cities and not just one zip-code, then zip-codes can be a worse control when estimating spillovers among peers. Zip-codes is therefore included as narrower control to test for both occurrences.

## 4.3 Datasets, Labels, and Functions

The datasets contain many variables, where not every variable is of particular use in the analysis I wish to perform. The description for the variables is gathered from the CMS website (Centers for Medicare & Medicaid Services, 2021, Medicare Provider Utilization and Payment Data: Part D Prescriber; Centers for Medicare & Medicaid Services, 2021, Medicare Provider Utilization and Payment Data: Physician and Other Supplier (Fee-For-Service))[3]. The variables of importance are NPI, which is the national provider identifier (id). city, state, and zip-code variables that explain where a given cardiologists' practice is located. The variables that hold cities and zip-codes will be used to identify migrants and migration patterns and the leave-out means. From Medicare Part D, I will use a variable that holds every unique prescription that is distributed to a beneficiary, a variable that holds all costs that are related to when a prescription is given. This amount includes ingredient cost, dispensing fee, sales tax, and any applicable vaccine administration fees and is based on the amounts paid by the Part D plan, Medicare beneficiary, government subsidies, and any other third-party payers. The variables for total drug costs and unique prescriptions also have a version that holds observations for beneficiaries aged 65 or older, which allows me to find out how many beneficiaries are above the age of 65. As Medicare Part D is targeted at the elderly, except for individuals with certain disabilities and chronic diseases, it is natural that the ratio of elders to non-elders is high. There are no variables that link the age of the beneficiary to any of the observations, so there is no way, based on the dataset variables, to know the age groups of beneficiaries that use Medicare Part D. This might pose some concerns about the validity of the results, as I cannot identify the demographic that each doctor is treating. The age of beneficiaries could explain certain variation in prescription-amounts or total costs, as disease likely increases with age, which in-turn, could have a higher

[3] In both CMS-data references, there is a pdf-file titled «Methodology» that describes every variable included in each dataset. Each variable description was acquired from these "Methodology"-files.

effect on costs and amount of medicine needed for treatment (National Institute of Aging, 2018). This may result in some doctors, migrants, or non-migrants, having an older beneficiary-base that result in higher costs from natural circumstances rather than local network effects.

In the data for Medicare Part B, they added zip-codes that are related to each observation and connected to each NPI. This allows for narrower control when I am running my estimations. It also contains city and state variables, so I can perform a similar analysis as the prescription analysis. The data for Medicare Fee-For-Service contain several new variables, but also similar variables to the Medicare Part D datasets. One of the new variables is HCPCS-codes that describes the specific medical service provided to a beneficiary. This allows me to analyze what services are provided, in what frequencies, and if they change over the timeline. This dataset holds a variable for individual NPI's that show their gender, that opens a new path of analysis and allows me to compare doctors based on gender. As with the dataset for prescriptions, it also holds information on costs and amounts provided. Variables regarding service-providing show how many services each NPI provide, and the costs related to these. I make use of the variable that counts every unique beneficiary that receives a service, and a variable that holds the average of Medicare allowed per service. This variable holds the sum that Medicare pays, all copayments and deductibles a beneficiary is responsible to pay and any amounts a third-party is responsible for. The inclusion of these variables allows me to perform a similar analysis to the Medicare Part D dataset, by finding leave-out and lagged-leave-out means based on city and zip-codes.

## 4.4 Imposed Sample Restrictions on Data

As I am using migrant cardiologists to identify spillovers among cardiologists, it is important that the NPI's that I include in the data are as similar as possible. If not, I would have a lot more factors to control for when analyzing, as different doctors likely have different prices related to prescription medicine (Medicare Part D) and treatment (Fee-For-Service). Differences based on specialty will likely not just be shown in the prices and amount prescribed, but in the type of drug that is being prescribed. Cardiologists will prescribe heart medicine and provide services to treat heart disease, while a doctor with a different specialty will prescribe specific medicine that fits their specialty. The amounts prescribed may change based on what specialty a physician holds, as some diseases likely require fewer prescriptions to treat the illness. Heart medicine will likely only be prescribed to a patient that has a chronic heart disease; it is therefore important to keep the variation in the data as low as possible to avoid skewed estimations. This led me to introduce sample restrictions to the datasets, by only using a clearly defined doctor specialization that both datasets use to differentiate different NPI's. Therefore, I impose restrictions on the specialty of the doctors I use in my analysis and will only analyze prescribing behavior among cardiologists. The same restriction is used when estimating the alternative models, to ensure that the assessment of the main finding's robustness is subject to as few underlying factors as possible.

## 4.5 Limitations: Medicare Part B & D

As mentioned, when presenting the datasets, one limitation in both datasets is the lack of information on beneficiary age. One variable is included that holds observations for beneficiaries that are 65 years old or older, but there is no distinction in exactly what age the beneficiary is, which could be a contributing factor to the number of services and (or) prescription medicine they need for their treatments. The Department of Health & Human Services provides an article on heart-disease, which shows that individuals aged 65 and up are more likely to suffer from heart diseases compared to those of a lower age (National Institute on Aging, 2018). This means that with age, the likelihood of obtaining a heart disease increases. This risk of heart disease will likely keep increasing with age as well, while also increasing in intensity, which can affect the amount of medicine needed to treat it. This will lead to higher costs, but can also increase per capita cost, by prescribing patented drugs instead of general drugs. By not being able to differentiate between doctors that provides to beneficiaries in different age-groups, besides over or under 65, the analysis might be comparing two similar doctors with completely different beneficiaries. Especially for the "extreme" cases of patient shares, either low elder share or a high elder share compared to the average cardiologist. In these groups of cardiologists, the age-difference in patients is not differentiable, which is a limitation in the data. This age-difference will likely also be different from city to city, as some cities are "pensioner-paradises" which have a higher degree of elders compared to other residents, which may affect the beneficiary age-groups. If a cardiologist has a higher degree of 90-year-old beneficiaries than another cardiologist, the severity of their illness may depend on their age. If this is the case, drug costs may be higher. This possible variation is partly controlled for through the city fixed effects, but as the variation happens within the variable, it could affect estimations of the models.

The same can be said for beneficiaries that are under the age of 65. This is especially true for the beneficiaries that receive benefits from Medicare Part D, as it is a prescription benefit designed for the elderly, apart from a handful of chronic diseases that make beneficiaries under the age of 65 eligible for Part D prescription benefits. We can identify beneficiaries that are under the age of 65, which by eliminations means they have a chronic disease, but as with any beneficiary in the two age groups in the datasets, we cannot differentiate between how much younger than 65 they are.

## 4.6 Descriptive Statistics

I will now present descriptive statistics on cardiologist practice within Medicare Part D. First, I will present characteristics of all cardiologists in the time-period 2013-2018. Then, I present characteristics of movers and non-movers as means over the entire time-period.

| Table 4.6.1 | 1<br>Unique | 2<br>Mean | 3<br>Mean | 4<br>Mean (USD) | 5<br>Mean (USD) |
|---|---|---|---|---|---|
| Year | Total NB of Cardiologists | Total NB of Patients | Total NB of Claims > 65 | PC Cost All | PC Cost > 65 |
| 2013 | 21949 | 2994.619 | 1899.724 | $1887.393 | $5224.929 |
| 2014 | 22066 | 3039.118 | 1929.663 | $1928.182 | $5293.364 |
| 2015 | 20162 | 3060.307 | 1943.441 | $2083.918 | $5668.576 |
| 2016 | 19743 | 3126.211 | 1979.456 | $2128.291 | $5737.016 |
| 2017 | 19619 | 3117.622 | 1961.083 | $2106.713 | $5677.352 |
| 2018 | 19118 | 3132.639 | 1952.819 | $1974.007 | $5510.130 |

Table 4.6.1 highlights the characteristics of each doctor taking part in Medicare Part D during the time-period 2013 to 2018. The number of doctors is show by the first column, followed by total patients in the second column, total claims of a drug for beneficiaries over the age of 65 in the third column, per capita costs for all beneficiaries in the fourth column and lastly, per capita cost only for beneficiaries over the age of 65 in the fifth column. Column (2) and (3) are

shown as means and expressed as the number of claims for prescription medicine. Column (4) and (5) are expressed as means and expressed in PC cost in USD ($).

The first column expresses how many cardiologists provide for Medicare Part D. From 2013 to 2014 the number of cardiologists in the sample increases by 117, but in the years following 2014 the number of cardiologists decrease until it reaches 19 118 in 2018. The decrease in number of cardiologists may be the cause of different effects, some cardiologists may leave the Medicare Part D program either by choice or by retiring. As the data do not hold variables that control for why cardiologists leave the dataset, these reasons are merely speculation and not definite. The number of cardiologists each year is satisfactory for the analysis.

The total patients a doctor sees each year is slowly increasing even when taking into consideration that fewer cardiologists take part in Medicare Part D each year, where the mean in 2018 was 3132 patients each year. It drops slightly on the mean in 2017 but increases again from 2017 to 2018. These only consider patients the cardiologists see when prescribing medicine and does not reflect their entire practice.

Total claims for a drug for beneficiaries over the age of 65 is increasing from 2013 to 2016 but fall slightly from 2016 to 2018. The total claims over 65 variable shows that on the mean, the majority of beneficiaries a doctor see in a year are the intended age group for Medicare Part D, while a sizeable number of patients a cardiologist sees in a year is not over the age of 65.

Per capita cost for all beneficiaries is increasing for the time-period between 2013-2016 like total claims but decrease between 2016 and 2018 to $1974. Per capita cost for beneficiaries over the age of 65 increases rapidly from 2013 to 2016 but decreases to $5510 in 2018.

Table (4.6.2) on characteristics of non-migrant cardiologists vs. Migrant cardiologists:

| Table 4.6.2 | 1 Share | 2 Mean | 3 Mean | 4 Mean (USD) | 5 Mean (USD) |
|---|---|---|---|---|---|
| Mover | Male-share | Total NB of Patients | Total NB of Claims > 65 | PC Cost All | PC Cost > 65 |
| No | 0.7270609 | 3203.656 | 2034.422 | $2026.992 | $5495.805 |
| Yes | 0.6796864 | 2152.898 | 1284.958 | $1923.441 | $5607.604 |

Table 4.6.2 highlights differences in characteristics between migrant doctors and non-migrant doctors. Migrants are identified in Table 4.6.2 if mover denotes "Yes", and non-migrants are identified if mover denotes "No". The first column is a dummy variable and stores the gender of each cardiologist in the dataset. It shows that the mean of cardiologists who are male are higher for non-migrants compared to migrants, where non-migrants are around 72% male, while migrants are 67% male. The means are expressed as the mean share of male cardiologists for both migrants and non-migrants. The rest of the columns are expressed in mean as well. The second column shows the total number of patients, where non-migrants have on average around 1050 more patients than migrant cardiologists. This difference in number of patients is also shown in the number of elders they prescribe to, displayed in the third column. Non-migrants prescribe to 2034 elders on average, while migrant cardiologists prescribe to 1285 elders on average. The fourth column shows that per capita cost for all types of patients is almost equal, where non-migrants have \$2027 average per capita cost, while migrants have \$1923 average in per capita cost. In the fifth and final column is per capita cost for elders only. Non-migrants have average per capita cost of \$5495 dollars while migrants have average per capita cost of \$5607. These columns show a stark difference between migrating and non-migrant cardiologists. On average, non-migrants have higher per capita costs related to all beneficiaries of Medicare Part D, while migrant cardiologists have higher per capita cost for elderly beneficiaries. Migrants also tend to a lot fewer beneficiaries on average compared to non-migrants.

## 4.7 Migration Patterns

With the inclusion of cities and states in the datasets provided by CMS, migration patterns can be identified, and can be an important factor when estimating spillovers. To identify migration patterns, I divided all states in the datasets according to the U.S Census Bureau regions, that consist of four regions in total; Northeast, Midwest, South and West (United States Census Bureau, 2021). These four regions cover all states within the U.S. mainland, while a fifth region was added to include U.S. territory that is not a part of the mainland in the U.S. It is natural for most migration to take place within regions rather than from one region to another, as the U.S. consists of huge amounts of landmass, and moving to the other side of the country is a big journey. Regions include many states, that also are quite large and differing in size, which makes it natural for migrants to move within states rather than outside of regions.

| **Table 4.7.1** | | | Region [n-1] | | | |
|---|---|---|---|---|---|---|
| Region [n] | Northeast | Midwest | South | West | Others | Total |
| | | | | | | |
| Northeast | 31,329 | 44 | 66 | 13 | 0 | 31,452 |
| | 25.54 | 0.04 | 0.05 | 0.01 | 0.00 | 25.64 |
| | | | | | | |
| Midwest | 40 | 25,021 | 86 | 34 | 0 | 25,181 |
| | 0.03 | 20.40 | 0.07 | 0.03 | 0.00 | 20.53 |
| | | | | | | |
| South | 120 | 155 | 42,993 | 46 | 7 | 43,321 |
| | 0.10 | 0.13 | 35.05 | 0.04 | 0.01 | 35.32 |
| | | | | | | |
| West | 56 | 103 | 92 | 21,077 | 1 | 21,329 |
| | 0.05 | 0.08 | 0.08 | 17.18 | 0.00 | 17.39 |
| | | | | | | |
| Others | 1 | 2 | 1 | 0 | 1,370 | 1,374 |
| | 0.00 | 0.00 | 0.00 | 0.00 | 1.12 | 1.12 |
| | | | | | | |
| Total | 31,546 | 25,325 | 43,238 | 21,170 | 1,378 | 122,657 |
| | 25.72 | 20.65 | 35.25 | 17.26 | 1.12 | 100.00 |

Table 4.7.1. reports all migration patterns, these include movers within regions, movers between regions and non-movers. The migration patterns are concentrated, as hypothesized, within regions. When Region[n-1] = Region[n] they show either non-migrants or movers within regions. The bottom of each column shows the total cardiologists that practice or have practiced in that region in any year of the time-period. The right-side of each row shows how many cardiologists operate in a region at time, n. It therefore displays whether a cardiologist has moved to or from a region between time: n-1 and n. In the bottom right corner is the total number of observations for all the cardiologists in the datasets, this sums all observations for each year and is therefore arbitrarily large compared to unique observations of cardiologists. The total number of observations across all years are 122 657 cardiologists.

| **Table 4.7.2** | | | Region [n-1] | | | |
|---|---|---|---|---|---|---|
| Region [n] | Northeast | Midwest | South | West | Others | Total |
| | | | | | | |
| Northeast | 3,042 | 44 | 64 | 13 | 0 | 3,163 |
| | 20.38 | 0.29 | 0.43 | 0.09 | 0.00 | 21.19 |
| | | | | | | |
| Midwest | 40 | 3,283 | 86 | 34 | 0 | 3,443 |
| | 0.27 | 22.00 | 0.58 | 0.23 | 0.00 | 23.07 |
| | | | | | | |
| South | 120 | 155 | 5,222 | 46 | 7 | 5,550 |
| | 0.80 | 1.04 | 34.99 | 0.31 | 0.05 | 37.18 |
| | | | | | | |
| West | 56 | 103 | 92 | 2,458 | 1 | 2,710 |
| | 0.38 | 0.69 | 0.62 | 16.47 | 0.01 | 18.16 |
| | | | | | | |
| Others | 1 | 2 | 1 | 0 | 56 | 60 |
| | 0.01 | 0.01 | 0.01 | 0.00 | 0.38 | 0.40 |
| | | | | | | |
| Total | 3,259 | 3,587 | 5,465 | 2,551 | 64 | 14,926 |
| | 21.83 | 24.03 | 36.61 | 17.09 | 0.43 | 100.00 |

Table 4.7.2 excludes non-migrants from the migration patterns and focuses solely on migrating cardiologists both within and between regions. Table 4.7.2 shows the magnitude of within-region migration and how much larger it is compared to between region migration. The total number of migrant cardiologists in the time-period is 14 926, with the most notable migration pattern happening within the South-region in the U.S.

| **Table 4.7.3** | | Region [n-1] | | | | |
|---|---|---|---|---|---|---|
| Region [n] | Northeast | Midwest | South | West | Others | Total |
| | | | | | | |
| Northeast | 28,287 | 0 | 2 | 0 | 0 | 28,289 |
| | 26.26 | 0.00 | 0.00 | 0.00 | 0.00 | 26.26 |
| | | | | | | |
| Midwest | 0 | 21,738 | 0 | 0 | 0 | 21,738 |
| | 0.00 | 20.18 | 0.00 | 0.00 | 0.00 | 20.18 |
| | | | | | | |
| South | 0 | 0 | 37,771 | 0 | 0 | 37,771 |
| | 0.00 | 0.00 | 35.06 | 0.00 | 0.00 | 35.06 |
| | | | | | | |
| West | 0 | 0 | 0 | 18,619 | 0 | 18,619 |
| | 0.00 | 0.00 | 0.00 | 17.28 | 0.00 | 17.28 |
| | | | | | | |
| Others | 0 | 0 | 0 | 0 | 1,314 | 1,314 |
| | 0.00 | 0.00 | 0.00 | 0.00 | 1.22 | 1.22 |
| | | | | | | |
| Total | 28,287 | 21,738 | 37,773 | 18,619 | 1,314 | 107,731 |
| | 26.26 | 20.18 | 35.06 | 17.28 | 1.22 | 100.00 |

Table 4.7.3 shows all cardiologists that are designated as non-migrants. The total of non-migrant cardiologists, aggregated for the entire time-period is 107 731 cardiologists, where the South-region has the highest number of cardiologists in the time-period, with 37 771 cardiologist-observations. Table 4.7.3 shows that most cardiologists in the time-period does not migrate at all.

# 5 Results

This section will be divided into the following parts: I will first present my main results. Then, I will assess the sensitivity of the main method and model to alternative specifications, and finally I present an interaction-term between elder-shares and the main estimates. The main results are based on the main model presented in section 3, where equation (2) and (3) are used with a de-meaning regression to estimate the models. Main findings are presented in their own table, where I cluster the standard errors at city level. The alternative models are based on equation (4) to (9) from the alternative models. Alternative estimates are presented in their own tables, where I cluster SEs on city-level or zip-code level based on the entity that leave-out-means are derived from.

In all estimates provided, both main results and alternative approaches, pc-cost regarding either prescriptions or services are utilized as the dependent variable. It is constructed in the following way: First, I calculate the pc-cost for all cardiologists in the datasets by taking total drug costs and divide it by prescriptions, both unique and re-prescribed medicine. For Medicare Fee-For-Service, the average service cost is divided by service-amount for individual cardiologist $i$ over all years. Finally, I sort pc-cost by city and year before taking the mean of all individuals' pc-cost which provides a time-variant city pc-cost. The pc-cost for Medicare Fee-For-Service data uses individual pc-cost as the dependent variable instead of the mean of pc-cost used in the main estimates. The motivating factor when constructing the alternative models as complements to the analysis is to assess the robustness of findings from the main estimates. By keeping the models as similar as possible, but changing both the dependent and independent variable, and allowing for narrower controls (due to the difference in data composition), I will show that the nature of change in cardiologist behavior holds for more than one area of their practice. This is increasingly important when taking cardiologist practice-variation into account, i.e., whether a cardiologist provides mainly services or mainly prescriptions during a year.

In addition to the change in dependent and independent variable, I also provide estimates based on the absorbed indicator in the regression analysis. This will change the estimates and models focus on entities. The main results absorb NPI and will therefore use NPI as an entity to de-mean the estimates. For the alternative models I will instead absorb cities as an entity for the city-means, and zip-codes as an entity for the zip-means. Then I will estimate the main model using first differences rather than including individual FEs. Therefore, I exclude NPI FE for the first difference estimates. Finally, I present the interaction-model. I base my estimates of the interaction-term on the main model, but with the inclusion of an interaction-term between lagged-leave-out city-mean and elder-shares to untangle patient-composition's effect on prescribing-behavior.

Coefficients of the leave-out (city/zip) means and lagged leave-out (city/zip) means are the coefficients of interest in all models presented, except for the interaction coefficient for the given interaction model, and the first difference coefficient. Besides these coefficients, I will include the variables discussed in the alternative models that help explain variation not controlled for by the city FEs, year FEs, the dependent and independent variable. These individual characteristics variables are included as NPI FEs are excluded. The control-variables used in the alternative models are variables that hold information about the number of unique services provided, male, dummy equal to 1 if place of work is a facility and the mean of average service cost. With these added individual-characteristics variables added, the alternative models are estimated.

## 5.1 Main Results

The main estimates are presented in table 5.1.1. Table 5.1.1 reports the leave-out city-mean and the lagged-leave-out city-mean as independent variables, with mean pc-cost as the dependent variable for both coefficients. Estimates are derived using equation (2) and (3) from section 3, and then de-meaning the model like equation (1.4) shows. The bottom of table 5.1.1 reports descriptive information about the estimates. The number of observations in the leave-out city-mean is N = 110 523 for period 2013-2018. When the lagged-leave-out city-mean is calculated, there is a fall in observations. This is due to the "lag"-part, where some observations are excluded due to the structure of the mean. The number of observations then fall from 110 523 to 101 670. In both estimates, we see that NPI FE, CITY FE and YEAR FE are all included to control for shocks happening to all individuals, all cities, and all years. When the regression is performed, and we de-mean the estimates, the only change in prescription behavior will be spillovers among peers, which is due to social interactions in a new local network in a city. Robust clustered SEs are reported under the coefficients where both estimates are clustered on the city-entity. When I clustered the SEs at city level, this changed the significantly for both the leave-out-mean and the lagged-leave-out-mean. This likely indicates that some correlation within the error-terms existed with regular robust SEs. The uncertainty of the estimates was therefore not represented fully with regular SEs, and SEs have been improved when clustering at city-level. All results are statistically significant at 1% and positive. Column (1) reports the coefficient of the leave-out city-mean. The coefficient reports that a cardiologist subject to spillovers from new peers in a new local network, are affected positively in their prescription-behavior. An increase in pc-cost of 1$ for the average cardiologist affected by spillovers from their peers the year they migrate, induce an additional increase in pc-cost of 0.785$ due to spillovers. Column (2) reports the lagged-leave-out city-mean. The coefficient reports that a cardiologist subject to spillovers from new peers in a new local network, are affected positively in their prescription-behavior. An increase in pc-cost of 1$ for the average cardiologist affected by spillovers from new peers a year after migrating, induce an additional increase in pc-cost of 0.788$ due to spillovers.

**Table 5.1.1**

| | (1)<br>Mean PC-Cost | (2)<br>Mean PC-Cost |
|---|---|---|
| Leave-Out City-Mean | $0.785^{***}$ | |
| | (0.0612) | |
| Lagged-Leave-Out City-Mean | | $0.788^{***}$ |
| | | (0.0620) |
| *N* | 110523 | 101670 |
| NPI FE | YES | YES |
| CITY FE | YES | YES |
| YEAR FE | YES | YES |
| CLUSTER SE | CITY | CITY |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

## 5.2 Alternative Models

### Medicare Fee-For-Service, Added Control and Zip-codes

As the alternative model is based on a different dataset, some computational challenges arose. Equations (4) through (9) are meant to be estimated with the inclusion of NPI FE, city FE, zip FE and year FE. Due to computational difficulties with the zip FE, the equations cannot be estimated in the intended way. I will therefore estimate the alternative model in two ways that are computationally possible, while also providing estimates as close to the model as possible. The first way is not including NPI FE entirely, but instead relying on individual characteristics-variables to explain individual variation. $\alpha_i$ will therefore change based on the entities being absorbed. The lag- and leave-out city-means will utilize city as the entity within $\alpha_i$. This is paired with yearly FE to control for all shocks not on individual basis. When zip-codes are added as a narrower geographic control, they are used within the $\alpha_i$-term instead of cities. Year FE are included here as well. As shown in equations (4) through (9), individual characteristics variables are added in steps to control for individual variation that would not be accounted for due to the exclusion of NPI FE.

In the second way of estimating the alternative model, I will perform the lagged- and leave-out city-means on Fee-For-Service data with NPI FE, city FE and year FE, as the computational difficulties only arise when zip-codes are utilized in the regression. The second method will include a variable on place of service and a variable on the unique number of services provided to increase explanatory power. These variables are likely already explained by the NPI FE as they are both linked to each NPI and explain variation between service-providing behavior of different cardiologists. If this is the case, the estimates will not be affected by their inclusion. The alternative models also include HCPCS-codes, but due to the large amount of them, including them would entail computational issues. Therefore, they are excluded from the alternative model with NPI FE, as the quantity and type of services will be explained by NPI FEs.

Results for the alternative models with the two different approaches are reported in table 5.2.1 and table 5.2.2 respectively (see Appendix for reported estimates). Table 5.2.1 reports the alternative model that excludes NPI FE from the regression but include individual characteristics as substitutes. Column (1) and (4) report the leave-out city-mean and lagged-leave-out city-mean for cardiologists that partake in Medicare Fee-For-Service. The reported coefficients are estimated from equations (4) and (5) in section 3. Column (2) and (5) report the leave-out zip-mean and lagged-leave-out zip-mean. The reported coefficients are estimated from equations (6) and (7). Column (3) and (6) report the leave-out zip-mean and lagged-leave-out zip-mean based on equation (8) and (9) with the highest number of individual control-variables included. All coefficients are positive and statistically significant, robust clustered SEs are reported under each coefficient. The bottom of the table reports information about each regression performed. N reports the number of observations used for the entire time-period, 2013-2018, and is highly inflated due to the nature of data-manipulation performed for this regression. The data was not aggregated for these estimates, and therefore show every individually reported service provided. This means that instead of having one observation that contains aggregated data by year and NPI like the main estimates, observations for a given NPI within a given year is based on every service provided by that NPI. For each NPI each year, the reported number of observations is therefore reflecting the number of services they provide in the entire time-period. R-squared and adjusted R-squared reports the variation that is being explained by the variables included in each model. For the city-means, it is quite low due to NPI FE not being included and very few individual control-variables added, but both R-squared and adjusted R-squared increase when individual controls are added, and with the inclusion of zip FE instead of city FE.

The reported coefficients of column (1) and (4) are likely not explaining the individual service-providing behavior changes, due to the nature of the variables not included in the regression. Rather, they can be interpreted as correlation between social interactions among cardiologists and positive changes in their service-providing behavior. As the dependent and independent variables included take the pc-cost-form, the coefficients translate to increases in pc-costs which is affected by service-providing behavior. The leave-out city-mean show that cardiologists that migrate, which induces social interactions in a new local network, are affected positively. An increase of 1$ in average pc-cost for a cardiologist, increases by 0.989$ dollars extra for cardiologists interacting with new peers in a new city the year the move is reported. The lagged-leave-out city-mean show that an increase of 1$ in average pc-cost induce an increase of an additional 0.991$ for cardiologists interacting with new peers, in a new city, a year after moving. These exact numbers are likely inflated and not representative for spillovers among peers. The positive and statistically significant direction the change is likely correct as they go in the same direction as the main estimates reported in table 5.1.1., where both make use of city-means to obtain the coefficients.

Column (2) and (5) report the first leave-out zip-mean and the first lagged-leave-out zip-mean. Zip FE are introduced which narrows down the geographic areas where social interactions occur, and spillovers can arise. With the inclusion of zip-codes, narrower individual-controls have been added. Namely, HCPCS-code FE have been added to control for service-type in individual service-providing behavior. SEs are clustered on zip-codes and reported under the coefficients. The coefficients for both the leave-out zip-mean and lagged-leave-out zip-mean fall from the first estimates. The leave-out zip-mean in column (2) show that an increase of 1$ in pc-cost for the average cardiologist, leads to an additional 0.62$ increase in pc-cost for cardiologists interacting with new peers, in a new zip-code, the same year they move. The lagged-leave-out zip-mean in column (5) show that an increase of 1$ in pc-cost for the average cardiologist, leads to an additional 0.61$ increase in pc-cost for a cardiologist interacting with new peers, in a new zip-code, a year after moving. The additional increase in pc-cost due to social interaction with new peers are due to spillovers changing their service-providing behavior. As with the city-means, the coefficients are likely inflated, as a lot of the individual characteristics remain outside the model. The uncertainty of the estimates is also reflected in how sharply they fell from column (1) and (4) to (2) and (5). With the inclusion of zip-codes, social interaction may occur in a much smaller geographic area as compared to the city-means. This might be the cause for the sudden decrease in estimated spillover-effect. Some interactions may happen across cities, as some facilities may be more highly specialized toward certain ailments, which makes social interactions across zip-codes (within cities) exempt from the estimates. The other cause of decrease may be the inclusion of HCPCS-FE. If this is the case, the decrease stem from more explained variation within the model and therefore improves the accuracy of the model.

Column (3) and (6) report the final estimates for zip-means with the narrowest controls added. In these estimates, more individual characteristics-variables are added to improve the explanatory power the model. The mean of average service cost, a dummy equal to 1 for male, and 0 for female and a variable for place of service, equal to “F” if it is a facility or “O” if it is not. Coefficients fall further with the inclusion of more individual control-variables. The leave-out zip-mean in column (3) show that an increase of 1$ in pc-cost for the average cardiologist, leads to an additional 0.526$ increase in pc-cost for cardiologists interacting with new peers, in a new zip-code, the same year they move. The lagged-leave-out zip-mean in column (5) show that an increase of 1$ in pc-cost for the average cardiologist, leads to an additional 0.515$ increase in pc-cost for a cardiologist interacting with new peers, in a new zip-code, a year after moving. This gives an indication to why spillovers decrease with more control-variables added. Firstly, some social interactions are likely not considered as the zip-codes are too narrow to capture all possible interactions in the local network a cardiologist migrate to. At the same time, individual control-variables improve the explanatory power of the estimates, so the decrease is also likely due to improved estimates. This is shown by including two instances of estimates using zip-codes where the only difference is added individual characteristics-variables.

The second method of estimating the alternative model is presented in table 5.2.2 (see Appendix for reported estimates). Column (1) report the leave-out city-mean and column (2) report the lagged-leave-out city-mean. The leave-out zip-mean show that an increase in pc-cost of 1$ for an average cardiologist leads to an additional 0.692$ increase in pc-cost for a cardiologist interacting with new peers, in a new city, the same year they move. The lagged-leave-out zip-mean show that an increase in pc-cost of 1$ for an average cardiologist leads to an additional 0.631$ increase in pc-cost for a cardiologist interacting with new peers, in a new city, a year after moving to the new city. Estimates reported in 5.2.2 are very similar in structure to the main estimates in table 5.1.1, as they both include NPI, city and year FE, while the alternative model includes some individual characteristics variables and use a different dataset. At the bottom of table 5.2.2 the number of observations is shown. The number of observations is different based on two factors. In the Medicare Fee-For-Service data, there are some new NPIs who provide services, but does not provide prescription drugs in Medicare, so the number of NPIs are a bit higher. In addition, the aggregation of data each year is done differently than in the Medicare Part D data. Aggregation in data for table 5.2.2 includes place of service in aggregation, so each year is aggregated based on NPI, city, year, and place of service. Therefore, there can be two observations each year for each cardiologist if they provide services both within a facility and a non-facility. The number of observations is therefore higher than in the main estimates.

The clustering both at city-level and at zip-code level does not affect the SEs as much as they did for the main results utilizing Medicare Part D data, indicating either a failure on my end to identify possible unobserved time-variant correlation from error to the FEs or (lagged) leave-out city (zip) means. The other possibility is that there exist less of these unobserved correlations within error-terms when estimating with the substitute-sample in Medicare Fee-For-Service data, which entails that SEs are estimated close to their true meaning even without the cluster.

### First Difference

The final alternative model is the first-difference model, which can be used as an alternative to the difference from the mean model used in both the main estimates and the previous alternative models (Angrist & Pischke, 2008, p. 224). The two different methods of using the FD model are presented in table 5.2.3 (see Appendix for reported estimates). Column (1) reports the direct method where instead of estimates being based on equation (1.4), the estimates are based on the general form shown in equation (1.5) and estimated using equation (10). Column (2) reports results based on the second FD method, where an indicator variable is added, taking the value of 1 for every positive individual FD, and value 0 for every individual FD less than or equal to 0. The main estimates are based on a regression-type that immediately perform differences from the mean on the variables, while the FD regressions for both methods were performed using regular OLS. This incurs computational issues with regards to the number of NPIs, so NPI FE are excluded from the regression. This will not be a problem, as estimates based on the FD will remove fixed effects in the same way as difference from the means. City FE and year FE are included for both variations, while also clustering SEs at city-level, as city-means are used in the regression. Clustered SEs at city-level report similarly to the main estimates, while also reflecting similar improvements compared to regular heteroskedasticity-robust SEs. This reinforces my initial assessment that correlation within error terms at city-level in the Medicare Part D sample is correlated with prescription-behavior. An additional benefit when assessing estimates based on FD with the indicator-variable method is that with the indicator-variable added to the control-variables, the independent variable for lagged city-means shows positive changes in city-means. This is due to the indicator-variable holding 0 for changes in city-means that are less than or equal to 0. The FD coefficients will therefore show what happens as a response to increases in the share of coworker costs. Column (1) reports a coefficient of the FD leave-out city-mean that is a bit smaller than the main estimates while retaining the same interpretation as the main estimates. Column (2) reports regular lagged-leave-out city-mean with the FD indicator variable included. The reported coefficient for lagged-leave-out city-mean is close to being identical to the lagged-leave-out city-mean from the main estimates. Both coefficients are positive, statistically significant and possess the same interpretation as the main estimates.

## 5.3 Interaction Term

### Elder Share and Its Implication for Prescription Behavior

| **Table 5.3.1 Year** | **Mean Elder Share** | **High Elder Share** | **Low Elder Share** |
|---|---|---|---|
| | **MEAN** | **MEAN** | **MEAN** |
| 2013 | .2257224 | .320283 | .1677408 |
| 2014 | .2295946 | .3180868 | .1742309 |
| 2015 | .2346032 | .3248392 | .1745037 |
| 2016 | .2419115 | .3203285 | .1793389 |
| 2017 | .2463474 | .3232864 | .177786 |
| 2018 | .2503582 | .3220655 | .1854706 |

To understand the interactions between elder shares and the lagged leave-out means, that I will discuss later in this section, we need descriptive statistics on elder-shares between cardiologists in Medicare Part D. Beneficiaries over the age of 65 are hereby referred to as “elders”. Displaying the disparities between cardiologists based on how many elderly patients they see each year can be important for understanding some of the observed relationships and estimates in the analysis of migrants and non-migrants. As previously mentioned, elders are on average more prone to suffering from heart disease than most of the population in any country. Therefore, it is important to consider and understand the implications of patient-shares for cardiologists, as the different shares of patients may affect costs each year for a cardiologist. In the first column, the mean of individual elder share among cardiologists is roughly 22.5-25% of total patients they see in a year during the time-period 2013-2018. The second row shows cardiologists that hold an elder share that is greater than the median elder share, which shows that the mean for cardiologists with high elder shares is roughly stabilized around 32% elders among their patients in the same period. For the cardiologists with a lower than median share of elders, the elders account for roughly 17-18% of all patients they see in a year. By looking at the difference in the means between cardiologists with high shares of elders and cardiologists with low shares of elders, one can see that on average, cardiologists with high shares have roughly 45% more elders compared to the ones with low shares. If the notion that treating a higher number of elders per year would lead to higher per capita costs because of health reasons, this will likely have a significant effect on per capita costs, as high share cardiologists have quite more elderly patients in a year than a cardiologist with low shares. It is also important to note that these are means of elder shares.

To address these concerns, I estimate an interaction-term between the main coefficient of interest, the lagged-leave-out city-mean, and a dummy-variable that is equal to 1 if individual elder-share is greater or equal to median elder-share and takes the value 0 if individual elder-share is less than median elder-share. Table 5.3.2 reports an interaction-term between the lagged-leave-out city-mean and dummy on elder-share, by using mean per capita cost as the dependent variable, including NPI, city, – and yearly FE (see Appendix for reported interaction-term). The interaction-term shows a relationship between high shares of elders and the lagged leave-out mean that is negative by 8.67%. These results contradict the earlier prediction, that a higher share of elders in the patient share leads to higher per capita costs as they are more prone to heart illness. The interaction-term is negative but not by a lot while also not being statistically significant. The number of observations is 101 661, which is very close to being identical to the number of observations in the main estimates. The difference in observations is based on a few observations in individual elder-share not existing[4], which is likely some outliers in the data that have not prescribed a lot during a given year, indicating that other parts of Medicare have dominated their practice for some years. Low elder-shares make up around half the observations in Table 5.3.2, as median-value has been used to differentiate between high-shares and low-shares of elders. As the interaction-term shows a negative interaction between the lagged-leave-out city-mean and high elder-shares, the opposite is reported in the case of low

[4] When referring to the observations as «not existing», this means that some observations return: «.», nothing, as there are some outlying NPIs that do not prescribe to elders for some years. The exact number of outlying observations is: 9, which is not large enough to have a significant impact on FD estimates.

elder-shares. The interaction-term between the lagged-leave-out city-mean and low elder-shares will therefore report a positive interaction of 8.67%, which is not statistically significant. As the interaction-terms are not statistically significant and SEs displaying high uncertainty, they should not be interpreted causally. They do show that cardiologists who prescribe to non-elders prescribe more than cardiologists with more elders in their patient-composition.

As Medicare Part D is set up to be prescription medicine insurance and is made primarily for the elderly but is also provided to certain individuals with chronic diseases regardless of age. This might be a factor that affects the lagged leave-out mean and per capita cost related to prescribing. As these diseases are chronic, one can assume that medicine is likely needed in given intervals based on the severity of the disease and if it worsens, will lead to higher usage of prescription medicine for a patient to keep their quality of life as high as possible. It is also natural to assume that individuals with chronic diseases can get higher health-benefits if they are prescribed patented drugs that are more effective at treating their respective disease. For elders that do not have chronic heart diseases, like high cholesterol or something similar that medicine can treat, this will likely mean less medicine in the short term compared to an individual that has a chronic and severe disease. So, the composition of individuals that are not elderly, but are eligible beneficiaries in Medicare Part D, is likely the factor that affects the interaction-terms.

# 6 Discussion

The results presented in the previous section show that prescription behavior is affected by interactions with new peers. Expressed in per capita cost, they increase by an additional 0,785$ for every 1$ increase in per capita cost due to spillovers from peers in either the same year when moving, or a year after moving. The spillovers from peers have a larger effect on cardiologists who prescribe as compared to cardiologists who provide services through Medicare Fee-For-Service. Cardiologist-behavior, regardless of them being prescribers or service-providers, seem to have a highly elastic behavior associated with their respective tasks. However, these results cannot necessarily be interpreted as causal. There are some aspects that need to be discussed.

Firstly, we need to consider whether the alternative models can be used confidently as robustness-assessments for the main estimates. This is based on the difference between prescribing-behavior and service-providing behavior, and whether service-providing can be used as a suitable substitution to prescribing behavior. In many regards they are similar, as spillovers likely affect which type of service a cardiologist chooses. However, prescribing is unique in one aspect: for every ailment and treatment chosen, a cardiologist has different prescription drugs to choose from, for the same treatment. They can prescribe either general drugs, or branded drugs, based on the healing-profile that is needed for a given beneficiary's treatment. A cardiologist who provides services likely does not have as many options for a given illness as compared to a doctor prescribing medicine for the same need. Spillovers will likely affect service-providers and prescribers differently due to the differences between the two tasks. Prescribers will likely be affected by knowledge-spillovers that increase their preference for given drugs, and since pc-cost increases, this is likely branded drugs. As service-providers likely have less options for the same illnesses, they will likely increase other complementary services to aid patients or increase their propensity to provide services. With these differences in mind, service-providers can likely be used as a substitute-sample to test the robustness of the main model, as they have the same specialization, the same method of identifying spillovers is used and these methods provide similar results in estimations. The differences in estimates are likely due to the computational difficulties when using zip-codes, zip-codes as a control-variable being too narrow which leads to less spillover-effect identified across cities, and partly natural differences between the two tasks. When considering both the estimates reported in table 5.2.1 where the method excludes NPI FE, and the estimates reported in table 5.2.2 where the method of estimation is as similar as possible to the main method, it is reasonable to assume that service-providing cardiologists can be used as a substitute-sample for prescribing cardiologists. This notion is reinforced by both samples not being representative of a cardiologists' entire practice and the similarities between the two samples.

Secondly, the nature of change in prescription behavior has not been untangled. Both the main estimates and alternative models find estimates that support the notion that prescription behavior is affected by spillovers from peers in local networks. These peer effects are highlighted using migrant cardiologists, as this is the only changed variable, from the fixed effects in the model. These changes in prescription behavior are reflected in the increase in pc-cost for migrant cardiologists following a move. The channel that influences these peer effects, that in turn affects the migrant cardiologist, is not controlled for in the analysis. Spillovers likely stem from knowledge-spillovers from the local network to the migrant, so that they increase prescribing of certain types of drugs. Since the change in prescription-behavior is shown in the analysis as increasing, this likely means that cardiologists who are affected by spillovers from peers, start prescribing more patented drugs than general drugs. This is not necessarily a positive or a negative increase in prescribing-behavior if the factors that drive this change is not highlighted. If the change in prescription-behavior happens on the condition that the cardiologist increase their knowledge on a patented drug's health-profile and start prescribing it to certain patients that could benefit from the more expensive drug, then it could be seen as a beneficial change in prescribing behavior. The increase could be seen as negative if the cardiologist start preferring a patented drug and prescribe it more, regardless of a patient's ailment and treatment-need. Prescribing patented drugs to patients who could get the same treatment much cheaper, increases health expenditures for both patients and the U.S. This would be considered a negative effect of peer effects. The analysis lacks the data and controls to identify the composition of change in prescription-behavior among cardiologists, which is not the aim of the analysis, but is still a flaw worth mentioning.

Thirdly, a cardiologists' change in prescribing-behavior could seem to identify spillovers from local networks when it could stem from a change in patient composition. The FE in the model should control for all time-invariant effects that affect prescribing behavior for individuals, cities, and years. This type of patient composition might not be controlled for by the FEs, as the difference in patient composition can occur within the variable with no way to control for it. The patient composition for every prescriber in Medicare Part D can be divided into two groups: elders and non-elders with chronic diseases. This could be a major flaw in the data that could influence the estimates. A cardiologist with an older elder share than another cardiologist is likely prescribing more expensive drugs, as older beneficiaries are prone to more severe ailments as compared to beneficiaries who are younger, but over 65. In the case that a cardiologist migrates, and the elder share is almost the same, but they prescribe to 20 percent more 90-year-olds, then this will not be identified in the data as beneficiary-age groups are not present. If this happens for a significant number of migrants, then the estimates may overstate the magnitude of spillover-effect from peers. The same reasoning can be applied to beneficiaries who are eligible due to a chronic disease. Estimates may be overstated if they see more beneficiaries with more severe chronic diseases in the new city, this rise in pc-cost due to more frequent prescribing and prescribing of more expensive drugs may be attributed to spillovers whereas it is due to patient unobserved patient composition. While this may be the case for certain cardiologists, it would be unlikely that every cardiologist that does migrate to a new city are subject to a patient composition in the exact way as described above. These patient compositions that migrants “move into” are likely distributed evenly, with some moving to cities where patient composition is almost the same, and some where patient composition is healthier. This could lead estimates to be overstated if the patient composition is less healthy for a significant number of cardiologists who is “treated” in the model. Estimates could also become understated if the opposite situation, to the one described above, arise. If a cardiologist “move into” a patient composition of a similar elder-share with 20 percent less 90-year-olds, then the change in prescribing behavior could be affected by them prescribing less patented drugs. It is more likely that both peer-effects and patient composition could influence estimated spillovers from peer effects, which could make estimates over- or understated depending on how much patient composition affects prescribing behavior. In addition, estimates could likely be over- or underestimated based on which of the two situations arise for most migrants. This problem would be solved if age-groups were more differentiated.

Fourth, longitude of data. A problem that could limit the interpretation of the estimates is the time-period of the data. The period this analysis is performed on is from 2013-2018 which is short term, which leads some of the estimates to not capture the full extent of peer effects for certain migrants. Migrants are identified in every year in the entire dataset, which means that some migrants will be identified in the later years in the data. Migrants that move from year 2017-2018 will not be marked as migrants until the city has changed in 2018. This means that the years outside the dataset for these migrants are not part of the estimated spillover-effects captured in the models. If this occurs for a significant number of treated cardiologists, this may lead to an overstatement or understatement of spillover-effects, as spillover-effects likely influence prescription-behavior over time. The treated cardiologists who are registered as movers in 2018 will not be part of the lagged-leave-out city-mean, as it estimates the effect of spillovers a year after migration. If these effects are stronger a year after, these estimates will be excluded from the model due to the short-term data, which would lead to understatements of estimates for some cardiologists. If the spillovers from peer-effects diminish in the long-term, or even in the short-term but outside the time-period within the data, this could lead to an overstatement of the results. If the data had been long-term, over 15-20 years for example, it would be easier to establish for how long spillovers affect prescribing and if they are persistent over time or if they diminish when cardiologists have fully adapted to local networks.

Fifth, selection bias and the reflection problem. The reflection problem is a frequent problem that could arise when attempting to identify peer effects (Calvó-Armengol et al., 2009, p. 1250; Sacerdote, 2011, p. 256). The reflection problem may affect the identified spillovers if individual $i's$ prescribing behavior influences their peers' mean prescribing behavior, and the peers' mean prescribing behavior can affect the individual cardiologist's prescribing behavior. A peer effect from an individual cardiologist would therefore be reflected, but multiplied, which leads to overstated estimates. Calvó-Armengol et al. (2009) solved this issue by allowing individuals to be part of more than one group at a time. My models limit local networks to take the form of a city or zip-code, where an individual can only be part of one local network at a time. This is a situation where the reflection problem could provide upward bias in the estimations if not controlled for. However, my method utilizes a variable that solves the reflection problem. The reflection problem is dealt with in the model by using leave-out-means that omits an individual cardiologist's own prescription behavior from the city-means, this eliminates the reflection problem (Molitor, 2018, p. 334).

Selection bias can affect the estimates when individual cardiologists sort into cities based on unobserved factors (Sacerdote, 2011, p.256-257). Selective sorting could arise if a cardiologist migrates to a city due to a prominent cardiologist operating in this area, or if cardiologists in a certain city is known for certain attributes or specialties. Individuals frequently sort into groups with similar individuals, which could lead to upward bias in the estimates (Sacerdote, 2011, p. 256). If selection bias was affecting the prescribing behavior of cardiologists, then it would be reflected in overstated spillovers among peers. Selection bias can be managed with the use of FE in environments where peer effects exist to account for selective sorting (Sacerdote, 2011, p. 257). The main estimates include NPI FE and city FE, which are both entities where selection bias can arise. It is therefore highly unlikely that selective sorting affects the estimates and their interpretation, which leads me to assume that selection bias is controlled for.

Results provide evidence that spillovers from peers in local networks change a cardiologists' prescribing-behavior. Prescribing-behavior change both in the year they move and in the year after moving, but the discussion above make it difficult to identify the results as causal. Different factors could influence the estimations, which could lead to either overstating or understating the coefficients of the estimates. These factors do not make the results insignificant though, and prescription behavior is likely affected by a higher preference for branded drugs due to knowledge spillovers from peers. This is shown in the increase in pc cost for cardiologists who are affected by spillovers. The change in prescription behavior cannot be attributed to positive or negative factors, as I am unable to untangle the intent behind the prescribing behavior with the data and models I have chosen.

# 7 Conclusion

In this thesis, I have studied how doctors react to local network effects. To identify spillovers from local peer networks, I use cardiologist prescribing behavior in Medicare Part D prescription coverage and analyze how cardiologists are affected by spillovers from local networks of peers in the U.S. The study is based on publicly available data provided by Centers for Medicare & Medicaid Services on costs and amounts prescribed by cardiologists in the time-period 2013-2018. The data provide information on place of practice, type of drug, beneficiary age-group and more. When combined, these variables represent prescribing behavior for individual cardiologists that prescribe for Medicare Part D. Spillovers are identified by using a fixed-effects model for panel data and identifying cardiologists who move to a new city and interact with new peers. After I control for individual, city, and year fixed effects, the only change a migrant is exposed to is new interactions with new local peer networks. The spillovers are estimated by difference from the mean the same year following a move, and a year after a move.

The results indicate that cardiologist prescribing behavior increased due to spillovers from their peers. An increase in pc-cost of 1$ for the average cardiologist affected by spillovers from their peers, the year they migrate, induce an additional increase in pc-cost of 0.785$ due to spillovers. An increase in pc-cost of 1$ for the average cardiologist affected by spillovers from new peers a year after migrating, induce an additional increase in pc-cost of 0.788$ due to spillovers. The results are supported by a robustness analysis that assess their validity, where a substitute-sample of service-providing cardiologists are utilized, and specification checks in the main model are introduced. The robustness analysis provides similar results which provide credibility regarding the direction of change in my main findings. There is likely no underlying shocks or confounders affecting the results, as individual, city and year fixed effects are controlled for, in addition to migrants being differentiated in their origin-region. Even with the fixed effects and robustness analysis providing credibility to my main findings, the results are still subject to uncertainty due to data and model limitations. The results are therefore not seen as causal, but rather show which direction peer effects change prescribing behavior.

The change in prescribing behavior likely stem from knowledge spillovers from peers that increase preference for certain, more expensive, patented prescription medicine. The change in preference for patented medicine can be seen in the same sense as related literature on technology diffusion through peer networks. Peer effects lead to knowledge spillovers, that increase a cardiologists' knowledge about the benefits of newer heart medicine, which induce them to provide these more frequently as compared to before the migration. There are likely two factors that affect whether the change in prescribing behavior can be seen as positive or negative for beneficiaries or the public health care system. If the preference for patented medicine increases regardless of the treatment a beneficiary needs, then some beneficiaries receive more expensive drugs with no increase in health benefit. This would be negative both for the public health sector and beneficiary, as cheaper general alternatives could exist and could provide similar benefits at a greatly reduced cost. The other possibility is that the preference for patented medicine increase prescribing behavior for cardiologists when they provide to beneficiaries that could benefit from patented medicine with a better health profile. If this occurred, beneficiaries would get medicine better suited to their needs, but at a higher price. Then, the change in prescribing behavior towards patented medicine would not necessarily induce wasteful usage of public and beneficiary funds. The results can not differentiate between the source of the change.

For future research, I suggest using prescribing behavior data, like Medicare Part D, with a more longitudinal timeline to analyze how elastic the change in prescribing behavior due to peer effects are. In addition, it would be interesting and beneficial to find out if increases in prescribing behavior due to spillovers from peers is due to negative or positive factors. If the increase were due to negative factors, it could be beneficial for beneficiaries and the public health care systems to develop policies that could increase efficient use of public funds. It would also be interesting to analyze whether these spillovers arise naturally or due to other factors, like prominent physicians or industry-payments. A final suggestion would be to test for different specializations in the field of medicine and analyze whether long-distance migrants are more affected by spillovers than short-distance migrants.

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# 9 Appendix

Table 5.2.1: First robustness assessment of main estimates. Medicare Fee-For-Service cardiologist sample used as substitute for Medicare Part D sample used in main estimates. Column (1) and (4) correspond to equation (4) through (5) in the alternative model formalized in section 5. Column (2) and (5) correspond to equation (6) and (7) in the alternative model. Column (3) and (6) correspond to equation (8) and (9) in alternative model. NPI FE excluded for all estimates due to computational difficulties. Individual characteristics included for each pair of leave-out-mean and lagged-leave-out-mean. Estimates identify spillovers' effect on per capita cost for service-providing cardiologists, who are interacting with a new local network in either a city or a zip-code. SE are clustered at city- or zip-code level based on the mean used in independent variable.

| Table 5.2.1 | (1) PC-Cost | (2) PC-Cost | (3) PC-Cost | (4) PC-Cost | (5) PC-Cost | (6) PC-Cost |
|---|---|---|---|---|---|---|
| Leave-Out City-Mean | 0.989*** | | | | | |
| | (0.00140) | | | | | |
| Leave-Out Zip-Mean | | 0.620*** | 0.526*** | | | |
| | | (0.0278) | (0.0317) | | | |
| Lagged-Leave-Out City-Mean | | | | 0.991*** | | |
| | | | | (0.00213) | | |
| Lagged-Leave-Out Zip-Mean | | | | | 0.610*** | 0.515*** |
| | | | | | (0.0290) | (0.0327) |
| *N* | 2835929 | 2835909 | 2835909 | 2824996 | 2798570 | 2798570 |
| $R^2$ | 0.024 | 0.401 | 0.408 | 0.024 | 0.401 | 0.407 |
| adj. $R^2$ | 0.023 | 0.398 | 0.405 | 0.023 | 0.398 | 0.404 |
| CITY FE | YES | NO | NO | YES | NO | NO |
| ZIP FE | NO | YES | YES | NO | YES | YES |
| HCPCS FE | NO | YES | YES | NO | YES | YES |
| YEAR FE | YES | YES | YES | YES | YES | YES |
| CLUSTER SE | CITY | ZIP | ZIP | CITY | ZIP | ZIP |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Table 5.2.2: Second robustness assessment of main estimates. The model mimics the main estimation-method, but Medicare Fee-For-Service cardiologist-sample is used as substitute for Medicare Part D cardiologist-sample. NPI FE, city FE, and year FE are included. Estimates identify spillovers' effect on per capita cost for service-providing cardiologists, who are interacting with a new local network in a city. SE are clustered at city-level.

| Table 5.2.2 | (1) PC-Cost | (2) PC-Cost |
|---|---|---|
| Leave-Out City-Mean | 0.692*** | |
| | (0.0872) | |
| Lagged-Leave-Out City-Mean | | 0.631*** |
| | | (0.0766) |
| *N* | 169638 | 159499 |
| NPI FE | YES | YES |
| YEAR FE | YES | YES |
| CITY FE | YES | YES |
| CLUSTER SE | CITY | CITY |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.2.3: Third robustness assessment of main estimates. The estimates are gathered by changing from difference from the mean to first differences, shown in equation (10) in the alternative models formalized in section 5. Estimates use the Medicare Part D cardiologist sample. NPI FE are excluded due to computational difficulties, city and year FE are included. Estimates identify spillovers' effect on per capita cost for prescribing cardiologists, who are interacting with a new local network in a city. SE are clustered at city-level.

| Table 5.2.3 | (1) FD Mean PC-cost | (2) Mean PC-cost |
|---|---|---|
| FD Leave-Out City-Mean | 0.746*** | |
| | (0.0530) | |
| Lagged-Leave-Out City-Mean | | 0.781*** |
| | | (0.0561) |
| Indicator FD | | 0.434 |
| | | (2.926) |
| *N* | 85186 | 101694 |
| NPI FE | NO | NO |
| CITY FE | YES | YES |
| YEAR FE | YES | YES |
| CLUSTER SE | CITY | CITY |

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5.3.2: Interaction-term with the main estimates. The fourth and final estimates show an interaction-term between the lagged-leave-out city-mean and a dummy that holds cardiologists with high and low shares of elders in their patient composition. Elder-Share Dummy = 1 – share of elders greater than or equal to the median elder-share. Elder-Share Dummy = 0 – share of elders lower than the median elder share. Interaction-terms reports a negative, but not statistically significant, correlation between high shares of elders and per capita cost. The opposite is reported for low elder shares, a positive but not statistically significant correlation.

| Table 5.3.2 | (1)<br>Mean PC-Cost |
|---|---|
| Lagged-Leave-Out City-Mean | 0.796$^{***}$ |
| | (13.33) |
| Elder-Share Dummy = 1 | 2.987 |
| | (1.26) |
| Interaction: Lagged-Leave-Out City-Mean and Elder-Share Dummy = 1 | -0.00867 |
| | (-1.56) |
| *N* | 101661 |

*t* statistics in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

# 10 List of Figures

# 11 List of Tables