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Competition and Physician Turnover: Evidence from Swedish Primary Care Units

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ABSTRACT

The Swedish government has over the years implemented several reforms to improve health care system and ensure continuity of care. One of the reforms, The Act on Free Choice, was implemented between 2007 and 2010 providing patients a free choice to choose a provider and private providers to freely enter the market; thereby, increasing the competition among providers. This paper contributes to the limited body of literature on competition and continuity of care by exploring the effect of increased competition on physician turnover in Swedish primary care units in following regions, Stockholm, Västra Götaland and Skåne, using a staggered difference-in-difference strategy applied with Two-Way Fixed Effects and stacked regression models. This paper also provides a survival analysis to explore the tenure of primary care physicians and which types of primary care units accounts for the physician turnover using the Cox Proportional Hazard and Kaplan-Meier models. Although the effect of increased competition on physician turnover, on an aggregated level across all regions, is modest, we observe significant effect on a regional basis where the regions respond differently to distances. Results from our survival analysis reveal several factors related to physicians and primary care units that influence physician turnover. Notably, younger physicians graduating from a Swedish medical school account for higher turnover. Moreover, primary care units employing eight or more physicians, and having a lower average age among physicians account for lower physician turnover.

Contents

1 Introduction

The ongoing relationship between a physician and a patient has proven to be a critical factor in the patient's health outcomes and the quality of care provided (Chanfreau-Coffinier et al., 2019; Rodriguez et al., 2007; Rodriguez et al., 2010; Rosenblatt et al., 2000; Starfield, 1994). Continuity of care is regarded as a fundamental component in primary care which can be expressed in terms of accessibility, longevity and quality (Haggerty et al., 2003; Myndigheten För Vård- och Omsorgsanalys, 2020).

The Swedish government has introduced several reforms to improve the health care system and ensure continuity of care. One of the notable reforms is the Act on Free Choice Systems which was implemented in various regions in Sweden between 2007 to 2010 (Swedish Code of Statues, 2008). The reform provided patients a free choice to select a provider, while also allowing private providers unhindered market entry (Dackehag & Ellegård, 2019; Dietrichson et al., 2020). The free entry mechanism led to increased competition among primary care providers. This gives us an opportunity to examine if the increased competition altered continuity in primary care. We define exposure to competition as the scenario in which a new Primary Care Unit (PCU) opens within a specified distance (measured in kilometers) from an existing PCU.

Although, we witnessed an increase in competition, the targets set by the Swedish government, along with the municipalities and regions, remained unmet. It was set in the target that 55% of the Swedish population should have a assigned physician in their PCUs by the end of 2022. This goal was fulfilled according to the primary care managers, but it remained unfulfilled from a patients' perspective as merely 30% of the population has a assigned physician in their PCUs(Myndigheten För Vård- och Omsorgsanalys, 2020).

There is a pressing need to strengthen this relationship and it is crucial to comprehend the factors influencing continuity in primary care. We define the disruption in continuity of care occurs when a physician relocates to a new PCU or ceases to practice. We, therefore, leverage the reform that increased the supply of PCUs as a treatment effect for identifying the change in physician turnover. The reform was implemented in 2008 in Stockholm whereas it was implemented in 2009 in Västra Götaland and Skåne (Swedish Competition Authority, 2012). We are, therefore, interested in studying the following question:

Research Question 1: *What is the effect of increased exposure to competition on physician turnover in Swedish primary care units in following regions: Stockholm, Västra Götaland and Skåne.*

We are, further, interested in identifying the specific types of PCUs that maintain a

low staff turnover and determining the characteristics of physicians that are more likely to contribute to turnover. To this end, we utilize a survival analysis via the Cox Proportional Hazard (PH) model and the Kaplan-Meier model, which allows us to observe and compare various factors that influence the risk of physician turnover at any given point. Therefore, our second research question is as follows:

Research Question 2: *What characteristics of a PCU or a physician increase the likelihood of physician turnover?*

We examine the effect of competition only after the reform was implemented in respective regions. Since each PCU became a subject of competition during different times, we use staggered difference-in-difference (DiD) design with variations in timing of treatment, also known as event study. We study the staggered DiD setting by utilizing the Two-Way Fixed Effects (TWFE) DiD model with staggered treatment adoption. TWFE is commonly used to obtain the staggered DiD estimates having multiple units being treated at different times with group and time fixed effects. However, recent findings suggest that these estimates are potentially biased in the presence of heterogeneous treatment effects in a DiD setting with staggered treatment timing (Athey & Imbens, 2022; Borusyak et al., 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). This issue arises due to "forbidden comparisons" which occur when a treated group is used as a control group for a group that is not yet treated (Goodman-Bacon, 2021). This leads us to use alternative approaches, the stacked DiD in our case, to account for this bias.

Our results show that, on an aggregate level spanning all regions, the effect of increased competition on physician turnover is modest. However, we observe significant effect on a regional basis, with different regions responding differently to distances. Results from our survival analysis reveal various factors related to physicians and primary care units (PCUs) that predict physician turnover. For instance, young physicians graduating from a Swedish medical school account for higher turnover. Further, PCUs employing 8 or more physicians and having lower average age among physicians in account for lower physician turnover.

To our knowledge, this has not been observed in Sweden yet. Most prior research is focused on investigating the effect of physician turnover on patient outcomes. However, little is known about the factors that disrupt continuity of care. Our contribution lies in our examination of the reform's effects on maintaining continuity within the Swedish context, an aspect highlighted by Fredriksson and Isaksson (2022). Additionally, we provide a descriptive analysis of physicians working in Swedish PCUs to improve the understanding of this scenario.

The remaining part of the paper proceeds as follows: section 2 provides an overview of the relevant literature related to our topic; section 3 delves into theoretical perspectives,

shedding light on the implications and underlying factors of competition within our context; section 4 presents our data and variables; section 5 articulates our research methodologies; section 6 highlights the limitations in our data; section 7 presents our results followed by a discussion in section 8; finally, we conclude our study in section 9.

2 Literature Review

The existing literature on continuity of care is extensive and focuses particularly on the implications of continuity of care. However, not much is studied about the factors contributing to it. In this section, we delve into research spanning both of these areas. Moreover, we study papers that use the same identification strategy as our study, the effect of increased competition due to reform. Lastly, we explore the literature on the implications of the reform on continuity of care in Sweden.

Empirical evidence shows that continuity of care has a positive effect on quality of care (Chanfreau-Coffinier et al., 2019; Rodriguez et al., 2007; Rodriguez et al., 2010), patient outcomes (Rosenblatt et al., 2000; Starfield, 1994) and health care costs including medical- and hospital services, and drugs (De Maeseneer et al., 2003; Hollander et al., 2009). Continuity of care also results in reduced number of visits to the emergency department, urgent care centers and hospitalizations (Barker et al., 2017; Ionescu-Ittu et al., 2007; Pourat et al., 2015; Rosenblatt et al., 2000; Sabety et al., 2021). Further, discontinuity of care results in lower rates of childhood immunization, cholesterol screening, cervical cancer screening and well-child visits (Plomondon et al., 2007). These studies underscore the significance of continuity of care, emphasizing the benefits that arise from a stable, ongoing relationship between a physician and the patient.

Within the literature on continuity of care, however, we are interested in the strand of literature that can explain the contributing factors disrupting the continuous relationship between physicians and patients in different health care settings. For effective policymaking, it is essential to identify the characteristics of physicians and healthcare centers that achieve greater continuity of care. A recent study by Bond et al. (2023) examine the physician turnover and the characteristics of physicians and health care centers that can explain physicians' turnover in the United States. The authors find that younger physicians are more likely to relocate from one practice to another compared to older physicians, whereas older physicians are more likely to leave and stop practicing compared to younger physicians. Even though older physicians are more likely to stop practicing, Kristjansson et al. (2013) find that patients experience higher continuity with older physicians. Further, Bond et al. (2023) find that physicians living in rural areas and female physicians are more likely to move than those living in urban areas and male physicians, respectively. By observing continuity across physician specialty, Bond et al. (2023) find that primary care physicians had the second highest annual rate of leaving (3.2%) and third highest rate of moving (4%).

While Bond et al. (2023) use Medicare billing[1] to identify physician turnover and whether they "leave" the practice or "move" from one practice to another in the United States, Kristjansson et al. (2013) define continuity of care based on relational continuity[2] where data was collected via patient, practice, and physician surveys in Ontario, Canada. This study observes practice, physician and patient characteristics to explain continuity of care. Results suggest that older patients and patients with more chronic diseases report higher levels of continuity compared to patients who are young and have less chronic diseases, respectively. Further, patients that experience more days of poor mental health per month, work full time, possess high school or higher education, have no regular provider and are registered in practices in rural areas exhibit lower level of continuity. Moreover, results based on practice characteristics show that practices that are closed on the weekends, have fewer number of nurses and have a smaller practice reports higher levels of continuity. Kristjansson et al. (2013) suggest that the latter may occur due to a covering effect where in larger practices, physicians are able to rely on other physicians to cover for them if needed.

The time of entry into a profession plays a pivotal role in explaining physician turnover. While many of the studies primarily base their analysis on surveys and cross-sectional designs, Singer et al. (1998) employs survival analysis. The study observes the tenure of primary care physicians in community and Migrant health Centers focusing on the tenure's correlation with physician characteristics. Results show that the risk of physicians leaving a practice is higher for those who are older at the time of employment and for full-time workers compared to their part-time counterparts. Further, health care centers with moderate productivity level (4,401 and 4,800 visits per physician per year) account for higher physician turnover than centers with lower or higher productivity level. This shows that lower or higher number of visits per physician per year than the moderate level increase the risk of physicians' turnover. The study also shows that the physicians turnover is higher when the physician marks another year of employment. The authors say that this effect may occur due to contractual agreements between employers and employees. Together these studies provide important insights into the description of which type of physicians or PCU contribute to continuity as we also aim to study.

The literature on competition in primary care is limited and at present, no previous research has investigated the effect of increased exposure to competition, due to The Act on Free Choice Systems, on physician turnover in PCUs in Sweden. However, there is a small body of literature using the same identification strategy as our paper with Swedish data (Dackehag & Ellegård, 2019; Dietrichson et al., 2020; Fogelberg, 2013).

[1]Medicare billing is the the process where healthcare providers submit claims to Medicare (the U.S. government health insurance program) in order to receive reimbursement for medical services provided to patients.

[2]Relational continuity refers to the ongoing beneficial relationship between a patient and its provider over time which is based on longevity and trust.

Dackehag and Ellegård (2019) examine the effect of increased exposure to competition on the number of registered diagnoses per visit for patients visiting primary care centers in Skåne, Sweden. They suggest that the increased competition from private providers has an impact on public primary care physicians. Specifically, patients registered in PCUs in areas exposed to higher levels of competition tend to receive more diagnoses compared to those in other regions. Dietrichson et al. (2020), on the other hand, find that increased competition has a minor positive impact on overall patient satisfaction but no effect on avoidable hospitalization rates or patient satisfaction with access to care. Fogelberg (2013) finds that the number of prescriptions of antibiotics increases as a result of increased competition.

A systematic review by Fredriksson and Isaksson (2022) comprises of all papers published regarding the Act of Free Coice in Sweden within the first 15 years of the reform's implementation. The findings reveal that, while the reform has enhanced the accessibility of PCUs, the benefits are not distributed uniformly across geographical and socioeconomic lines. This disparity stems from the fact that regions can no longer dictate the location of these new PCUs. With a free entry mechanism, privately owned PCUs have incentives to establish their practices where the competition is higher. Further, the implications of the reform on the quality of care remains ambiguous. One of the objectives of the reform was to enhance the quality of care; however, the objective remains unfulfilled. With free entry and free choice for patients to choose among providers, patients would now choose the provider with the highest quality and best access. However, this requires transparency in information on different quality measures of PCUs so that informed patients can choose a PCU with the highest quality. The lack of transparency and accessibility of information of relevant quality measures is an important function of the reform that is still not properly functioning. The study also emphasize the lack of knowledge regarding the impact of reform on cost, efficiency and continuity of care.

Since increased competition among PCUs stems from the reform, our paper complements studies that explore the impact of the reform on continuity of care.

3 Institutional Background

There are three tiers of governance in Sweden: national, regional, and local. The country is divided into 21 regions which have the responsibility to provide health care services to its residents. The regions are also responsible to set directives for all municipalities concerning health care operations and oversee the administration of healthcare budget (OECD, 2013).

The Swedish government has implemented several reforms to improve the Swedish healthcare system in terms of the long-term care. However, there is a pressing need for an improved information system that can provide transparency within the healthcare system to its citizens. This is essential since reforms, such as the Act on Free Choice, facilitate free patient choice and unhindered entry for private providers, thereby causing increased competition among providers (OECD, 2013). As previously highlighted, given the freedom to select providers, patients will choose those with the highest quality and best access. However, this implicitly assumes that the patients have access to necessary quality measures and information on PCUs to make informed decisions. One implication of this reform is that as patients are now the new driving force behind increased competition among providers, PCUs that offers higher quality will expand their operations, whereas PCUs that offer lower quality will either improve their service or exit the market (Fredriksson & Isaksson, 2022; OECD, 2013). For the reform to serve its purpose, transparency is indispensable which is, however, lacking according to Fredriksson and Isaksson (2022) and OECD (2013).

The mechanism by which a PCU exits a market is contingent on the availability of alternative PCUs for patients because units with lower quality exit only if patients move towards PCUs with better quality and access. The mechanism, however, do not function to the same extent in rural areas as in urban areas which have more alternatives and heightened competition. Therefore, patients are more likely to switch among PCUs in areas with higher competition. Similarly, units have higher incentives to operate in areas with higher competition.

Fredriksson and Isaksson (2022) suggest that proximity to a PCU is one of the most important factors in selection of a PCU by a patient. Considering the importance of proximity, coupled with the dearth of information available to patients, we believe that distance plays a pivotal role in a patients decision regarding PCU selection. Therefore, we estimate the effect of increased exposure to competition on physician turnover. Exposure to competition occurs when a new PCU opens within a 3, 5, 10 or 15 kilometer radius of an existing PCU at any given time. Our main analysis is based on 10 kilometer distance. We use 3, 5 and 15 kilometer as robustness check.

To the best of our knowledge, no previous study has examined this. Therefore, we do not have any reference point in terms of distances. Dackehag and Ellegård (2019) use 3 kilometer distance while estimating the effect of increased competition on the number of registered diagnoses per visit for patients visiting primary care units in Skåne. However, our study observes the physician turnover in region Stockholm, Västra Götaland and Skåne; with Stockholm being the largest region followed by Västra Götaland and Skåne. This demonstrates that we consider larger ranges of distances than those used by Dackehag and Ellegård (2019). Additionally, individuals' willingness to commute to work, in terms of time, is a significant factor to consider. Further, this willingness varies among the regions. For instance, in Stockholm, a 40 to 60-minute commute to work is not uncommon. However, we lack data on physicians' home addresses, so we cannot measure current distance from their homes to their workplace. We take these commuting norms, the importance of proximity, and the areas of the regions into account in determining which distances to consider for our main analysis.

Despite the regional variations in area, we posit that an analysis based on a 10 kilometer distance across all regions capturing some effect on the physician turnover. However, we also perform analysis on regional basis as we expect differences between the regions. We anticipate that the increased competition will have an immediate impact on physician turnover with the effect diminishing after the subsequent 1-2 years. As a result, we expect the initial 1-3 years post-treatment as the most relevant period for our analysis.

4 Data

This section begins by presenting our data on primary care units (PCU) followed by our data on physicians. We conclude by presenting our covariate and our finished dataset used in our analysis.

4.1 Primary Care Units

We use a register obtained from SCB containing information of all PCUs in Sweden between 2005-2017, including geographic coordinates, opening and closing dates and ownership details. This register consists of all PCUs in Sweden; however, we only use data related to Stockholm, Västra Götaland and Skåne due to time limitation. To this data, we add CFAR-number to each PCU by using another dataset obtained from SCB containing registered companies in Sweden, their addresses, CFAR-numbers, and ownership details. We manually match each PCU with their CFAR-number based on information provided in both datasets. A PCU is identified as unique when it has a distinct CFAR-number assigned to it.

4.2 CFAR-number

The CFAR-numbers we allocate to each PCU is an identification number of a workplace which is assigned by SCB. Every company in Sweden has at least one workplace. The difference between company and workplace is that the latter refers to any address, property, or group of properties where the company operates its business. Therefore, if a company operates in multiple addresses, each address will be assigned a unique CFAR-number. Having each PCU with a unique CFAR-number gives us an opportunity to combine this dataset with the dataset on physicians because each physician has a unique CFAR-number assigned to it indicating her workplace for a specific year.

There are instances, however, where we were unable to identify a unique CFAR-number for certain PCUs. To determine whether a CFAR-number belongs to a specific PCU, we rely on the organization number, address, PCU name and SNI-number[3]. However, there are limitation in the dataset from where we attain our CFAR-numbers. Issues like missing values, addresses registered to companies instead of PCUs, or incorrectly specified PCU names can impact our assessment. It was therefore not possible to identify a CFAR-number for all PCUs in our register. Moreover, certain PCUs are located in hospitals, and these might share the same CFAR-number as the hospital. We exclude such PCUs from our analysis because when we merge our physician data based on CFAR-number with the PCU data, having two different units with identical CFAR-numbers would make it impossible to accurately determine where

[3]The Swedish Standard Industrial Classification (SNI) number is a standard measure used to classify companies and workplaces based on the operations performed.

these physicians are employed. Therefore, we would not be able to distinguish the effect of increased competition on physicians' turnover since we cannot accurately capture if the physicians change workplace. Additionally, the number of physicians working in hospitals is far greater than those who working in PCUs, so we expect a higher turnover in hospitals. Further, during our observation period, some PCUs merged with others. These PCUs often belong to the same company and the resultant merged PCU often retained the CFAR-number of the unit that remained open. This situation poses two potential issues: firstly, it is unclear whether physicians continue to work within the same PCU post-merger or if they depart because of the merger. Secondly, the merged PCU has a CFAR-number that previously represented two distinct PCUs. To address these challenges, we exclude the merged PCUs from our dataset if the number of physicians increases disproportionately - specifically, if it nearly doubles - during the merger. While this issue is insignificant in our case, it is important to highlight.

Our inclusion criteria for PCUs in our analysis are that we can assign a unique CFAR-number to each PCU and the number of physicians working in a PCU is reasonable during the whole study period(for ex. some PCU has information on their staff online). Further, a PCU should be open for more than one year. PCUs that have been operating several years should not be closed for one random year in the middle of their operating period. In addition, PCUs should not be located inside hospital, and lastly, each PCU should be registered at the right address. We exclude PCUs that do not meet these criteria since the potential issues that may arise from violating these criteria might affect the analysis.

Based on the criteria set forth, we exclude a PCU that was only open for one year during our observed time. We further find PCUs that are operational throughout the whole period but are closed irregularly for one year and then opens again in our data. Due to time limitation, we cannot investigate to differentiate between actual closures of PCUs for a year from measurement error. Therefore, we exclude them. We also find PCUs that randomly closes for two different years, but we keep them. We can observe several different patterns in our data where PCU are randomly closed, so we set our threshold at two years. However, if the reason for these randomly occurring closures are due to measurement errors, this might bias our estimates since it affects the physician turnover. Further, we exclude PCUs that have unreasonably high number of physicians working for the whole period or a segment of the period under study. This can occur when a CFAR-number is shared with another health care unit or when a PCU hires temporary physicians to address short-staffing issues. We already exclude PCUs that we cannot distinguish from hospitals. We do see that a lot of physicians in these PCUs that have unreasonably high number of physicians only work for one year, but it is still not reasonable to exclude these PCUs because there are instances

where we could not distinguish if two health care units share the same CFAR-number or if the physicians are only temporarily employed to address the short-staffing issue. If we had monthly data, it would have been easier to see employment trends and take this effect into account. Although, we have information about the three main number sources of income and would be able to make assumptions on full-time and part-time employers, due to time limitation, we exclude these PCUs. There are still PCUs left with unreasonable high numbers of physicians. However, we exclude few PCUs compared to what we consider as high numbers of physicians working in a unit. We base our judgement on the average number of physicians in our whole dataset and certain PCUs share the information about the number of physicians' online. Additionally, since our definition of physicians includes assistant physicians, interns and residents, we have to consider higher numbers of physicians employed. Lastly, some PCUs are registered at wrong addresses or lack coordinates in our data. For such PCUs, we manually obtain the coordinates of those we could identify and drop the ones we could not ascertain.

Table 1 Descriptive statistics for primary care units

Variables	Obs	Mean	St.d	Min	Max
Phys count	6,520	7.855	5.427	1	47
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	415	1	0	1	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
PCU size					
Size <8	6,520	0.551	0.497	0	1
Size >7	6,520	0.449	0.497	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1

Table 1 presents summary statistics for the primary care units (PCU) in our dataset which comprises of 8.190 observations, representing 546 unique PCUs that have been operating at any given point between 2005 and 2019 in the regions of Stockholm, Västra Götaland, and Skåne. *Phys count* represents the number of physicians working in a respective PCU each year. From table 1 we recognize that each PCU across all three regions has, on average, 8 physicians employed, whereas the highest number of physicians employed in a PCU is 47. *Open* represents the number of years each PCU

stays open during our study period. We observe that a PCU, on average, stays open for approximately 12 years. *Event cum. no* represents the total number of exposure to competition for each PCU each year, irregardless of whether the region has implemented the reform or not. This counts the number of times each PCU has been exposed to competition across all years. The measure of exposure to competition is determined by whether a new PCU opens within a 10-kilometer radius. This criterion applies to the subsequent variables as well. We note that, on average, a PCU faces competition approximately 11 times throughout our study period. Additionally, there are a few PCUs that are exposed to competition more times than others. For instance, we notice that one of the PCUs is exposed to competition for 55 times. These PCU are most likely located in urban areas. *Event cum.* represents the total number of exposure to competition for each PCU across all years, with respect to the reform being implemented in year 2008. We see that a PCU is on average exposed to competition approximately 10 times between year 2008 to 2019. *Event first* represents the initial time a PCU is exposed to competition after the reform is implemented in a respective region. We use this variable to assign a PCU into the treament group if a new PCU has been opened within the range of 10 kilometers at any point of time. This variable only accounts for the initial exposure and can be used to count the number of treated and untreated PCUs. We see that out of 546 PCUs in our sample, 415 PCUs are exposed to competition any time after the reform was implemented. *Urban* represents the number of PCUs located in urban[4] areas. We observe that the majority of PCUs are located in urban areas. *PCU size* represents the number of PCUs that have 8 or more than 8 physicians employed. We find that the distribution of small and large PCUs does not significantly differ across regions. *Region* represents the number of PCUs located in either region Stockholm, Västra Götaland or Skåne. We notice that the majority of PCUs are located in region Stockholm, whereas Skåne has the least number of PCUs. Lastly, *treatment* represents the number of PCUs that are exposed to competition. A table detailing descriptive statistics on PCUs for each year between 2005 to 2019 can be found in the appendix A.7.

4.3 Physicians

We use data from "The Longitudinal Integrated Database for Health Insurance and Labor Market Research". also known as LISA-database, which is provided by SCB. This database contains information on all individuals from the age of 15 onwards who where registered in Sweden on 31st December in the respective year over our study period (2005 to 2019). This database contains variables such as age, income, level of education and CFAR-number for each individual. We merge this dataset with our PCU register using the CFAR-number to assign all individuals employed at the respective PCUs over the years. This process results in an unbalanced panel data spanning from 2005 to 2019. Instead of

[4]We classify urban areas as municipalities belonging to either group A and B in Sveriges Kommuner och Regioner (2023)

relying on the opening and closing dates provided in the PCU register, we determine the operational status of a PCU by the presence or absence of working physicians. We find this method to be more reliable.

We classify an individual as a physician if they are designated as an assistant physician, intern, resident, or physician, encompassing all specialization, during our study period. However, some individuals' designations fluctuate over time. For such instances, we assume that an individual is a physician if he/she has ever been identified as one. While this approach is practical, our definition of physician is not foolproof. Consequently, our definition of physician can influence our estimates. We utilize the standard measure of occupational classification[5] to identify our physicians. However, the classification of occupation changed in 2014. Before 2014, assistant physicians, interns, residents, and physicians, across all specialties, were grouped under a single occupation category: physicians. In our analysis, we do not distinguish between assistant physicians, interns, residents, and physicians; rather we collectively refer to all of them as 'physicians' throughout our observation period. We cannot distinguish these since the classification of occupation changed during our studied time period, which limit our study and might cause bias.

Potential challenges arise by not distinguishing these roles, particularly due to the inherent transitional nature of certain positions. For instance, medical students who finish their 9th semester in Sweden can be employed as an assistant physician. They might work during their summer vacation before graduating or for shorter durations before being offered an internship position. Moreover, an assistant physician eventually becomes an intern with an internship lasting for 18 months in Sweden. Post-internship, the intern might opt for speicialization: a residency training that can last approximately 5 years or longer, depending on the area of the specialization. It is not only the duration of these temporary occupations that may affect the physician turnover but also the location of the internship and residency. The vacancies for internship and residencies are scarce and an individual might accept a vacancy in a healthcare center considering it as a stepping stone in its career. They might accept the vacancy due to high competition but not based on where they want to stay afterwards. This implies that we can expect a change in our physician turnover at intervals like 1, 2 or 5 years, reflecting the completion of these transitional roles.

Table 2 presents summary statistics for physicians in our dataset which comprises of 51.201 observations, representing 10.259 unique physicians who have worked in the regions of Stockholm, Västra Götaland, and Skåne between 2005 and 2019 . *Age* represents the age of all physicians in our sample. The range spans from 19 to 82 years of age, with the average age of physicians in our data being approximately 48 years. In Sweden, the

[5]Swedish Standard Classification of occupations(SSYK) based on four digits

Table 2 Descriptive statistics for physicians

Variables	Obs	Mean	St.d	Min	Max
Age	51,201	47.88	12.06	19	82
Quit	10,259	1.086	0.932	0	7
First age	10,259	41.29	12.19	19	80
Tenure PCU	15,500	3.281	3.133	1	15
Duration	10,259	4.991	4.259	1	15
Graduates					
Swedish	51,201	0.277	0.447	0	1
International	51,201	0.723	0.447	0	1
Work					
Work 1	46,596	0.661	0.473	0	1
Work 2	46,596	0.237	0.425	0	1
Work 3	46,596	0.102	0.303	0	1
Gender					
Male	51,201	0.442	0.497	0	1
Female	51,201	0.558	0.497	0	1

youngest age at which an individual can qualify as an assistant physician is approximately 22, given that high school graduation typically occurs at 18 years of age. The presence of the youngest physician in our data likely results from a measurement error. Since this occurs only once in our data, it should not skew our estimates. *Quit* represents the number of times a physician leaves a practice during the observed time period. The physicians in our data leave a practice on average one time, whereas the maximum number of time a physician has left a practice is 7 times. *First age* represents the age of physicians entering the workforce for the first time in our data. On average, physicians in our sample begin working in a PCU at the age of 41. *Tenure PCU* represents the number of years a physician works in a PCU. Physicians, in our sample, work for 3 years in one PCU on average. *Duration* represents the number of years a physician works in our sample. We observe a physician on average works over 5 years in our sample. *Graduates* represents the share of physicians that graduated from either a Swedish medical school or an international medical school. We find that the majority of our physicians, 72%, graduate from an international medical school whereas 28% graduate from an Swedish medical school. *Work* represents the number of sources of income. We have information on up to three source of income. The majority, however, has only one income source. Regarding *Gender*, there are slightly more females than males in our sample. A table detailing gender-based descriptive statistics can be found in the appendix A.6.

4.4 Final Dataset

After defining our physicians, we are left with our unbalanced panel data with physicians working in respective PCUs over the period 2005 to 2019. We generate our outcome variable, *vc quit*, that measures the number of physicians who left their practice in that

particular PCU for that particular year. We define physician turnover as a physician who left its practice. However, we cannot distinguish whether the cause is relocation to another unit, pension, death, or any other. We further generate our covariate, *avg age*: the average age of all physicians in a PCU for each year. We also generate other descriptive variables. We include the average age of physicians in PCU as a covariate as this can explain variation in the physician turnover. We believe that age has an significant effect on physician turnover as seen from previous studies where older physicians accounts for higher level of physician turnover. Additionally, figure 24 shows the average tenure of a physician in PCU by age and we notice that older physicians tend to have longer tenures in PCUs than the younger physicians.

We use geographic coordinates to calculate the distance between each PCU to determine exposure to competition. A PCU is considered exposed to competition if another PCU opens within a radius of 3, 5, 10 or 15 kilometers of it. Our primary analysis is based on a 10 kilometers radius, wheras the other distances serve as robustness checks for our estimates.

A PCU can only be subjected to competition only after the implementation of a regional reform, and the timing can vary for each PCU. For Region Stockholm, the reform was implemented in 2008, while for Region Västra Götaland and Region Skåne, the reform took effect in 2009. This time disparity creates missing values for certain estimated coefficient, particularly when we account for both leads (time after treatment) and lags (time before treatment) in our model. For example, the *Lead11* captures the impact of increased competition on physician turnover 11 years after the event. However, this is only applicable for Stockholm.

This issue is insignificant, and we do not interpret the estimates far from the event date. This is due to several reasons. First, the number of observations decrease significantly farther away from the event date. Second, a vast majority of the PCUs experienced competition in the very year the reform was implemented. This means that PCUs that were exposed much later would have fewer observations as we account for more leads and lags. For example, a PCU exposed in 2017 will have up to 12 lags but only approximalely 10% of the total number of observations were exposed in the year since most of them got exposed in 2008 and 2009. Third, the year 2019 lacks a control group. Lastly, while our model only accounts for a PCU's initial exposure to competition, we note that many PCUs in our dataset faced competition multiple times. If we do not limit exposure to just the first instance post-reform, multiple exposures could influence our results.

5 Empirical Strategy

This section begins with our event study where we discuss about the identification strategy, the potential issues with the estimation strategy and the approach to handle these issues. Subsequently, we introduce our model specifications and estimation methods where we use Two-Way Fixed Effects (TWFE) and stacked DiD to answer our first research question: *What is the effect of increased exposure to competition on physician turnover in Swedish primary care units in following regions: Stockholm, Västra Götaland and Skåne.* The second part of this section involves our survival analysis where we answer our second research question, *what characteristics of a PCU or a physician increase the likelihood of physician turnover?*, with the Cox Proportional Hazard (PH) model and Kaplan-Meier model.

5.1 Event Study

5.1.1 Identification

Our identification strategy rests on the geolocation of PCUs wherein we assign a unit into the treatment group if a new unit has been opened within the radius of 10 kilometers at any point of time. For robustness check, we use different ranges i.e. 3, 5 or 15 kilometers. To exploit this variation of when a PCU is exposed to competition and answer our first research question, we use a staggered difference-in-difference (DiD) design with variations in timing of treatment. A PCU can only be subjected to competition only after the reform at a regional level is implemented. In many cases, when dealing with staggered difference-in-differences designs, researchers utilize the Two-Way Fixed Effects (TWFE) model to derive the estimands. However, recent findings suggest that these estimates are potentially biased in the presence of heterogeneous treatment effects in a DiD setting with staggered treatment timing (Athey & Imbens, 2022; Borusyak et al., 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Sun & Abraham, 2021). This issue arises due to "forbidden comparisons" which occurs when a treated group is used as a control group for a "later-treated" group (Goodman-Bacon, 2021).

To understand this issue further, we introduce the canonical 2x2 DiD design with a single treatment, two periods (pre- and post- treatment) and two groups ("treated" group and "control" group). This design allows us to compare the changes in the average outcomes between pre- and post- treatment time of treated group and control group. The validity of the canonical DiD estimand rely on the assumption that control and treatment groups follow the same trend in the absence of treatment, also known as the parallel trends assumption (David & Pischke, 2009).

However, with multiple units being treated at different time, we now have three groups: "never-treated" group, "earlier-treated" group and "later-treated" group. This

results in four possible 2x2 DiD comparisons instead of one as in the basic DiD setting where the never treated group is used as a control group for the treated group. The existence of multiple comparisons leads the estimates obtained from TWFE regression in the staggered DiD setting to use "earlier-treated" as control group for "later-treated" groups, which causes the issue of "forbidden comparisons" (Goodman-Bacon, 2021). This means that one of the control groups in this 2x2 setting will be those observations that have already been exposed to treatment, which the TWFE model cannot control for. The issue of "forbidden comparison" occurs since the "earlier-treated" may still have treatment effects from being treated (Baker et al., 2022; Goodman-Bacon, 2021). This implies that the effect from the treatment on the outcome for the "earlier-treated" group will sustain over the coming periods, and if this effect varies over time when this group is used as a control group, then the issue of "forbidden comparison" arises.

The presence of heterogeneous treatment effects in a staggered setting where units receive treatment at different points in time causes the impact of the treatment to vary across units over time (Goodman-Bacon, 2021). In our case, for example, the size of a PCU that opens nearby can affect the physician turnover since some physicians may prefer working in a PCU with more or less health care staff, or the location of PCU might affect the decision of physicians changing workplace. However, violation of the homogeneous treatment effects does not automatically imply a violation of the parallel trends assumption. The latter may still hold but the bias that arise with heterogeneous treatment effects are believed to exist in a large part of research with TWFE regression in the staggered DiD setting. These estimates obtained with TWFE may be significant but with the wrong sign or produce Type-1 or Type-2 errors (Baker et al., 2022; Borusyak et al., 2021; Goodman-Bacon, 2021).

This issue has been broadly discussed by several researchers in recent years (Athey & Imbens, 2022; Baker et al., 2022; Borusyak et al., 2021; Callaway & Sant'Anna, 2021; de Chaisemartin & D'Haultfœuille, 2020; Goodman-Bacon, 2021; Roth et al., 2023; Sun & Abraham, 2021) where the majority aims to solve this issue of "forbidden comparisons" by providing alternative estimators that aim to alleviate the bias that arises from this issue by using appropriate comparison group as control groups. Nevertheless, all these new alternative estimates vary in terms of the level of intricacy and adaptability, and the choice of observations to use as control group. While some of these estimators use both "never-treated" and "later-treated" as control groups, others only use "never-treated" group as a control group.

The literature has not yet settled for a standard way of dealing with this issue, but we use the stacked DiD approach which is one of the alternative estimators suggested by Baker et al. (2022). This approach may not be one of the latest discoveries of dealing with this issue but is well known, easy to implement and transparent. We,

therefore, use the stacked regression to make causal interpretations and TWFE mainly for comparison.

5.1.2 Assumptions

We use the staggered difference-in-difference (DiD) design with variations in timing of treatment to observe the effect of increased exposure to competition on physician turnover in Swedish PCUs in Skåne, Västra Götaland and Stockholm. We apply TWFE and stacked DiD model to obtain the estimated coefficient of interest ,δ_g, which is the average treatment effect on the treated (ATT) for a treatment-timing cohort e at any point in time for both the static and dynamic specifications. We define the parameter ATT as the "group-time average treatment effect" as Callaway and Sant'Anna (2021):

$$ATT(e,\tau) \equiv E[Y_{i,\tau}(1) - Y_{i,\tau}(0)|E_i = e] \tag{5.1}$$

Where E_i denote the calendar time when unit i receives its first treatment and $E_i = e$ represents all PCUs that receives treatment at time period e. This specification is similar to the ATT obtained from the canonical DiD but modified for applications with staggered treatment timing. This specification allows for the presence of treatment effect heterogeneity across treatment-timing cohorts e or over time periods τ.

We need five assumptions for the models to identify a valid estimate for $ATT(e,\tau)$; parallel trend assumption, no spillover effects, no anticipation effects, treatment timing exogeneity and treatment effects homogeneity (Baker et al., 2022; Callaway & Sant'Anna, 2021; David & Pischke, 2009; Goodman-Bacon, 2021).

Parallel trends assumption, as introduced earlier, states that the difference in the outcome for control and treatment group should be constant over time in the absence of treatment. Figure 1 shows our estimated coefficients for pre- and post-treatment periods with the 95% confidence intervals obtained from the stacked regression for all regions within the radius of 10 kilometers. Significant estimates from the pre-treatment period may identify any existence of any pre-trends and a violation of the parallel trend assumption. As previously stated, the number of observations drops significantly for estimates farther away from the event time 0, i.e. when a PCU is exposed to competition. This occurs since most of our PCUs face competition in the same year the reform was introduced. PCUs that experienced competition in year 2008 or 2009 do not have any lagged values at 4 or 5 and earlier periods. From the data in table 25 to 28, it is apparent that approximately 62% of PCUs experienced competition in years 2008 and 2009, and approximately 79% of PCUs experienced competition between years 2008 and 2011. This means that the lagged values from 8 and earlier periods have insignificant observations which may result in false significant estimates, as we observe in figure 1. Based on this reasoning, we do not put emphasis on lagged values 8 or earlier pre-treatment periods and we do not observe any pre-treatment effects. Meaning, in our case, the difference in

physician turnover for treated and untreated PCU is assumed to be constant over time in the absence of treatment.

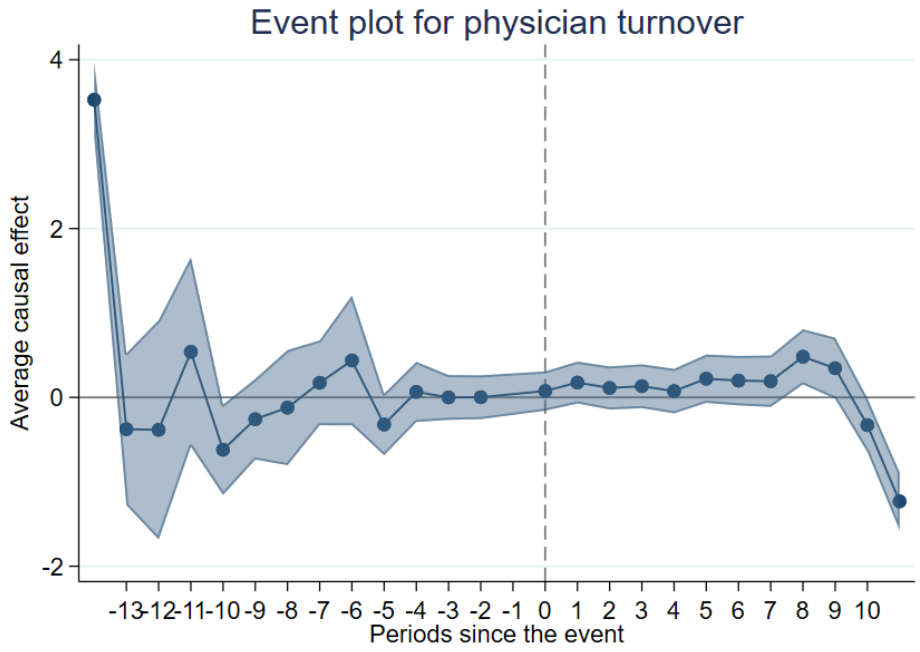

Figure 1

The assumption of no spillover effects, also known as Stable Unit Treatment Value Assumption (SUTVA), implies that the potential outcome for a unit depends only on it being exposed to the treatment and not due to other units being treated. This implies that the exposure to competition on one PCU should not affect the physician turnover in another PCU. We believe if a PCU is not exposed to competition, then the physician turnover should not be affected by other units being a subject of increased competition because we assume that this PCU is sufficiently far from the PCU that is exposed to competition to have a direct effect on its physician turnover. The first effect is the physician turnover in the PCU in question i.e. if a physician moves from that PCU to another, then the physician turnover in another PCU will be affected but not necessarily due to the exposure of competition by the first PCU. Moreover, we do not have information about whether physicians who account for the turnover leave due to retirement, death or move to another PCU. Therefore, we cannot account for the movement between PCUs. Consequently, we do not expect to violate this assumption.

However, if competition is higher in a local area as more PCUs open up in an area, this can affect our control group since more PCUs are now being a subject to treatment and we get less "never-treated" groups. This is a potential weakness in this study. However, as we do have enough control groups, we are not affected by this limitation.

The assumption of no anticipation effects rules out any treatment effects prior to

treatment. This assumption may be violated if we observe that physicians change their behaviour prior to treatment and leave the PCU that they currently work in before that PCU is exposed to competition. This may occur if the physicians anticipate that there will be a new opening of a PCU nearby in advance and change their behaviour accordingly. Region Halland was the first and only region in Sweden that implemented the reform in 2007, so the reform was relatively new before our study regions implemented the reform. Stockholm implemented the reform in 2008 whereas Skåne and Västra Götaland introduced reforms in 2009. According to our data, most of the PCUs opened within the same year after the reform was implemented. As the reforms were implemented within a relatively short time span, any positive changes in the PCUs due to the reform, in terms of workload or other appealing factors for physicians, might not have emerged yet and altered the physicians behaviour in advance. For this reason, we do not believe that our estimates suffer from anticipation effects. However, the possibility of anticipation effect might exist in local areas where the competition is higher as the incentive to open a new PCU is higher in areas with higher demand for healthcare. One way to investigate the presence of anticipation effects is through pre-trends, however, as seen in figure 1, we do not observe any pre-trends in our data. Therefore, we believe that the assumption of no anticipation effect holds.

The assumption of treatment effects homogeneity was introduced earlier in this section where the estimates obtained from TWFE regression will most likely violate. We use the stacked DiD regression to provide unbiased estimates of the $ATT(e, \tau)$. The stacked approach compares treatment group with relevant control groups, which have not yet been treated Baker et al. (2022) and Butts and Gardner (2022). We further explain the methodology of this approach in later section as this is a more robust way of obtaining the estimand for the staggered DiD design than the TWFE regression.

The assumption of treatment timing exogeneity imply that the timing of when a PCU is exposed to competition is random and not systematically correlated to other unobserved factors that might affect the physician turnover. This assumption emphasizes the timing of the treatment and in our case mean that the timing of when a PCU is exposed to competition is not related to factors that affect the physician turnover. We believe that the opening of a PCU is primarily driven by the demand of care in specific areas and not by factors that may affect physician turnover. Meaning, health care providers will open PCU where the local residents densely populated since proximity has shown to be a important factor for patients choice when choosing a health care provider. For this reasoning, we believe that the assumption of treatment effects homogeneity holds.

Our main analysis which aims to answer our first research question, *the effect of increased exposure to competition on physician turnover in Swedish PCU in region Skåne, Västra Götaland and Stockholm*, is based on the 10 kilometers of distance across all

regions. Analysis on 3, 5 and 15 kilometers of distance for all regions is performed to verify the robustness of our estimates. Additional analyses on all distances (3, 5, 10 and 15 km) for each region individually is performed as complementary to understand if there is any regional effects rather than aggregated effects. Further, We perform analysis with and without a covariate for robustness check.

5.1.3 Static Two-Way Fixed Effects Difference-in-Difference

We use the static TWFE regression with staggered DiD setting to obtain $ATT(e, \tau)$. Estimating with the static specification provides a single treatment effect for all post-treatment periods. This specification assumes that the effect of PCU being exposed to competition occurs immediately and persist over the post-treatment period.(Sun & Abraham, 2021).

$$turnover_{it} = \delta_g \sum_{k \geq 0}^{11} D_{it}^k + \beta * avgage_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{5.2}$$

Where $turnover_{it}$ is the number of physicians that leave PCU $i = 1, ..., 546$ at time $t = 2005, 2006, ..., 2019$. g is a collection of disjoint sets of our time relative to treatment indicator $k \in [-14, 11]$, which includes all pre and post treatment periods and are centered around the time of event ($k = 0$). An event occurs when a PCU i is exposed to competition at calendar time t. In the static case, we have $g = [0, 11]$ comprising all our post treatment periods. We define $D_{it}^k = 1\{t - E_i = k\}$ as our treatment indicator that takes on the value one when a PCU i at calendar time t in treatment cohort E_i being k periods away from initial event time is exposed to competition. E_i is the calendar time when unit i receives its first treatment. For PCUs that were never exposed to competition, $D_{it}^k = 0$ and $E_i = \infty$. In the static case, $D_{i,t}^k = 1\{E_i \leq t = k\}$, demonstrating that our treatment indicator equals one for all post treatment periods. Our coefficient of interest ,δ_g, captures the treatment effect for all periods after the initial treatment period. $avgage_{it}$ is our covariate which is the average age of all physicians working in a PCU i at time t. α_i and γ_t are unit and time fixed effects accounting for unobserved characteristics that vary over time and among PCUs. Further, the standard errors are clustered at the PCU level.

5.1.4 Dynamic Two-Way Fixed Effects Difference-in-Difference

In addition to the static specification, we further use dynamic specification which allows us to observe the effects of increased competition on physician turnover over the years, after the event occurs. The inclusion of periods before the treatment allows us to identify any pre-trends and anticipation effects (Roth, 2022; Sun & Abraham, 2021). We believe that the effect of an additional PCU opening nearby on physician turnover is diminishing over time, which makes the dynamic model an important approach to use.

$$turnover_{it} = \sum_{k=-14}^{-2} \delta_k D_{it}^k + \sum_{k=0}^{11} \delta_k D_{it}^k + \beta * avgage_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{5.3}$$

In this fully dynamic specification we include all time relative to treatment periods except for period prior to being exposed to competiton, which is our baseline group $k \in [-14, 11], k \neq -1$.

The first summation in equation 5.3 will capture all time periods prior to the treatment, often referred to as "lags", while the second summation embodies the time period after the treatment, known as "leads". As earlier mentioned, we expect the initial 1-3 years post-treatment as the most relevant period for our analysis. This corresponds to the coefficient ,δ_k, in equation 5.3 for $k = 1, 2, 3$. Similar to the static specification, α_i and γ_t are unit and time fixed effects accounting for unobserved characteristics that vary over time and among PCUs. Additionally, the standard errors are clustered at the PCU level.

5.1.5 Stacked Difference-in-Difference

We implement the stacked diff-in-diff as in (Cengiz et al., 2019; Deshpande & Li, 2019). The stacked DiD model aims to modify the staggered setting to separate 2x2 datasets for each treatment-timing cohort e including the "clean" control groups, which consists of units that have never been treated during these periods. This is accomplished by creating new datasets c for each treatment-timing cohort e including observations on that treated cohort k periods before, and k periods after the initial event time, as well as all “clean” control groups that exists during that specific period. These new datasets are then stacked for each treatment-timing cohort to estimate the TWFE DiD regression equation for either the static (5.2) or dynamic (5.3) specification (Baker et al., 2022; Butts & Gardner, 2022; Cengiz et al., 2019; Cunningham, 2021; Deshpande & Li, 2019). The new datasets c represents the treatment-timing cohorts e but with "clean" control groups, which we now will refer to as the new treatment-timing cohorts c.

The difference in the notation in stacked model is the inclusion of an index that identifies each new dataset c. This approach allows us to compare each individual new treatment-timing cohort to the "never-treated" group. In this model, we only use PCUs that have never been treated as control groups. The exclusion of control groups that give rise to "forbidden comparisons" makes this estimation method more robust than the TWFE DiD regression.

When creating these new treatment-timing cohorts c, if there are twice as many PCUs experiencing competition at cohort c compared to cohort $c+1$, then the estimates for the new treatment-timing cohort c will weigh twice as much as the estimates from cohort $c+1$. Additionally, certain "never-treated" PCUs might appear multiple times in the control group in these new treatment-timing cohorts c which also effect this weighting. This

implicit weighting of the observations might bias the estimates. We eliminate this implicit weighting by averaging across all new treatment-timing cohorts c to obtain cohorts with equal weights. We use standard errors clustered at the PCU level in our analysis.

5.2 Survival Analysis

We use the Cox Proportional Hazard (PH) model to answer our second research question: *what characteristics of a PCU or a physician increase the likelihood of physician turnover?*. This is one of the various statistical methods used in a survival analysis, with the primary interest to model and examine the time-to-event data (Cox, 1972). This type of analysis is commonly used in health studies where the researcher wants to investigate the expected time it takes before a particular event occurs, such as time from first diagnosis till death or time from first heart attack to a second heart attack. We employ the Cox PH Model in our analysis to examine the duration from when a particular physician starts working at PCU i until they depart from that same PCU. In addition to Cox PH model, we apply another similar survival model ,Kaplan Meier, to visually compare physician and PCU characteristics. Kaplan Meier is also one of the most used methods in Survival analysis and is a nonparametric method (Kaplan & Meier, 1958). Instead of statistical analysis, this method is only used for visual interpretation of our covariates. The Cox PH model allows us to further understand which types of physicians are more inclined to remain or leave, and within which specific types of PCUs.

The Cox PH regression model where the hazard at time t for individual i is expressed as follows:

$$h_i(t) = h_0(t)exp(\beta_1 x_{i1} + ... + \beta_1 x_{ik}) \tag{5.4}$$

Where $h_0(t)$ represents the baseline hazard function that describes the hazard rate for the baseline group wherein all the covariates, $\mathbf{x}_{ik}$, equal zero. The hazard rate is the instantaneous risk that an individual can get exposed to the event at that particular time (Jenkins, 2005). Further, $\mathbf{x}_{ik}$ represents the k number of covariates for individual i with their respective coefficient β_k. The Cox PH model is essentially a non-parametric model since we do not assume any specific distribution for the baseline hazard function. However, we assume a functional form for covariates, thereby making it semi-parametric (Jenkins, 2005).

We estimate the Cox PH regression model in equation (5.4) with the partial maximum likelihood which can be used for models where the baseline hazard function is unspecified. The label "partial" in "partial likelihood" is used since the likelihood function only accounts for the probabilities of those individuals who experience the event and not those who get censored (Jenkins, 2005). The latter occurs when the time to event of interest is not observed for certain individuals either because the individual is not experiencing

the event before the study termination or the individual drops out (right censored), or when we cannot observe the time when the event occurred (left censored). The partial likelihood is a product over all observed failure times t_i, where each term is the ratio of the hazard of the individual who experienced the event to the sum of the hazards of all individuals in the risk set at that time (Jenkins, 2005). The partial maximum likelihood is expressed as follows:

$$L(\beta) = \prod_{j=1}^{D} \frac{exp(\beta * x_i{}')}{\sum_{j \in R(t_i)} exp(\beta * x_j{}')} \tag{5.5}$$

Where the vectors $\mathbf{x}_j$ and $\mathbf{x}_i$ represents the set of covariates for individuals j and i, respectively. $R(t_i)$ denote the "risk set" which contains all individuals who are currently at risk of experiencing the event just prior to the failure time t_i. The numerator contains information on individuals who has experienced the event and the denominator contains information on individuals who has yet not experienced the event.

The estimated hazard ratios are obtained by maximizing the partial likelihood function. A hazard ratio of one indicates that the hazard in both baseline and intervention group is the same, implying that there is no difference in the risk of the event occurring between the two groups at any given time point. Hazard ratio greater than 1 indicate that the intervention group is experiencing the event to a higher degree than the baseline group.

In survival analysis, the occurrence of two or more subjects experiencing the event simultaneously is called "tied events". This can cause potential issues since the Cox PH model uses the ranking of event times to obtain its estimates. To estimate the likelihood of an event to occur, the "risk set" which contains all individuals who are currently at risk of experiencing the event, is ordered and updated for each event time. The ordering or ranking of the event time is essential for determining the likelihood of an event's occurrence. To sort the issue with "tied events" we apply the Breslow method which averages the "risk set" over the tied events.

Cox PH model assumes that the hazard ratio is constant over time. We test this assumption with a test for the scaled Schoenfeld residuals. Moreover, we test this assumption visually by plotting the survival function over time for each covariate with the survival function being log transformed twice on the y-axis and time being log transformed once on the x-axis, "log-log" plots. The null hypothesis in the scaled Schoenfeld residuals test states that the hazard ratios are constant over time (W. Hosmer Jr. et al., 2011). For the Log-log plots, we assume that the assumption of proportional hazard holds if the curves are parallel. The curves cross when the ratio of the hazard functions is not constant at any given time. We also test the equality of survival function with a log-rank test with the null hypothesis that states that the two groups have identical survival distribution

(W. Hosmer Jr. et al., 2011).

This model excludes observations that are exposed to the event in the same year the analysis starts. In other words, physicians that quit the same year they start working in a PCU are excluded because the observed time does not constitute a complete year. As a result. 26% of the physicians are excluded, with the majority being the youngest physicians in our data. Therefore, our analysis does not include a significant portion of the youngest physicians.

Since the majority of our physicians change practice several times during the observed time period, we count each time a physician leaves a practice as a new physician in our data. By doing this, we account for each time-to-event possibility in our data and not just observe the first time a physician leaves. The trade-off is that these new physicians might be more representative in our analysis, but we take advantage of all events of physician turnover in our data.

6 Limitation

There are certain limitations due to which this paper may not be able to capture the effect of increased competition. First, as observed in our data, the number of physicians has been increasing in Sweden for the past decade according to Socialstyrelsen (2019). Higher employment rate naturally leads to higher physician turnover. However, with increasing number of newly built Primary Care Unit (PCU) and a constant demand for health, we do not believe this effect gives rise to any bias in our analysis.

Second, certain areas are more affected by competition which can influence physician turnover. For instance, a physician's inclination to relocate because of a new PCU opening might depend on whether their current workplace is in an area with several existing PCUs. In such regions, the introduction of an additional PCU might not significantly impact a physician's decision to move. We do not take this effect into account. Additionally, the opening of a new PCU might solely not be the biggest force for the physicians to relocate, other factors such as work conditions, number of physicians, etc may be a bigger force for the physician to move from one practice to another one. Moreover, the distance from the PCU to hospital might also effect the physicians motivation to relocate. PCU that are located near hospitals may have better cooperation with each other and complement each others services, which may lead to a better work environment for physicians.

Third, certain PCUs are exposed to competition several times, particularly in urban areas. Although we vary our ranges by using distances of 3, 5, 10 and 15 km, the distances might vary among different regions. However, we apply a uniform distance metric across all areas rather than adjusting it based on the specific region. Additionally, we know that our PCU is exposed even before reform but we only consider those PCU that are exposed to competition after the reform is implemented in their region.

Fourth, each physician is assigned a CFAR-number based on its largest source of income. We possess data about the three main sources of income for a physician. However, the CFAR-number assigned to each physician corresponds to the workplace that generates the highest income for the physician for the current year. From table 2 we see that about 66% of physicians have only one source of income, 24% two, 10% three. If a physician has two workplaces and its work distribution varies between the two places over the years, it may appear that the physician is frequently changing workplaces. For instance, if, in 2010, a physician is contributing 40% time in unit A and 60% in unit B, it appears that the physician is working in unit B. However, if in subsequent year, the same physician works more than 50% in unit A, it will appear that the physician has moved to unit A. So, even if the physician works at the current one, it will seem like it has moved. We do not take this effect into account.

7 Results

7.1 Event study

Table 3 presents our estimated coefficients from both the TWFE and stacked regression based on equations (5.2) and (5.3) for all regions related to our first research question, *to examine the effect of increased exposure to competition on physician turnover in Swedish PCUs in regions: Skåne, Västra Götaland and Stockholm.* In our main analysis, we assume that a PCU is exposed to competition if a new PCU is opened within the range of 10 kilometers at any point in time. The last two columns in table 3 include our covariate, *PCU age*, and the first two columns are estimated without our covariate.

If there was any effect of a newly opened PCU on physician turnover, we believe that we would observe a significant effect within the first three years after exposure to competition which corresponds to *lead 0* to *lead 3* in our table. However, as shown in table 3, we do not have enough evidence to observe an effect of increased competition on physician turnover for Stockholm, Skåne and Västra Götaland together on a relevant post treatment period. This holds for both the estimated coefficient obtained from the TWFE regression and stacked regression. This implies that physicians, in our data, do not leave their practice when there is a new PCU opening within 10 kilometers range.

The results from the static specification in table 3 show a small effect on the physician turnover for both the TWFE regression and stacked regression without controlling for the average age of the PCU, although with a low precision. This implies that when a new PCU opens within 10 kilometers range, the number of physicians leaving the PCU is, on average, 1.13 for both the TWFE and stacked regression. However, we interpret this with caution since the results are significant at 10% level and one estimate obtained from the TWFE model. Though we do not state any significant effects on 10% significance level, there is some indication of a possible effect which is of interest. An indication of an existing effect is still of interest but needs to be further observed to prove its validity. The results for the static specification for both models without controlling for the average age of the PCU in table 3 show no evidence of an effect of competition on physician turnover. We cannot reject the null hypothesis that there is no effect, we cannot conclude that the effect is either positive or negative.

Observing all regions within the radius of 10 kilometers did not result in any significant effect of increased competition on physician turnover. We only get a minimal effect from the static specification, but with low precision.

Table 3 Staggered diff-in-diff estimates for region Stockholm, Västra Götaland and Skåne with 10 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.131*	0.127*	0.0728	0.0531
	(0.0788)	(0.0727)	(0.0862)	(0.0786)
PCU age			-0.0269***	-0.0204***
			(0.00401)	(0.00170)
cons	1.279***	1.303***	2.690***	2.429***
	(0.0706)	(0.0131)	(0.214)	(0.0861)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.272	-0.321*	-0.237	-0.270
	(0.183)	(0.186)	(0.200)	(0.206)
Lag 4	0.140	0.0654	0.176	0.0947
	(0.175)	(0.182)	(0.191)	(0.199)
Lag 3	0.0546	-0.0000955	0.120	0.0725
	(0.126)	(0.135)	(0.139)	(0.146)
Lag 2	0.0302	0.00202	0.0600	0.0493
	(0.118)	(0.132)	(0.129)	(0.146)
Lead 0	0.0663	0.0757	0.0636	0.0894
	(0.106)	(0.118)	(0.114)	(0.128)
Lead 1	0.179	0.176	0.132	0.144
	(0.114)	(0.127)	(0.124)	(0.137)
Lead 2	0.146	0.112	0.0944	0.0794
	(0.117)	(0.130)	(0.127)	(0.143)
Lead 3	0.126	0.133	0.0608	0.0886
	(0.124)	(0.132)	(0.133)	(0.144)
Lead 4	0.110	0.0749	0.0445	0.0226
	(0.127)	(0.134)	(0.136)	(0.145)
Lead 5	0.324**	0.222	0.268*	0.177
	(0.142)	(0.146)	(0.151)	(0.157)
cons	1.209***	1.305***	2.554***	2.426***
	(0.130)	(0.0208)	(0.240)	(0.0885)
N	6520	21227	6099	19040

Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01

7.1.1 Event study by distances (Appendix A.1)

We perform the same analysis as presented in section 7.1 but with distances of 3, 5 and 15 kilometers separately as a robustness check. We want to investigate whether our estimated coefficient is sensitive to distance. We check this by studying whether estimated coefficient are consistent over different distances or not.

Table 6 to table 8 in appendix A.1 illustrate our estimated coefficients from both the TWFE and stacked regressions of equations (5.2) and (5.3) for all regions with distances 3, 5 and 15 km respectively. Each PCU is exposed to competition if a new PCU is opened within the range of 3,5 or 15 kilometers at any point in time. The last two columns in table 6 to 8 include our covariate, *PCU age*, and the first two columns are estimated without our covariate.

Results from the static specification in table 6 to table 8 show no significant effect of increased competition on physician turnover for both the TWFE regression and stacked regression, with and without covariate. This means that we do not have enough evidence to observe an effect of increased competition on physician turnover for regions Stockholm, Skåne and Västra Götaland together for the distances 3,5 or 15 kilometers at any point in time. This shows that the average physician working in our sample are not leaving their current practice when there is a new PCU opening within 3, 5 or 15 kilometers.

The same applies for the results from the dynamic specification in table 6 to table 8 with no significant effects on physician turnover from an increase in competition within 3, 5 or 15 kilometer.

7.1.2 Event study by region (Appendix A.2)

We perform the same analysis as presented in section 7.1 for each region separately for distances 3, 5, 10 and 15 kilometers to observe the effect on regional basis. The analysis on regional basis allows us to observe if the effect differ for each region.

Table 9 to 20 in appendix A.2 illustrate our estimated coefficients from both the TWFE and stacked regression of equation (5.2) and (5.3) for all regions separately for distance 3, 5, 10 and 15 respectively. Each PCU is exposed to competition if a new PCU is opened within the range of 3, 5, 10 or 15 kilometers at any point in time. The last two columns include our covariate, *PCU age*, and the first two columns are estimated without our covariate.

Results from the static specification in table 9 to table 20 show no significant effect of competition on physician turnover for neither region Skåne nor region Västra Götaland for any of the distances. However, based on the estimated coefficients from the stacked regression with no covariate for region Stockholm in table 17, we observe a positive effect on physician turnover when a new PCU opens within 3 kilometers. On average, there are 0.239 physicians leaving their PCUs when a new PCU opens within 3 kilometers in region Stockholm. Further, table 19, for region Stockholm shows a small positive effect with

low precision for the TWFE regression with no covariate at a 10 kilometers distance. We interpret this with caution due to 10% significance level. Further, in table 20 for region Stockholm with the distance of 15 kilometers, we observe significant results based on the TWFE regression with and without covariate. Additionally, in the same table but with the stacked regression with covariate, we observe significant effect at 10% level which is interpreted with caution.

Results from table Table 9 to table 20 show positive dynamic treatment effect in region Skåne at a distance of 3 and 5 kilometers and in region Västra Götaland at 10 kilometers distance. In table 9, we observe a significant effect of competition on physician turnover for region Skåne with estimates obtained with TWFE and stacked regressions where the models without covariate produce 5% significance and with covariate 10% significance. The former results indicate that, on average, approximately 0.5 physicians leave their PCU in the same year when a new PCU opens within a 3-kilometer radius in the Skåne region.

From table 14 we observe a positive significant effect for region Västra Götaland two years after a new PCU opens within 5 kilometers radius. The TWFE gives us significant results at 5% significance level without covariate. This implies that, on average, 0.4 physicians leave their PCUs two years after a new PCU opens within 5 kilometers range in region Västra Götaland. However, with covariates, we obtain results at 10% significance level. Similarly, the stacked model provides significant results at 10% level without covariate. These results at 10% significance level are interpreted with caution. In table 15 for region Västra Götaland with a range of 10 kilometers of distance, we observe a positive significant effect the same year a new PCU is opened using the TWFE regression with covariate. In the same table, positive effects with low precision are shown for TWFE regression with covariate for one and two years after a new PCU opens. Additionally, positive effects with low precision are also shown for the TWFE regression without the covariate for the same year, one year after and two years after a new PCU opens within 10 kilometers radius in Västra Götaland.

Observing the outputs from the regions separately, we see that region Stockholm accounts for positive effects obtained from the static specification and regions Västra Götaland and Skåne account for the dynamic effects over time.

7.2 Survival Analysis: Assumptions (Appendix A.5)

In this section, we present results obtained from tests on the proportional hazard assumption and the equality of the survivor functions. To test the former assumption we perform the test of Schoenfield residuals and observe the log-log plots. The latter assumption is tested using the log-rank test of equality.

The test of Schoenfield residuals shows that our model do not violate the PH assumption. We cannot reject the null hypothesis that hazard ratios being constant

over time.

The log-log plot in figure 18 to 23 illustrates the survival function over time for each covariate with the survival function being log transformed twice on the y-axis and time being log transformed once on the x-axis. In figure 18, we see the curves for the survival function for male and female physicians as relatively close and parallel but cross at time 2 approximately. The same applies for the covariate *urban* in figure 23 but the curves cross at time 1.5. The log-log plot for the covariate *PCU age* exhibits parallel curves but the youngest cohort fluctuates which occurs due to low number of observations. As previously mentioned, the model excludes a large number of young physicians. For remaining covariates, PCU size, graduates and age, we observe a parallel curve confirming to the assumption.

The log-rank test of identical distribution is violated for the covariates *female* and *urban*.

We conclude that the assumption of constant hazard ratio is only violated for *female* and *urban* even with a valid test of Schoenfield residuals. For this reason, we interpret the results for female physicians and physicians working in PCUs located in urban areas with caution. However, these variables are not highly correlated with other covariates in our model.

7.3 Cox Proportional Hazard Model

Table 5 shows our estimated hazard ratios obtained with Cox Proportional Hazard model for all physicians during the observed time period (2005-2019). As shown in table 5, the estimated hazard ratios are statistically significant for all covariates except *urban* which is significant at 10% level. The number physicians in this model is 9479; out of which 7582 experience the event of leaving a PCU.

From table 5 we see that the hazard ratio for females is 0.948, indicating that female physicians leave a PCU at a 5.2% lower rate than male physicians. This suggests that female physicians are less likely to leave a PCU within any given point of time than the male physicians in our data, which we interpret with caution. The estimated hazard ratios for physicians graduating from international medical schools is 0.878, indicating that physicians that graduate from a medical school outside Sweden leave a PCU at a 12,2% slower rate than physicians that graduate from Swedish medical school in our sample. When estimating the hazard ratios for the *age* variable, our baseline group consists of our youngest physicians, aged 20 to 35, against which we compare the other age cohorts. The estimated hazard ratio for physicians between the ages of 36 to 50 is 0.716. This denotes that physicians between the age of 36 to 50 leave a PCU at a 28,4% slower rate than our youngest physicians between the ages of 20 to 35. Further, wee identify that the probability for leaving a PCU decreases with age suggesting that older physicians leave a practice at a slower rate than youngest physicians in our data.

Physicians between the ages of 51 to 60, and 60 or older leave a PCU at a rate 36.7% and 54% slower than the youngest physicians in our data, respectively. When estimating the hazard ratios for the *PCU age* variable, we use PCUs with physicians of average age ranging from 20 to 40 as our baseline group which we compare with other age groups. The estimated hazard ratio for PCU with physicians of average age ranging between 41 to 45 is 1.131. This demonstrates that PCUs with physicians of average age ranging between 41 to 45 leave a PCU at a 13.1% higher rate than our baseline group. We see that the older *PCU age* cohorts have a higher rate of leaving a PCU. To be precise, PCUs with physicians of average age ranging between 46 to 55, and 56 or older, leave a PCU at a rate 46,7% and 66,7% faster than our baseline group. This implies that the physicians in our sample prefer to work in PCU where the average age is lower. Further, physicians working in urban areas are more likely to leave a practice than those working in rural areas. However, this estimated coefficient is significant at 10% level; therefore, we interpret the result with caution. Lastly, the estimated hazard ratios for PCU with 8 or more physicians employed is 0.689. This means that physicians working in a PCU with 8 or more physicians employed leave a PCU at a rate 31.1% slower than physicians working in a PCU with less than 8 physicians employed. This means that physicians in our sample prefer to work in a PCU with 8 or more physicians employed.

Table 5 Cox Proportional Hazard estimates

	Hazard Ratio
Female	0.948***
	(0.0190)
Graduates	0.878***
	(0.0208)
Age 20-35	1
	(.)
Age 36-50	0.716***
	(0.0202)
Age 51-60	0.633***
	(0.0215)
Age 60>	0.460***
	(0.0160)
PCU age 20-40	1
	(.)
PCU age 41-45	1.131**
	(0.0578)
PCU age 46-55	1.497***
	(0.0717)
PCU age 56>	1.667***
	(0.0919)
Urban	1.066*
	(0.0354)
PCU size	0.689***
	(0.0156)
N	9479
N fail	7582

Note: Variable names in the left column represent the independent variables in our model. Standard errors in the parentheses.

7.4 Kaplan-Meier (Appendix A.3)

Graph 2 to 11 illustrate the survival functions over time for each covariate with the number of physicians at risk for each plotted time on the x-axis. At time 0, all physicians in our data have not yet experienced the event of leaving a practice. Moreover, over time, the probability of not experiencing the event decreases for each group. Graph 2 and 7, for females and urban areas respectively, confirm our previous findings from the log-log plots (18 to 23) wherein the survival curves that cross. So, we do not interpret them. By observing all graphs on our covariates, graph 2 to 11, we notice that the rate of leaving a PCU is highest after working for only one year in a PCU. This implies that the physicians in our sample tend to leave a PCU to a greater extent after working for one year. Further, this effect diminishes over time.

From figure 3 we observe that in PCUs with 8 or more physicians employed, approximately 73% of the physicians do not leave the PCU after one year as compared to 61% in PCUs with less than 8 physicians employed. This means that almost 39% of the physicians working in smaller PCU leave after one year and 27% leaves in larger PCUs after one year. After working two years, approximately 43% of the physicians are still working in smaller PCUs and approximately 58% of the physicians are still working in larger PCUs. Figure 3 also show that the initial number of physicians in larger PCUs is significantly higher than the smaller PCUs. We conclude that larger PCUs with 8 or more physicians employed tend to retain their staff for longer periods compared to smaller PCUs.

From figure 4 we see that physicians graduating from international medical schools tend to stay in a PCU for a longer duration than physicians graduating from Swedish medical schools. Moreover, there are a higher number of physicians graduating from international medical schools than Swedish medical schools in our sample. The probability of not leaving a practice after working for one year is approximately 70% and 65% for international and Swedish graduates, respectively. We also see that 45% of physicians graduated from international medical schools leave their PCUs after working two years as compared to 55% of physicians graduating from Swedish medical schools. After 7 years of working, only 20% of physicians graduating from international medical schools and 10% of physicians graduating from Swedish medical schools are still working in the same PCU.

The survival function for physicians based on their age show that the youngest physicians, between age 20-35, have the highest probability of leaving at any given time, as seen in figure 5. The oldest physicians in our sample, 60 and older, tend to stay the longest in practice. Approximately 20% of oldest physicians in our data leave a practice after one year as compared to approximately 43% of youngest physicians. After three years of working, approximately 43% of oldest physicians and approximately 25% of the

youngest physicians are still working in the same PCU. This implies that the older one gets, the longer one stays in the same PCU. The rate of leaving a PCU is relative similar for the both age cohorts, 36-50 and 51-60, during our observed time period.

Figure 6 shows the survival function for the average age of physicians working in a PCU. Physicians working in PCU where the average age is between 20 to 40 have the lowest probability of leaving. The rate of leaving a PCU increases as the average age of the physicians working in a PCU increases. This implies that the physicians in our sample prefer to work in a PCU where the average age of physicians employed are younger, rather than older. After working one year, the probability of not leaving a practice for the youngest cohort, 20 to 40, is approximately 75% and 61% for our oldest cohort, 56 and older.

Figure 8 shows the survival functions for the youngest and oldest age cohorts, 20 to 35 and 60 years and older, together with the survival functions for PCUs with 8 or more physicians employed and less than 8 physicians employed. The youngest physicians working in smaller PCUs have the highest probability of leaving a PCU, whereas the oldest physicians working in larger PCUs have the lowest probability of leaving. After working one year, approximately 44% of the youngest physicians and 76% of the oldest physicians are still working in a small PCU with less than 8 physicians employed. Whereas approximately 60% of the youngest physicians and 81% of the oldest physicians are still working in a larger PCU with 8 or more physicians employed. Older physicians have a higher probability of staying regardless of the size of the PCU. They do not get as effected by the size of the PCU as the younger physicians. After working 6 years, no physician between the age of 20 to 35 worked in a small PCU, but there were still approximately 40% of physicians in the older cohort that are still working by that time. Results further show that younger physicians working in both small and larger PCUs are more likely to leave, than the older physicians. Older physicians tend to stay longer than younger physicians in both smaller and larger PCUs. This is in line with earlier results where younger have a higher probability of leaving a practice than older physicians.

Figure 9 shows the survival functions for the youngest and oldest age cohorts, 20 to 35 and 60 years and older, together with physicians graduating from either Swedish or international medical schools. We see that younger physicians leave their practice with a higher probability than older. This applies to physicians who graduated from either international or Swedish medical schools. But those who graduated from international medical schools tend to stay longer than those who graduated from Swedish medical schools.

Figure 10 shows the survival functions for the youngest and oldest age cohorts for the average age in PCU together with physicians graduating from either Swedish or international medical schools. We see that the younger the average age of the physicians

working in PCU is, the higher the probability of not leaving that PCU, for both Swedish and international graduates.

Figure 11 shows the survival functions for the youngest and oldest age cohorts for the average age in PCU together with the survival functions for PCUs with 8 or more physicians employed and less than 8 physicians employed. The rate of leaving a PCU is relatively similar for our oldest physicians working in both larger and smaller PCU, as well as the youngest physicians working in smaller PCU. But the probability of leaving is substantially lower for the youngest physicians working in larger PCU with 8 or more physicians employed.

8 Discussion

8.1 Event study

The aim of this study is to observe the relationship between increased competition in PCUs and the physician turnover, with both traditional and new alternative methods to answer first research question. In addition, the study also aims to identify the characteristics of the physicians and PCUs that account for higher or lower levels of physician turnover to answer second research question.

Our main analysis considers all regions and focuses on instances where a new PCU is introduced within 10 kilometers of an existing PCU, potentially exposing it to competition (see Table 3). However, our findings indicate no significant effect of increased competition on physician turnover, not only for the 10-kilometer distance but also for other distances such as 3, 5, and 15 kilometers A.1. This holds for both for the static and dynamic specifications.

The analysis at regional level presented in appendix A.2, on the other hand, shows significant effect of increased competition on physician turnover. However, the response is heterogeneous and there are two distinct findings between the regions. Firstly, we obtain significant results for Stockholm with the static specification whereas for Västra Götaland and Skåne, dynamic specification provides significant results. Secondly, we observe significant effects in Stockholm for distances 3,10 and 15 kilometers; in Västra Götaland, we find significant effects for 5 and 10 kilometers range; in Skåne, the effect is apparent at 3 and 5 kilometers distance.

The main finding here is that the analysis based on all regions together did not show any significant effect whereas the analysis on regional basis shows not only certain significant effects but also that the regions reach to distances differently. We believe that the analysis on regional basis showed significance because the different regions react to distances differently, which was not captured by the main analysis estimating all regions together. The significant effect on regional basis we believe occurs due to the residents of each region react to increased competition differently. With residence reaction we mean their willingness to commute to work differ in the regions because of the differences in area in each region. Meaning, the residents of region Skåne might not be willing to commute to work for the same length as the residents of region Stockholm since region Skåne is smaller in area than region Stockholm. The inclusion of all regions in the main analysis may offset this effect. Regions that are bigger in area having significant effect on larger distances also indicate the difference in reaction in the regions. We did not take the distance between workplace and home into account since we do not have the physicians registered home addresses. Additionally, we did not take local markets into account in terms of areas that

are exposed to higher and lower levels of competition. For example, in areas where there is higher level of competition, which is often urban areas, the physicians might be more prone to move practice than in areas where there is less competition. Even though we assume that each PCU is similar in term of equipment's etc. there might be that it differs in such way that we cannot control which makes up the decision of physicians to move. With differences in both the willingness to commute and local markets for the regions, we believe that the distances we applied in this study may not be able to capture the true effect of increased competition. There might exist other ranges that capture the effect of increased competition on physician turnover. There is also a possibility that our study setting did not manage to capture the true effect. Additionally, certain PCU is exposed to competition more times than others, but we only account for the first time the PCU is exposed after the reform is implemented in the region. The cumulative effect of exposure to competition might be a significant effect we did not account for and PCU located in urban areas are exposed more times to competition than PCU in rural areas.

We observe a few differences in the models we used to estimate the effect of increased competition on physician turnover in different regions in appendix A.2. Firstly, we notice that the estimated coefficients in models without covariate produce more significant results than models that include covariate. This implies that the inclusion of covariate may offset the insignificant effect of the increased competition. Althouth, in the absence of the covariate, the treatment effect may seem significant, but, in fact, the omitted covariate is accounting for the false significant effect.

Secondly, we find that the estimated coefficients from the TWFE regression produce more significant results than the stacked regression. This may occur because TWFE model produces biased estimates resulting erroneously in false significant result. Since we assume that the TWFE produce biased estimates, we put emphasis on significant results that are obtained using the stacked regression. The only two estimated coefficients with significance level at 5% obtained by the stacked regression are for Stockholm with a distance of 3 kilometers for the static specification with no covariance and for Skåne within a 3 kilometers range for the dynamic specification with no covariance. We also obtain estimates at 10% significance level with the stacked regression for Stockholm with the static specification at 15 kilometers circle, for region Västra Götaland with the dynamic specification at 5 kilometers range and for Skåne with the dynamic specification within a distance of 3 kilometers. This confirms earlier suspicion about larger regions may need different distances, often larger distances, and that the local markets might differ in the regions.

Lastly, we observe that static specification captures the significant effect in Stockholm, whereas dynamic specification accounts for the effect in regions Västra Götaland and Skåne. However, there might be differences in the regions. Therefore,

Stockholm is more sensitive to an immediate and constant effect which was captured by the static specification whereas smaller regions might have a delayed effect of the increase in competition. These differences might occur due to variations in infrastructure, resources and local behaviours in the regions.

Further, our definition of physician turnover might also affect the estimates since we use the absolute number of physicians leaving a PCU. If the number of physicians working across PCUs differ significantly, then the magnitude of physician turnover for a PCU may change. To elaborate, the effect of one physician leaving a small PCU is not the same as one physician leaving a larger PCU, since more physicians work in a larger PCUs and are likely to leave than in smaller PCUs. The physician turnover in smaller PCUs might not be captured to the same extent as the physician turnover in larger PCUs. Therefore, we expect smaller (greater) physician turnover in smaller (larger) PCUs.

For future research, other measures of physician turnover might be used. From the Kaplan-Meier graph 3, we see that the initial number of physicians working in larger PCU is also far more than the smaller PCU. From table 1, we see that the larger PCUs constitute 45%, while the smaller PCUs make up the remaining 55%. Meaning, with large differences in the number of physicians working in larger and smaller PCU and having more PCU with smaller number of physicians employed, our PCU might not be comparable in terms of the number of physicians working, hence the size of the PCU. Larger PCU have on average far more physicians than the average number of physicians in smaller PCU which should be taken into account in future research.

In our data, there are many physicians who only works for one year, where the majority of these are the younger physicians. We believe that the inclusion of assistant physicians, interns, and residents in the definition of physicians, as earlier mentioned, have a large impact for the outcome of our analysis. The natural occurrence of assistant physicians, interns, and residents leaving a practice is due to these being only temporary occupations which will alter our estimations on the physician turnover. This may lead to an overestimation of physician turnover in certain years of working depending on the natural duration of these occupations. As earlier mentioned, medical internship lasts for 18 months in Sweden, residency lasts for approximately five years depending on the speciality and being an assistant physician lasts between the 9th semester of medical school in Sweden until admitted to the medical internship, in our data. Future research should take this into account and preferably observe the physicians from year 2014 onwards when it is possible to distinguish these occupations.

We believe that there are other factors than increased competition that also effect a physician's decision to leave which is workload. In our study, we use the number of physicians working in a PCU as an indicator of how well structured a PCU is, and this may account as a weak indicator of the workload for physicians. This since higher number

of physicians working in a PCU might indicate less workload. The number of patients per physician would also be a good indicator of a physician's workload and more specialized nurses in a PCU is also preferable. However, due to time limitations we could not account for these better indicators. Maybe the new private PCU did not offer less workload that their current practice so the incitements to move was small.

8.2 Survival analysis

Our survival analysis with the Cox proportional Hazard model and Kaplan Meier provides descriptive information about which physicians and PCUs account for physician turnover and helps us to answer our second research question. Our analysis demonstrate that a young physician who graduated from a Swedish medical school working in a PCU with less than 8 young physicians employed is more likely to leave. Higher turnover for younger physicians exemplifies the temporary nature of their occupation as previously mentioned. Secondly, young professionals have the proclivity to change career aspiration more often than the older professionals. Further, younger physicians are less likely to have kids and spouses than older physicians, making them less bound and therefore, they may tend to move more often than the older.

Moreover, physicians graduating from a medical school outside Sweden may experience their schooling differently than those who graduated in Sweden, which might create different traditions of not leaving a practice to the same extent as Swedish graduates. We also observe that PCUs with more physicians employed are more likely to keep their physicians for a longer duration. The workload might differ in small and large PCUs. In larger PCUs, the workload might be more balanced such that in the event of an physician being absent due to illness or an unexpected event, the additional workload falls on greater number of physicians. We believe that larger PCUs have more nurses, which also affect the workload for physicians in a positive way. This is important for policy makers and PCU managers to take into account.

One surprising result is that the PCUs with higher average age of physicians account for higher rate of turnover. This implies that physicians prefer to work in PCUs where the average age of the physicians employed are between 20 and 40, than work in PCUs with higher average age. A higher average age can be an indication of a higher number of senior physician specialists working in a PCU. It can be argued that higher knowledge, due to more experience, in the field will contribute to a lower physician turnover, especially for younger physicians that appreciate advice and guidance. However, this contradicts our findings. This might occur due to older physicians holding to their traditional way of working, being not too open for changes, which might affect the young physicians entering negatively. Younger physicians have more time to shape their own pattern than older, which might make them more flexible and more desirable to work with. Long shot but the result also might occur sine it is more expensive to hire senior specialists,

so PCU with higher average age might have less staff, but with less staff you have shortage of physicians so you hire more younger temporary staff which is younger, and these temporary physicians might account for the high turnover in these PCU with older physicians on average.

9 Conclusion

The effect of increased competition on physician turnover is modest in Sweden. However, we observe significant effect on regional basis where the regions react differently to distances. We believe that the analysis on regional basis show significance because the different regions react to increased competition differently. Further, results from our survival analysis reveal various factors related to physicians and primary care units (PCUs) that predict physician turnover. For instance, young physicians graduating from a Swedish medical school account for higher turnover. Further, PCUs employing 8 or more physicians and having lower average age among physicians in account for lower physician turnover.

With data on all physicians and PCUs in Sweden, our results can be generalized to settings beyond Sweden with similar health care structure. However, more adjustments to the data are needed. Future research may adapt distances based on the region and create local markets based on the level of competition in that area.

We suggest that future research focus on distinguishing temporary occupations from permanent physician roles. With Swedish data, this distinction becomes feasible starting from the year 2014. It is also essential to study how the workload affects physician turnover since we find that larger PCUs account for lower turnover, so future research should obtain better measures for workload. For policy makers and PCU managers, we suggest a more comprehensive inclusion of workload in budgetary decisions and increase the number of physicians. We further recommend developing strategies to lower the physician turnover for younger physicians.

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A Appendix

A.1 Appendix Robustness

Table 6 Staggered diff-in-diff estimates for region Stockholm, Västra Götaland and Skåne with 3 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.114	0.115	0.0946	0.0832
	(0.0800)	(0.0727)	(0.0835)	(0.0751)
PCU age			-0.0271***	-0.0159***
			(0.00401)	(0.00157)
cons	1.279***	1.470***	2.700***	2.352***
	(0.0707)	(0.00576)	(0.214)	(0.0766)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.206	-0.204	-0.205	-0.183
	(0.181)	(0.182)	(0.198)	(0.200)
Lag 4	0.248	0.239	0.244	0.245
	(0.163)	(0.165)	(0.169)	(0.173)
Lag 3	0.0896	0.0702	0.127	0.119
	(0.134)	(0.136)	(0.144)	(0.146)
Lag 2	0.0528	0.0260	0.0578	0.0370
	(0.115)	(0.123)	(0.123)	(0.131)
Lead 0	0.174	0.162	0.200	0.191
	(0.134)	(0.140)	(0.139)	(0.145)
Lead 1	0.0878	0.137	0.0805	0.138
	(0.130)	(0.137)	(0.135)	(0.143)
Lead 2	0.119	0.150	0.0962	0.138
	(0.131)	(0.135)	(0.136)	(0.142)
Lead 3	0.155	0.180	0.121	0.160
	(0.135)	(0.139)	(0.140)	(0.145)
Lead 4	0.171	0.155	0.157	0.152
	(0.138)	(0.141)	(0.143)	(0.148)
Lead 5	0.228	0.179	0.206	0.165
	(0.162)	(0.165)	(0.168)	(0.173)
cons	1.181***	1.464***	2.555***	2.340***
	(0.110)	(0.0109)	(0.233)	(0.0772)
N	6520	34504	6099	31514

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 7 Staggered diff-in-diff estimates for region Stockholm, Västra Götaland and Skåne with 5 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.0990	0.0704	0.0665	0.0254
	(0.0817)	(0.0750)	(0.0867)	(0.0788)
PCU age			-0.0270***	-0.0153***
			(0.00401)	(0.00166)
cons	1.279***	1.396***	2.695***	2.259***
	(0.0707)	(0.00872)	(0.214)	(0.0821)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.277	-0.296	-0.327	-0.318
	(0.191)	(0.194)	(0.206)	(0.212)
Lag 4	0.252	0.201	0.282	0.229
	(0.173)	(0.175)	(0.183)	(0.186)
Lag 3	0.173	0.111	0.229	0.172
	(0.136)	(0.136)	(0.148)	(0.147)
Lag 2	-0.00879	-0.0424	0.000856	-0.0251
	(0.113)	(0.123)	(0.123)	(0.135)
Lead 0	0.0456	0.0556	0.0569	0.0711
	(0.118)	(0.124)	(0.125)	(0.131)
Lead 1	0.189	0.217	0.177	0.214
	(0.126)	(0.134)	(0.134)	(0.143)
Lead 2	0.124	0.113	0.0859	0.0847
	(0.125)	(0.129)	(0.132)	(0.139)
Lead 3	0.123	0.131	0.0704	0.0951
	(0.129)	(0.134)	(0.136)	(0.143)
Lead 4	0.141	0.120	0.0997	0.0877
	(0.138)	(0.142)	(0.145)	(0.151)
Lead 5	0.292*	0.208	0.264	0.193
	(0.155)	(0.159)	(0.164)	(0.169)
cons	1.132***	1.390***	2.501***	2.252***
	(0.123)	(0.0148)	(0.239)	(0.0835)
N	6520	28025	6099	25343

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 8 Staggered diff-in-diff estimates for region Stockholm, Västra Götaland and Skåne with 15 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.0810	0.123	0.0580	0.108
	(0.0859)	(0.0804)	(0.0933)	(0.0857)
PCU age			-0.0270***	-0.0266***
			(0.00401)	(0.00198)
cons	1.278***	1.360***	2.695***	2.761***
	(0.0706)	(0.0208)	(0.214)	(0.0994)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.535**	-0.623**	-0.595**	-0.707**
	(0.245)	(0.252)	(0.285)	(0.291)
Lag 4	-0.268*	-0.428**	-0.306*	-0.485***
	(0.157)	(0.170)	(0.171)	(0.187)
Lag 3	-0.201	-0.232	-0.227	-0.289*
	(0.130)	(0.156)	(0.140)	(0.170)
Lag 2	-0.241**	-0.296**	-0.259**	-0.322**
	(0.115)	(0.145)	(0.124)	(0.160)
Lead 0	-0.0817	-0.0956	-0.104	-0.110
	(0.110)	(0.139)	(0.121)	(0.153)
Lead 1	-0.0310	-0.0799	-0.0742	-0.131
	(0.121)	(0.141)	(0.134)	(0.155)
Lead 2	-0.0452	-0.0909	-0.0774	-0.123
	(0.126)	(0.150)	(0.138)	(0.166)
Lead 3	-0.139	-0.197	-0.194	-0.253
	(0.131)	(0.150)	(0.142)	(0.164)
Lead 4	-0.0529	-0.160	-0.115	-0.222
	(0.138)	(0.154)	(0.149)	(0.169)
Lead 5	0.201	0.102	0.142	0.0383
	(0.154)	(0.163)	(0.166)	(0.178)
cons	1.482***	1.434***	2.902***	2.859***
	(0.143)	(0.0363)	(0.253)	(0.108)
N	6520	16145	6099	14629

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

A.2 Appendix: Event study by region

Table 9 Staggered diff-in-diff estimates for region Skåne with 3 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.199	0.219	0.152	0.198
	(0.154)	(0.145)	(0.163)	(0.150)
PCU age			-0.0235***	-0.0125***
			(0.00769)	(0.00323)
cons	1.235***	1.384***	2.495***	2.109***
	(0.110)	(0.0100)	(0.397)	(0.161)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.0795	-0.0200	-0.108	-0.0303
	(0.268)	(0.253)	(0.276)	(0.269)
Lag 4	0.419	0.464	0.453	0.518
	(0.292)	(0.297)	(0.312)	(0.319)
Lag 3	0.0237	-0.0370	0.111	0.0575
	(0.270)	(0.261)	(0.298)	(0.282)
Lag 2	0.293	0.228	0.334	0.247
	(0.215)	(0.221)	(0.233)	(0.242)
Lead 0	0.487**	0.506**	0.477*	0.517*
	(0.237)	(0.255)	(0.260)	(0.277)
Lead 1	0.262	0.315	0.262	0.331
	(0.237)	(0.244)	(0.246)	(0.256)
Lead 2	0.329	0.220	0.305	0.217
	(0.235)	(0.247)	(0.244)	(0.263)
Lead 3	0.149	0.157	0.147	0.169
	(0.247)	(0.261)	(0.262)	(0.280)
Lead 4	0.0756	0.0438	0.0705	0.0437
	(0.236)	(0.242)	(0.249)	(0.262)
Lead 5	0.290	0.258	0.264	0.259
	(0.303)	(0.311)	(0.321)	(0.331)
cons	1.106***	1.369***	2.264***	2.070***
	(0.170)	(0.0188)	(0.404)	(0.160)
N	1822	9292	1688	8451

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 10 Staggered diff-in-diff estimates for region Skåne with 5 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.225	0.222	0.165	0.187
	(0.152)	(0.151)	(0.162)	(0.157)
PCU age			-0.0235***	-0.0120***
			(0.00768)	(0.00351)
cons	1.238***	1.326***	2.495***	2.035***
	(0.110)	(0.0136)	(0.397)	(0.175)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.102	-0.0804	-0.119	-0.0692
	(0.294)	(0.275)	(0.318)	(0.312)
Lag 4	0.349	0.384	0.407	0.464
	(0.310)	(0.308)	(0.333)	(0.334)
Lag 3	-0.148	-0.268	-0.0338	-0.168
	(0.266)	(0.259)	(0.295)	(0.278)
Lag 2	0.0572	0.0135	0.102	0.0357
	(0.216)	(0.217)	(0.234)	(0.238)
Lead 0	0.346*	0.355	0.344	0.376
	(0.209)	(0.227)	(0.228)	(0.246)
Lead 1	0.295	0.332	0.312	0.358
	(0.228)	(0.242)	(0.235)	(0.253)
Lead 2	0.249	0.0744	0.214	0.0677
	(0.213)	(0.228)	(0.216)	(0.244)
Lead 3	0.171	0.147	0.178	0.168
	(0.244)	(0.259)	(0.261)	(0.279)
Lead 4	-0.0507	-0.136	-0.110	-0.207
	(0.246)	(0.259)	(0.262)	(0.283)
Lead 5	0.155	0.0584	0.112	0.0405
	(0.293)	(0.304)	(0.313)	(0.325)
cons	1.083***	1.322***	2.246***	2.008***
	(0.198)	(0.0224)	(0.417)	(0.174)
N	1822	8230	1688	7389

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 11 Staggered diff-in-diff estimates for region Skåne with 10 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.133	0.161	0.0237	0.0861
	(0.147)	(0.141)	(0.163)	(0.157)
PCU age			-0.0236***	-0.0123***
			(0.00769)	(0.00333)
cons	1.238***	1.266***	2.498***	1.991***
	(0.110)	(0.0199)	(0.397)	(0.169)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.0565	-0.0899	-0.000810	0.0108
	(0.276)	(0.241)	(0.302)	(0.271)
Lag 4	0.301	0.270	0.377	0.356
	(0.308)	(0.298)	(0.355)	(0.339)
Lag 3	-0.105	-0.300	0.0195	-0.183
	(0.259)	(0.251)	(0.300)	(0.273)
Lag 2	0.286	0.224	0.356	0.250
	(0.221)	(0.235)	(0.242)	(0.255)
Lead 0	0.292	0.302	0.306	0.352
	(0.190)	(0.210)	(0.212)	(0.233)
Lead 1	0.220	0.207	0.153	0.172
	(0.210)	(0.227)	(0.224)	(0.246)
Lead 2	0.185	-0.0253	0.106	-0.0364
	(0.205)	(0.223)	(0.209)	(0.241)
Lead 3	0.121	0.122	0.0855	0.0995
	(0.233)	(0.242)	(0.255)	(0.270)
Lead 4	-0.207	-0.338	-0.325	-0.456
	(0.241)	(0.268)	(0.266)	(0.304)
Lead 5	0.375	0.346	0.316	0.349
	(0.305)	(0.283)	(0.328)	(0.303)
cons	1.032***	1.253***	2.172***	1.940***
	(0.242)	(0.0328)	(0.458)	(0.167)
N	1822	6422	1688	5743

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 12 Staggered diff-in-diff estimates for region Skåne with 15 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.0707	0.227	0.0346	0.242
	(0.185)	(0.173)	(0.203)	(0.193)
PCU age			-0.0236***	-0.0161***
			(0.00766)	(0.00414)
cons	1.236***	1.262***	2.502***	2.195***
	(0.110)	(0.0428)	(0.395)	(0.212)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.812**	-0.923**	-0.938**	-1.045**
	(0.393)	(0.411)	(0.456)	(0.481)
Lag 4	-0.613**	-0.780***	-0.669**	-0.866***
	(0.256)	(0.288)	(0.282)	(0.324)
Lag 3	-0.571*	-0.841**	-0.580*	-0.967**
	(0.310)	(0.346)	(0.336)	(0.383)
Lag 2	-0.164	-0.321	-0.155	-0.402
	(0.266)	(0.318)	(0.283)	(0.349)
Lead 0	-0.0958	-0.256	-0.101	-0.260
	(0.244)	(0.312)	(0.272)	(0.355)
Lead 1	-0.173	-0.398	-0.218	-0.482
	(0.278)	(0.310)	(0.304)	(0.350)
Lead 2	-0.178	-0.469	-0.223	-0.535
	(0.269)	(0.307)	(0.297)	(0.348)
Lead 3	-0.216	-0.384	-0.245	-0.440
	(0.308)	(0.348)	(0.345)	(0.402)
Lead 4	-0.343	-0.579	-0.424	-0.694
	(0.326)	(0.374)	(0.372)	(0.449)
Lead 5	0.115	0.0945	0.0518	0.0579
	(0.374)	(0.329)	(0.424)	(0.377)
cons	1.725***	1.399***	2.992***	2.283***
	(0.261)	(0.0906)	(0.498)	(0.232)
N	1822	4279	1688	3708

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 13 Staggered diff-in-diff estimates for region Västra Götaland with 3 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.0686	-0.0323	0.0479	-0.0702
	(0.123)	(0.126)	(0.125)	(0.127)
PCU age			-0.0239***	-0.0189***
			(0.00666)	(0.00226)
cons	1.025***	1.290***	2.276***	2.281***
	(0.133)	(0.00819)	(0.373)	(0.110)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	0.144	0.159	0.230	0.266
	(0.331)	(0.334)	(0.404)	(0.401)
Lag 4	0.413*	0.416*	0.399	0.402
	(0.244)	(0.242)	(0.254)	(0.254)
Lag 3	0.251	0.295	0.373	0.400
	(0.235)	(0.239)	(0.257)	(0.260)
Lag 2	0.236	0.192	0.278	0.213
	(0.230)	(0.225)	(0.246)	(0.241)
Lead 0	0.250	0.210	0.317	0.279
	(0.235)	(0.240)	(0.253)	(0.258)
Lead 1	0.282	0.287	0.302	0.302
	(0.205)	(0.210)	(0.217)	(0.223)
Lead 2	0.324	0.319	0.359	0.344
	(0.217)	(0.215)	(0.234)	(0.231)
Lead 3	0.314	0.311	0.295	0.297
	(0.235)	(0.239)	(0.247)	(0.252)
Lead 4	0.240	0.269	0.273	0.312
	(0.250)	(0.258)	(0.260)	(0.267)
Lead 5	0.325	0.185	0.347	0.186
	(0.268)	(0.275)	(0.275)	(0.281)
cons	0.785***	1.267***	2.038***	2.261***
	(0.176)	(0.0145)	(0.399)	(0.110)
N	2206	11782	2060	10855

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 14 Staggered diff-in-diff estimates for region Västra Götaland with 5 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.170	0.0749	0.133	0.0222
	(0.124)	(0.134)	(0.130)	(0.137)
PCU age			-0.0237***	-0.0200***
			(0.00666)	(0.00246)
cons	1.026***	1.244***	2.263***	2.298***
	(0.132)	(0.0123)	(0.373)	(0.121)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.252	-0.230	-0.281	-0.225
	(0.312)	(0.320)	(0.373)	(0.375)
Lag 4	0.278	0.234	0.247	0.212
	(0.259)	(0.255)	(0.273)	(0.271)
Lag 3	0.419*	0.405	0.517**	0.484*
	(0.237)	(0.250)	(0.259)	(0.273)
Lag 2	0.188	0.0979	0.190	0.0888
	(0.231)	(0.228)	(0.253)	(0.251)
Lead 0	0.288	0.288	0.338	0.337
	(0.218)	(0.225)	(0.243)	(0.249)
Lead 1	0.317	0.281	0.280	0.250
	(0.194)	(0.201)	(0.213)	(0.219)
Lead 2	0.426**	0.348*	0.392*	0.310
	(0.204)	(0.208)	(0.220)	(0.226)
Lead 3	0.342	0.326	0.281	0.278
	(0.218)	(0.224)	(0.232)	(0.240)
Lead 4	0.378*	0.428*	0.358	0.436*
	(0.227)	(0.242)	(0.238)	(0.253)
Lead 5	0.471*	0.273	0.441	0.234
	(0.254)	(0.266)	(0.267)	(0.276)
cons	0.839***	1.225***	2.121***	2.290***
	(0.193)	(0.0189)	(0.404)	(0.123)
N	2206	10099	2060	9262

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 15 Staggered diff-in-diff estimates for region Västra Götaland with 10 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.184	0.120	0.155	0.0791
	(0.125)	(0.132)	(0.135)	(0.138)
PCU age			-0.0236***	-0.0222***
			(0.00669)	(0.00270)
cons	1.024***	1.231***	2.256***	2.406***
	(0.132)	(0.0168)	(0.374)	(0.135)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.193	-0.273	-0.0938	-0.169
	(0.336)	(0.329)	(0.370)	(0.362)
Lag 4	0.0123	-0.104	0.0118	-0.0888
	(0.236)	(0.254)	(0.249)	(0.270)
Lag 3	0.564**	0.557**	0.656***	0.640**
	(0.229)	(0.257)	(0.248)	(0.272)
Lag 2	0.217	0.129	0.278	0.196
	(0.235)	(0.233)	(0.259)	(0.259)
Lead 0	0.353*	0.290	0.443**	0.387
	(0.191)	(0.211)	(0.221)	(0.243)
Lead 1	0.351*	0.276	0.338*	0.266
	(0.178)	(0.188)	(0.199)	(0.210)
Lead 2	0.373*	0.262	0.376*	0.262
	(0.192)	(0.207)	(0.209)	(0.229)
Lead 3	0.368*	0.302	0.369	0.318
	(0.213)	(0.221)	(0.228)	(0.238)
Lead 4	0.375*	0.355	0.377	0.368
	(0.212)	(0.233)	(0.229)	(0.251)
Lead 5	0.471**	0.262	0.452*	0.246
	(0.231)	(0.253)	(0.246)	(0.270)
cons	1.006***	1.213***	2.220***	2.379***
	(0.200)	(0.0243)	(0.384)	(0.137)
N	2206	8425	2060	7723

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 16 Staggered diff-in-diff estimates for region Västra Götaland with 15 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.120	0.0910	0.112	0.0477
	(0.127)	(0.126)	(0.138)	(0.133)
PCU age			-0.0238***	-0.0282***
			(0.00666)	(0.00306)
cons	1.024***	1.293***	2.271***	2.747***
	(0.133)	(0.0212)	(0.372)	(0.151)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.566	-0.586	-0.546	-0.565
	(0.443)	(0.437)	(0.514)	(0.500)
Lag 4	-0.261	-0.272	-0.320	-0.300
	(0.279)	(0.257)	(0.301)	(0.277)
Lag 3	0.246	0.270	0.244	0.256
	(0.223)	(0.256)	(0.239)	(0.275)
Lag 2	-0.161	-0.195	-0.170	-0.195
	(0.192)	(0.214)	(0.217)	(0.242)
Lead 0	0.102	0.119	0.143	0.180
	(0.196)	(0.219)	(0.232)	(0.256)
Lead 1	0.00205	-0.0619	-0.0452	-0.120
	(0.192)	(0.203)	(0.220)	(0.233)
Lead 2	0.0695	0.0167	0.0328	-0.0414
	(0.205)	(0.225)	(0.226)	(0.250)
Lead 3	-0.0331	-0.112	-0.0826	-0.160
	(0.217)	(0.236)	(0.236)	(0.259)
Lead 4	0.0921	0.128	0.0383	0.0906
	(0.223)	(0.246)	(0.246)	(0.270)
Lead 5	0.254	0.0925	0.185	0.0403
	(0.238)	(0.264)	(0.256)	(0.282)
cons	1.255***	1.319***	2.582***	2.796***
	(0.257)	(0.0356)	(0.437)	(0.157)
N	2206	7030	2060	6499

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 17 Staggered diff-in-diff estimates for region Stockholm with 3 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.166	0.239**	0.172	0.192
	(0.143)	(0.121)	(0.153)	(0.131)
PCU age			-0.0320***	-0.0179***
			(0.00722)	(0.00371)
cons	1.531***	1.829***	3.186***	2.852***
	(0.124)	(0.0166)	(0.382)	(0.177)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.511	-0.532	-0.497	-0.485
	(0.335)	(0.380)	(0.346)	(0.398)
Lag 4	0.0755	-0.0151	0.105	0.0371
	(0.306)	(0.334)	(0.322)	(0.353)
Lag 3	0.115	0.163	0.109	0.185
	(0.239)	(0.254)	(0.255)	(0.275)
Lag 2	-0.00680	-0.0285	-0.00633	-0.00193
	(0.191)	(0.230)	(0.203)	(0.250)
Lead 0	0.151	0.114	0.216	0.179
	(0.214)	(0.244)	(0.218)	(0.251)
Lead 1	-0.0269	0.101	-0.0339	0.102
	(0.244)	(0.272)	(0.257)	(0.289)
Lead 2	0.0679	0.128	0.0410	0.106
	(0.238)	(0.254)	(0.252)	(0.270)
Lead 3	0.220	0.312	0.200	0.293
	(0.236)	(0.246)	(0.250)	(0.263)
Lead 4	0.359	0.343	0.326	0.334
	(0.240)	(0.245)	(0.259)	(0.263)
Lead 5	0.282	0.199	0.255	0.173
	(0.296)	(0.313)	(0.318)	(0.335)
cons	1.520***	1.832***	3.160***	2.850***
	(0.226)	(0.0345)	(0.437)	(0.180)
N	2492	9642	2351	8748

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 18 Staggered diff-in-diff estimates for region Stockholm with 5 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.00784	-0.117	0.00927	-0.224
	(0.162)	(0.137)	(0.174)	(0.152)
PCU age			-0.0312***	-0.0151***
			(0.00700)	(0.00343)
cons	1.522***	1.828***	3.138***	2.763***
	(0.125)	(0.0333)	(0.370)	(0.173)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.164	-0.349	-0.166	-0.331
	(0.373)	(0.440)	(0.374)	(0.458)
Lag 4	0.404	0.152	0.533	0.289
	(0.329)	(0.359)	(0.344)	(0.387)
Lag 3	0.470*	0.462*	0.528*	0.543*
	(0.252)	(0.271)	(0.272)	(0.304)
Lag 2	0.195	0.136	0.254	0.203
	(0.200)	(0.236)	(0.219)	(0.274)
Lead 0	-0.0630	-0.112	-0.0170	-0.0435
	(0.203)	(0.229)	(0.212)	(0.241)
Lead 1	0.162	0.237	0.161	0.252
	(0.243)	(0.291)	(0.263)	(0.322)
Lead 2	0.0414	0.00564	-0.000334	-0.0404
	(0.236)	(0.272)	(0.255)	(0.298)
Lead 3	0.0670	0.127	-0.00155	0.0376
	(0.239)	(0.272)	(0.260)	(0.301)
Lead 4	0.218	0.0948	0.156	0.0290
	(0.251)	(0.276)	(0.274)	(0.302)
Lead 5	0.303	0.147	0.275	0.125
	(0.309)	(0.343)	(0.336)	(0.377)
cons	1.157***	1.792***	2.710***	2.699***
	(0.258)	(0.0632)	(0.457)	(0.187)
N	2492	6518	2351	5822

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 19 Staggered diff-in-diff estimates for region Stockholm with 10 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.270*	0.179	0.279	0.00774
	(0.152)	(0.137)	(0.171)	(0.160)
PCU age			-0.0319***	-0.0271***
			(0.00695)	(0.00396)
cons	1.531***	1.558***	3.181***	3.145***
	(0.123)	(0.0604)	(0.367)	(0.216)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.530	-0.763	-0.507	-0.680
	(0.354)	(0.477)	(0.417)	(0.553)
Lag 4	0.512	0.272	0.578	0.434
	(0.592)	(0.592)	(0.657)	(0.671)
Lag 3	0.0831	0.0280	0.116	0.130
	(0.277)	(0.311)	(0.320)	(0.369)
Lag 2	0.389	0.368	0.495	0.585
	(0.326)	(0.307)	(0.375)	(0.372)
Lead 0	0.143	-0.0786	0.166	-0.0522
	(0.191)	(0.237)	(0.200)	(0.261)
Lead 1	0.325	0.311	0.295	0.304
	(0.271)	(0.318)	(0.308)	(0.374)
Lead 2	0.363	0.308	0.298	0.260
	(0.256)	(0.318)	(0.291)	(0.369)
Lead 3	0.298	0.352	0.172	0.254
	(0.249)	(0.274)	(0.278)	(0.346)
Lead 4	0.496**	0.380	0.357	0.311
	(0.243)	(0.257)	(0.271)	(0.303)
Lead 5	0.484*	0.282	0.340	0.201
	(0.269)	(0.295)	(0.291)	(0.338)
cons	1.443***	1.543***	3.178***	3.135***
	(0.292)	(0.101)	(0.469)	(0.243)
N	2492	4166	2351	3624

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

Table 20 Staggered diff-in-diff estimates for region Stockholm with 15 kilometer distance

	A. Static model			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
ATT	0.340**	0.185	0.402**	0.306*
	(0.166)	(0.139)	(0.180)	(0.160)
PCU age			-0.0320***	-0.0361***
			(0.00703)	(0.00534)
cons	1.533***	1.656***	3.186***	3.425***
	(0.123)	(0.0836)	(0.370)	(0.284)
	B. Dynamic treatment effects			
	TWFE (no cov)	Stacked (no cov)	TWFE (cov)	Stacked (cov)
Lag 5	-0.284	-0.837	-0.520	-0.876
	(0.438)	(0.566)	(0.494)	(0.710)
Lag 4	0.0958	-0.428	0.0153	-0.374
	(0.540)	(0.538)	(0.703)	(0.692)
Lag 3	-0.0770	-0.384	-0.254	-0.597
	(0.281)	(0.387)	(0.347)	(0.390)
Lag 2	0.000546	-0.0649	-0.0696	-0.154
	(0.376)	(0.300)	(0.461)	(0.329)
Lead 0	0.133	-0.0666	0.166	-0.0133
	(0.186)	(0.274)	(0.191)	(0.266)
Lead 1	0.194	0.248	0.256	0.284
	(0.267)	(0.321)	(0.301)	(0.333)
Lead 2	0.255	0.340	0.350	0.511
	(0.254)	(0.329)	(0.293)	(0.391)
Lead 3	-0.0368	0.0463	-0.00724	0.0766
	(0.245)	(0.294)	(0.271)	(0.330)
Lead 4	0.307	0.0573	0.307	0.101
	(0.239)	(0.277)	(0.267)	(0.309)
Lead 5	0.441*	0.264	0.495*	0.335
	(0.264)	(0.349)	(0.282)	(0.380)
cons	1.569***	1.885***	3.521***	3.769***
	(0.312)	(0.158)	(0.485)	(0.312)
N	2492	3218	2351	2984

*Note: Variable names in the left column represent the independent variables in our model with post-treatment period as ´Lead´ and pre-treatment period as ´Lag´. Standard errors in the parentheses clustered by primare care units.*P<0.1, **P<0.05, ***P<0.01*

A.3 Appendix: Kaplan-Meier Graph

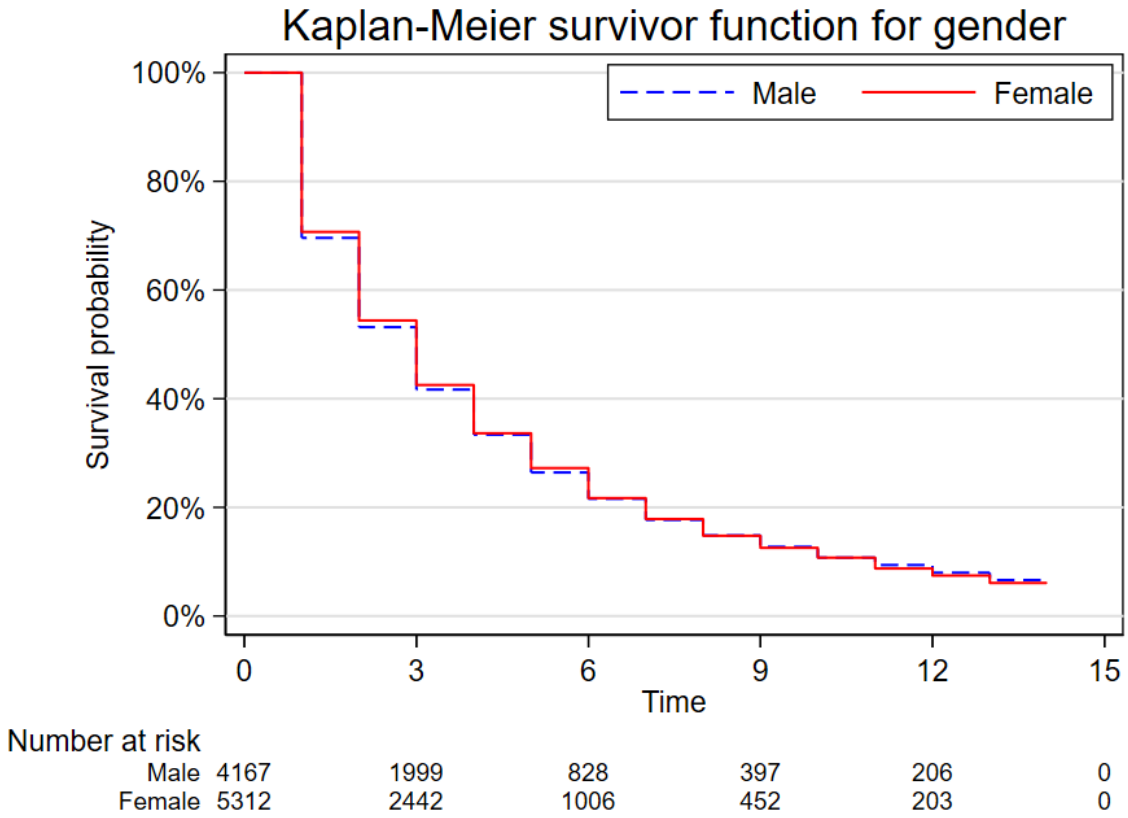

Figure 2

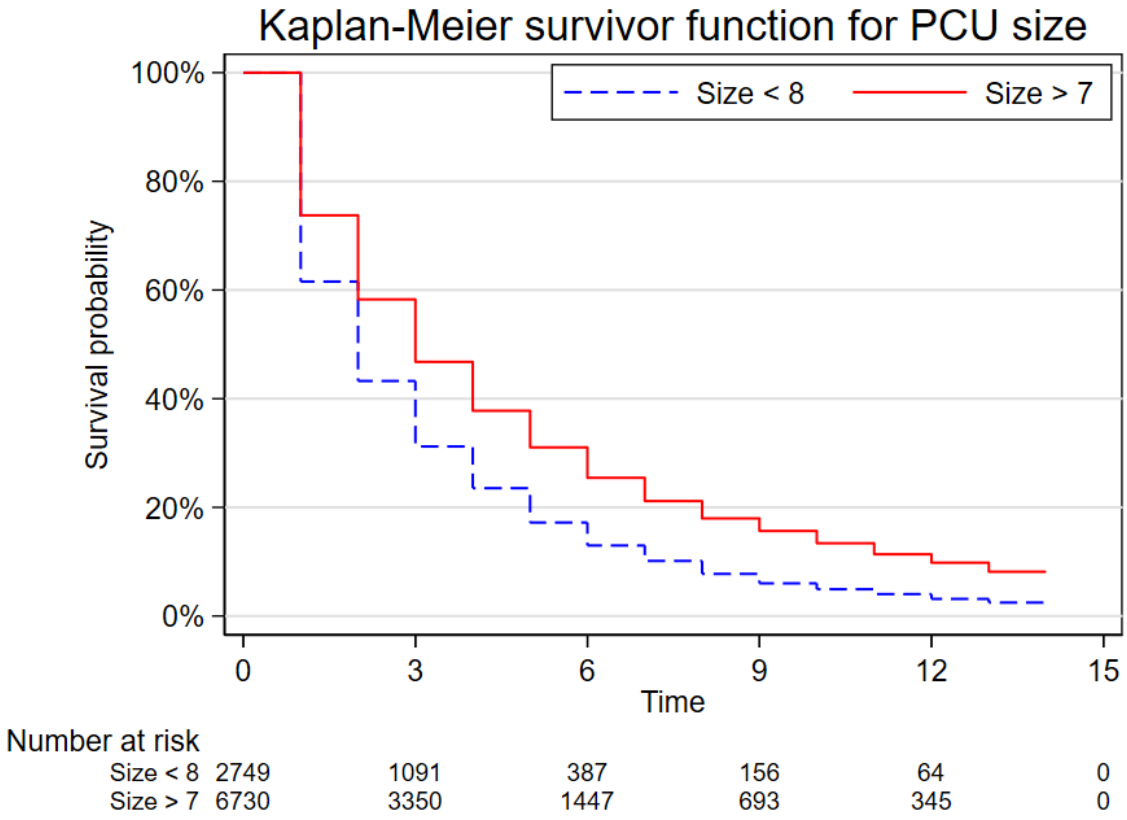

Figure 3

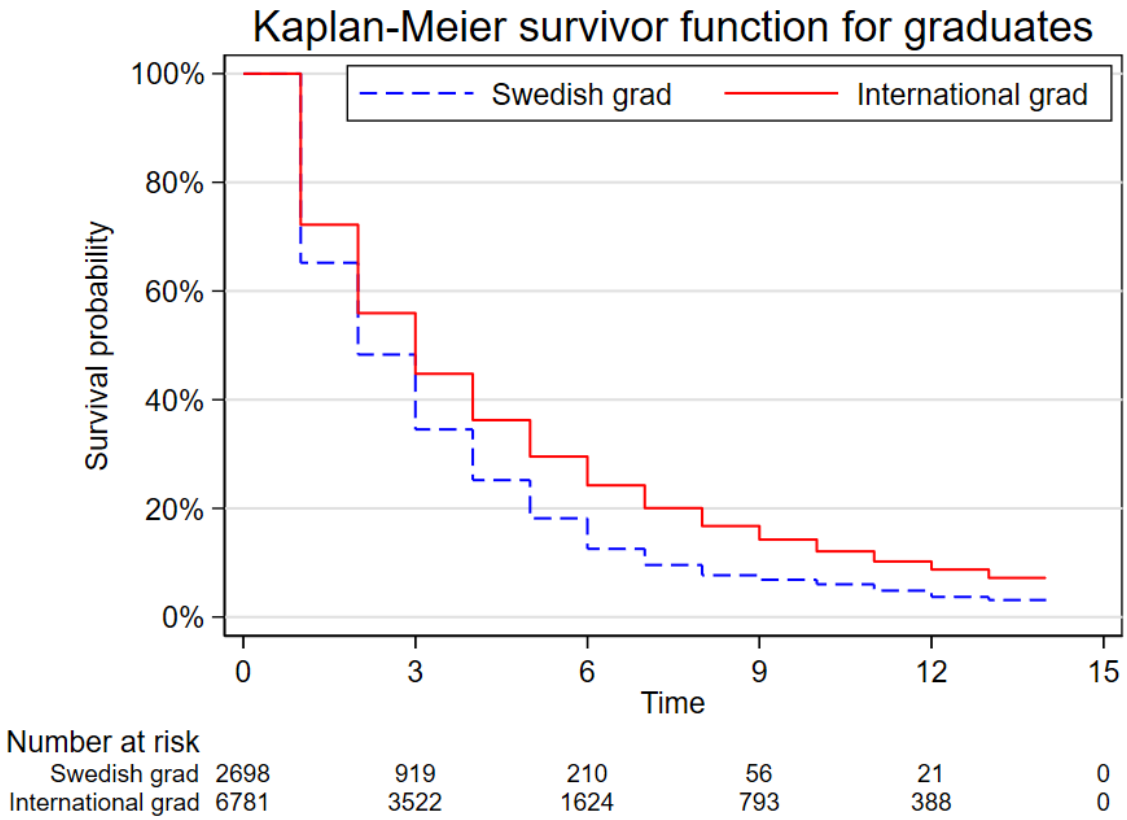

Figure 4

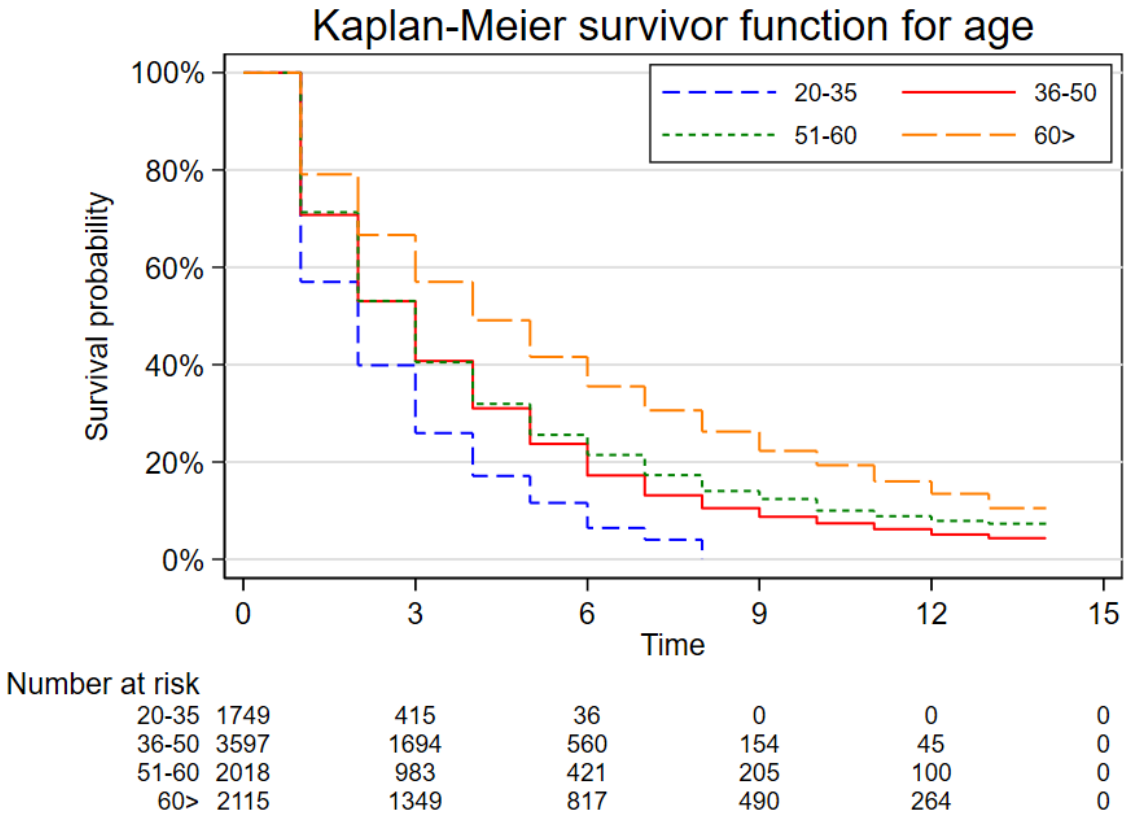

Figure 5

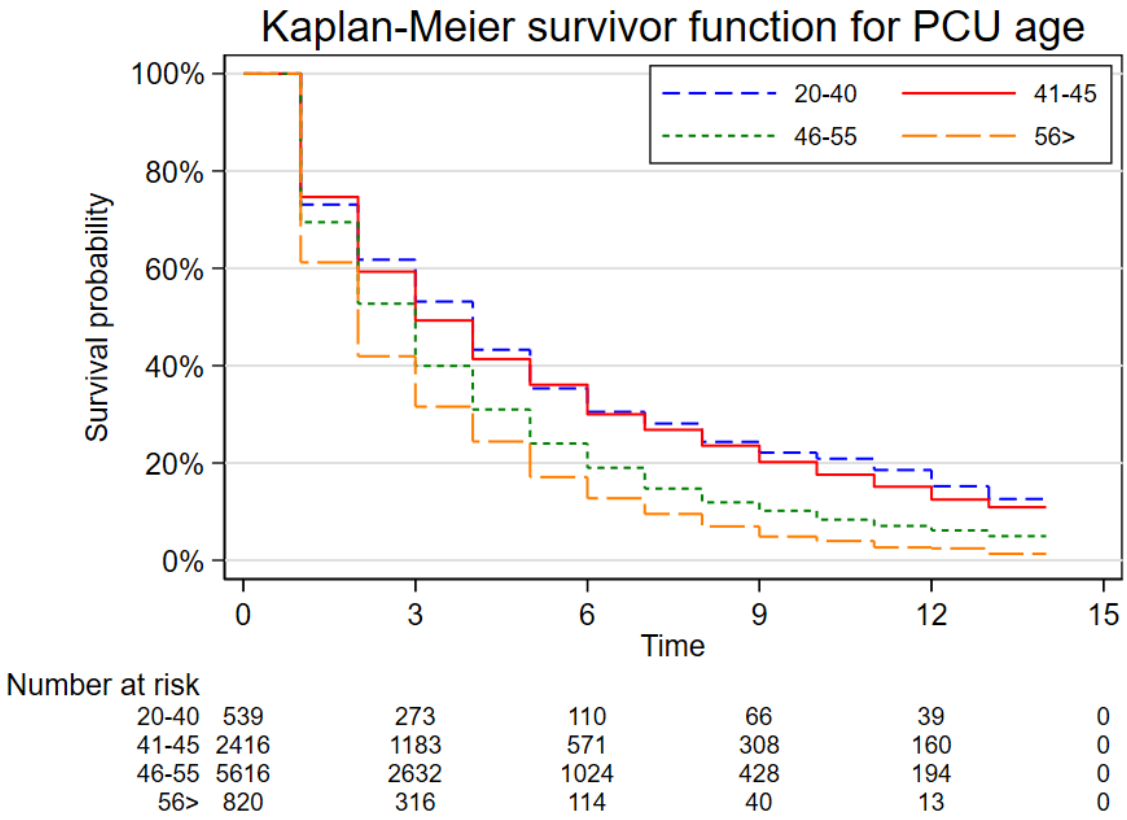

Figure 6

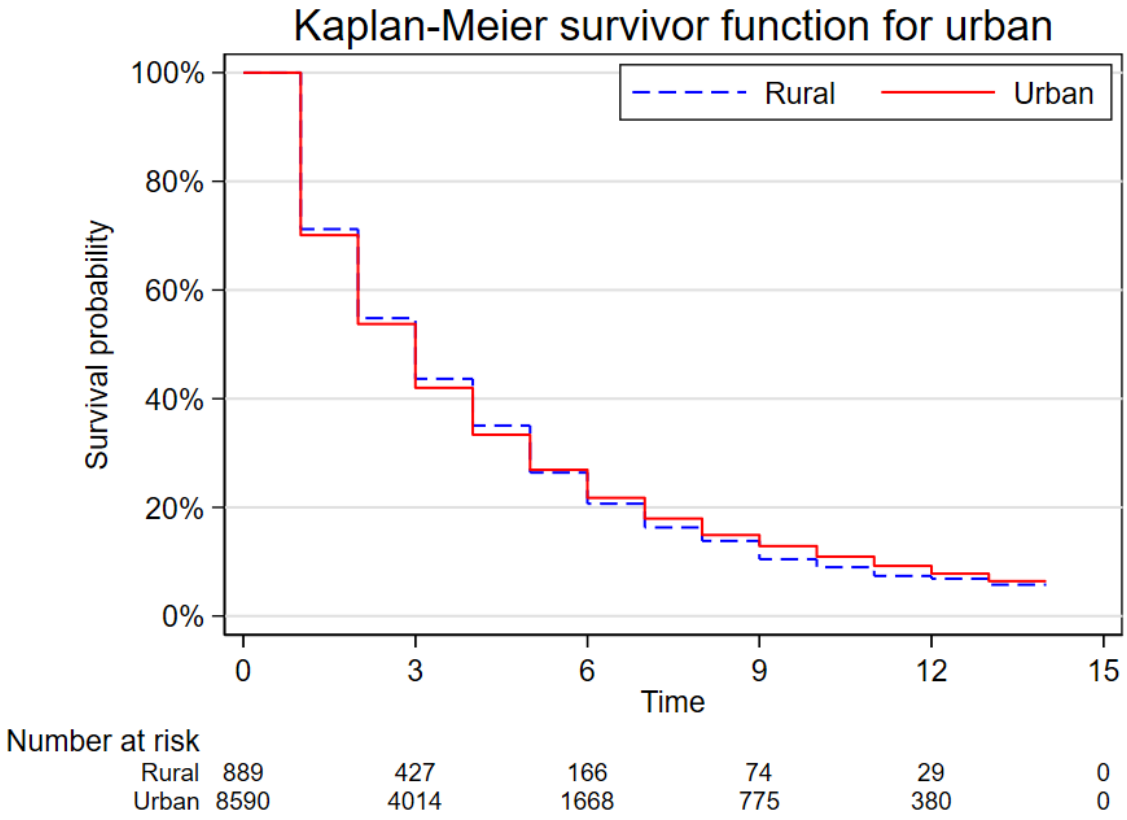

Figure 7

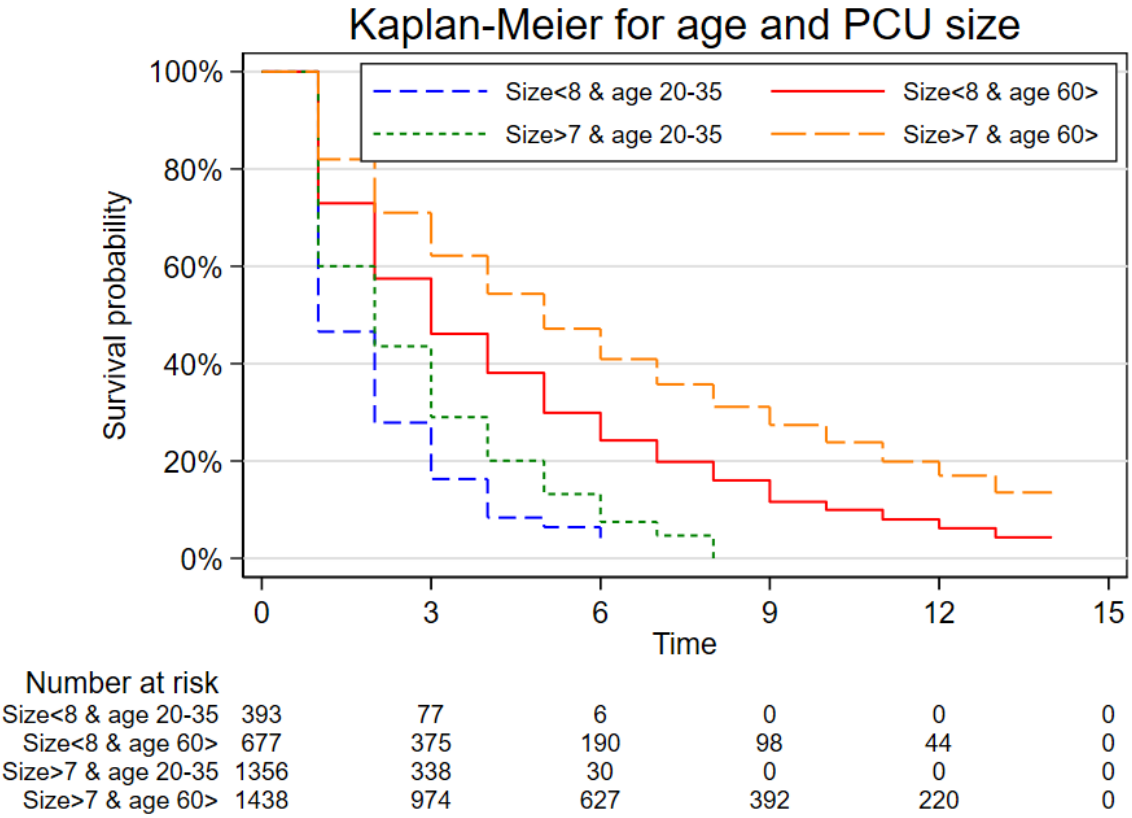

Figure 8

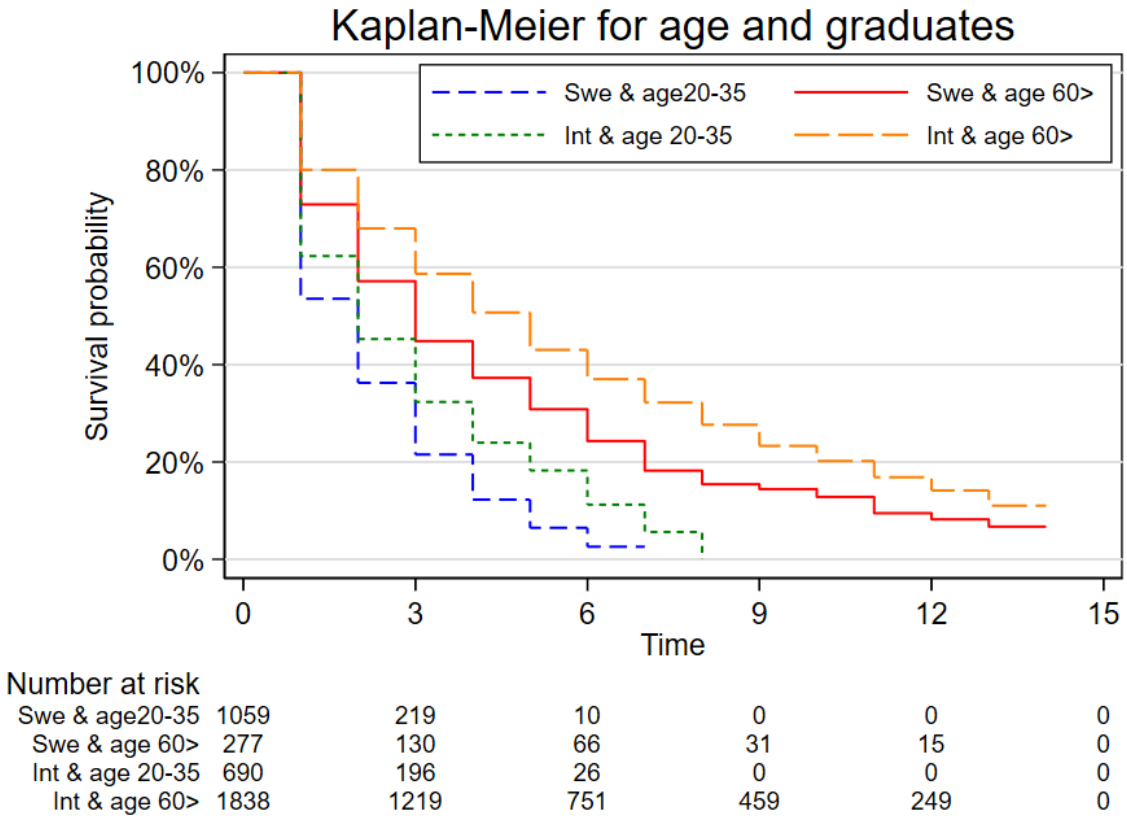

Figure 9

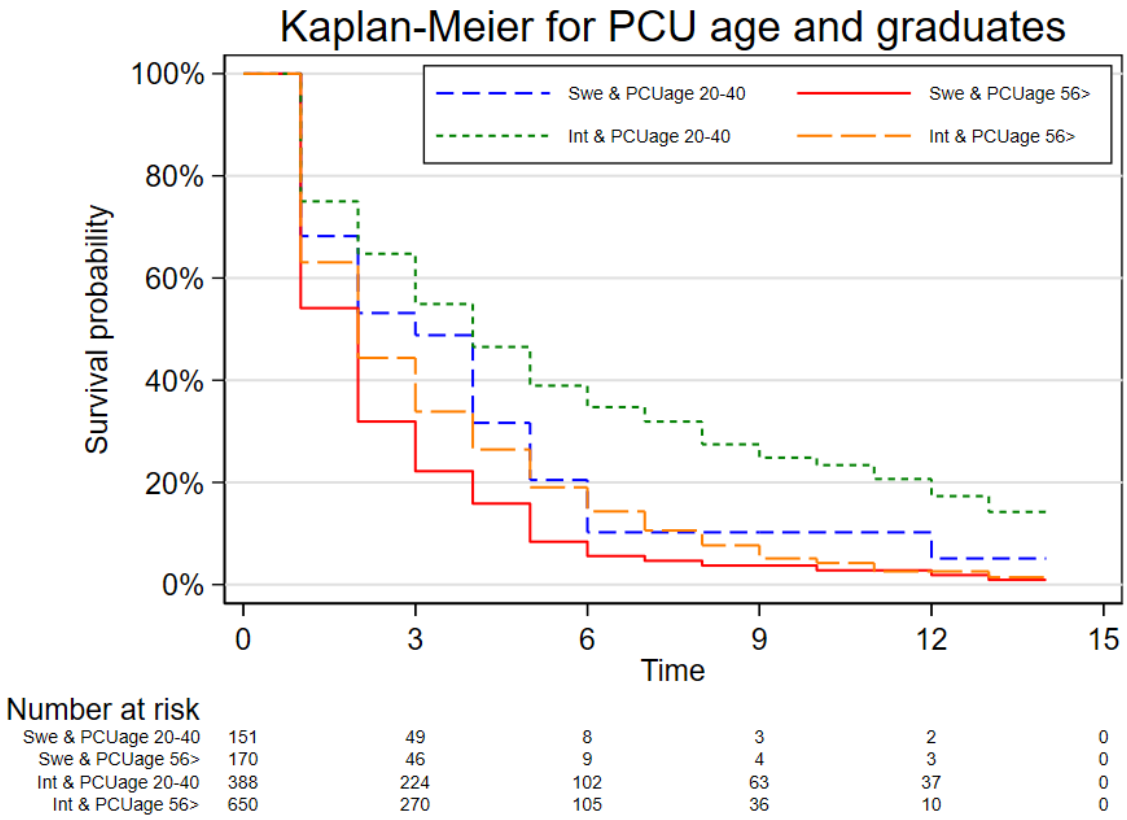

Figure 10

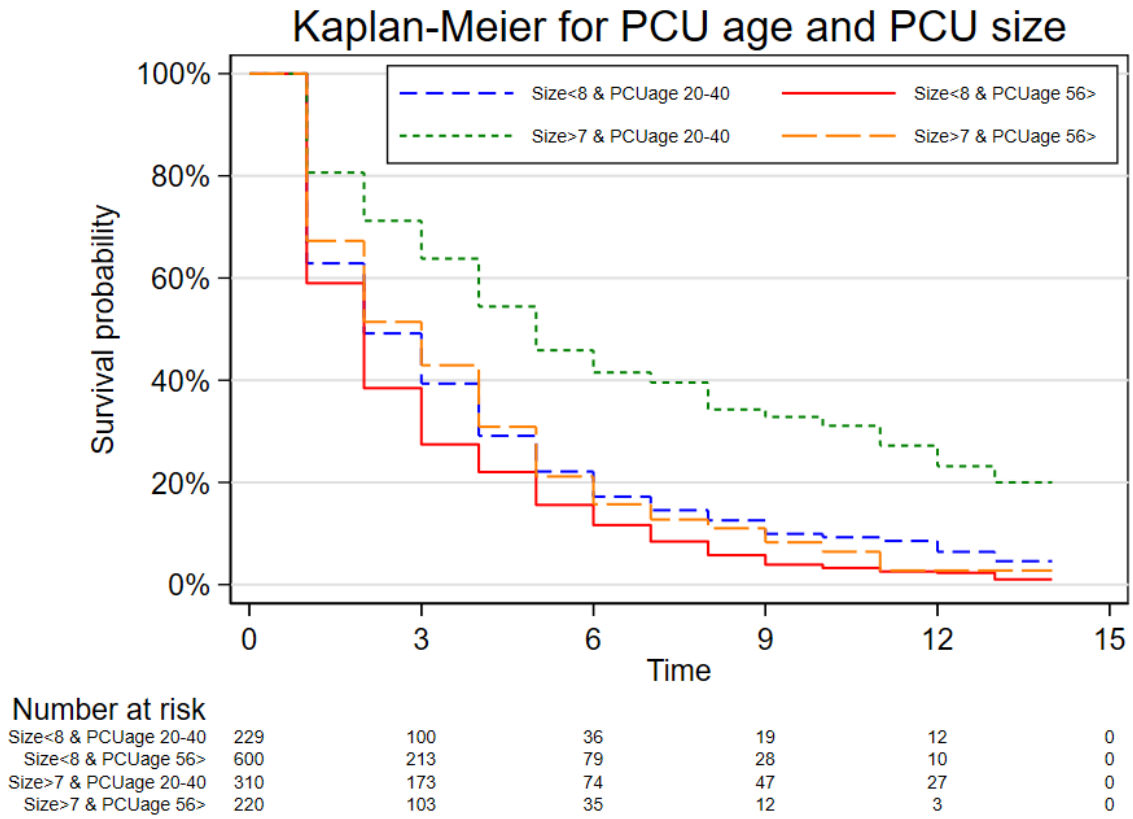
Kaplan-Meier for PCU age and PCU size
Survival probability
100%
80%
60%
40%
20%
0%
Size<8 & PCUage 20-40
Size<8 & PCUage 56>
Size>7 & PCUage 20-40
Size>7 & PCUage 56>
0
3
6
9
12
15
Time
Number at risk
Size<8 & PCUage 20-40 229 100 36 19 12 0
Size<8 & PCUage 56> 600 213 79 28 10 0
Size>7 & PCUage 20-40 310 173 74 47 27 0
Size>7 & PCUage 56> 220 103 35 12 3 0

Figure 11

A.4 Appendix: Cox Proportional Hazard Model Graph

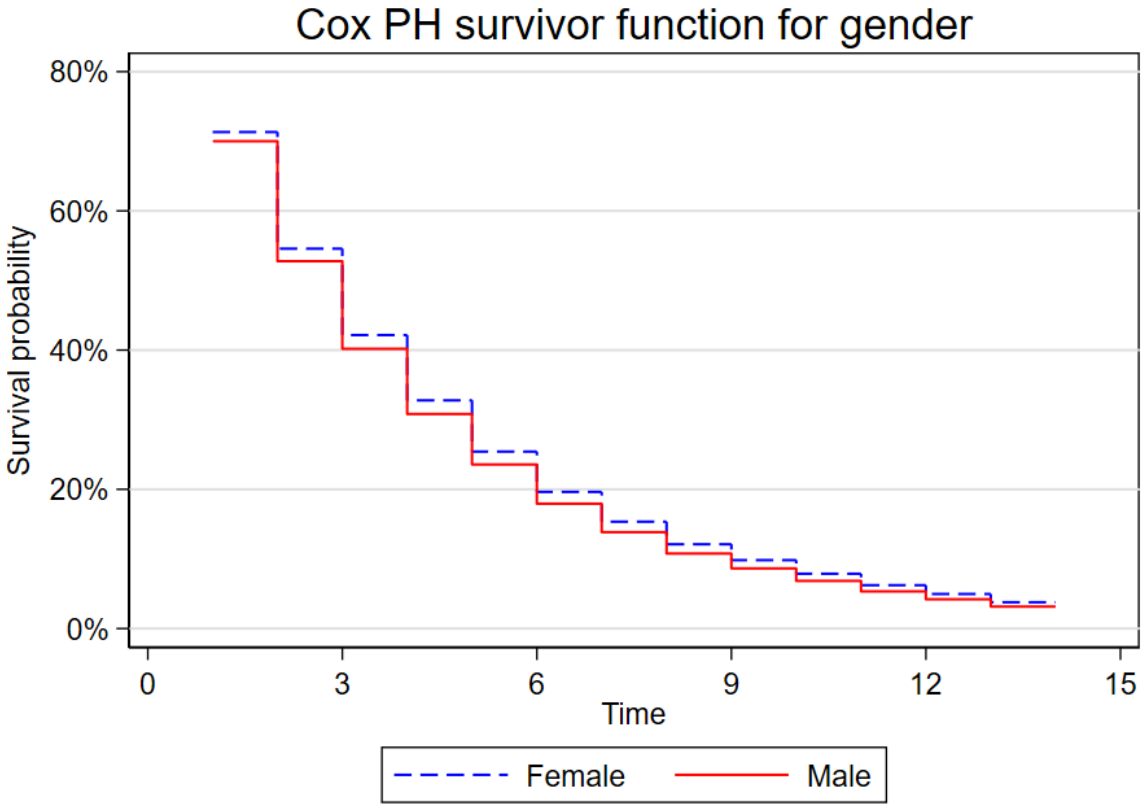

Figure 12

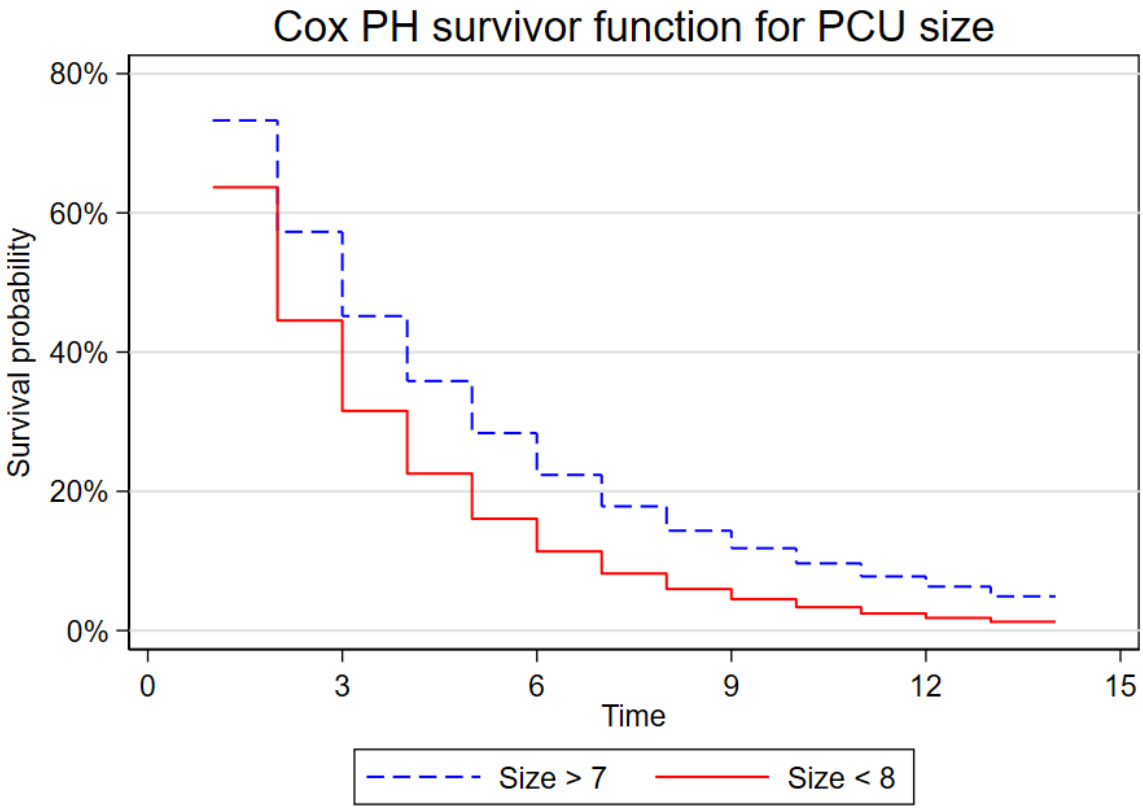
Cox PH survivor function for PCU size
80%
60%
40%
20%
0%
Survival probability
0
3
6
9
12
15
Time
Size > 7
Size < 8

Figure 13

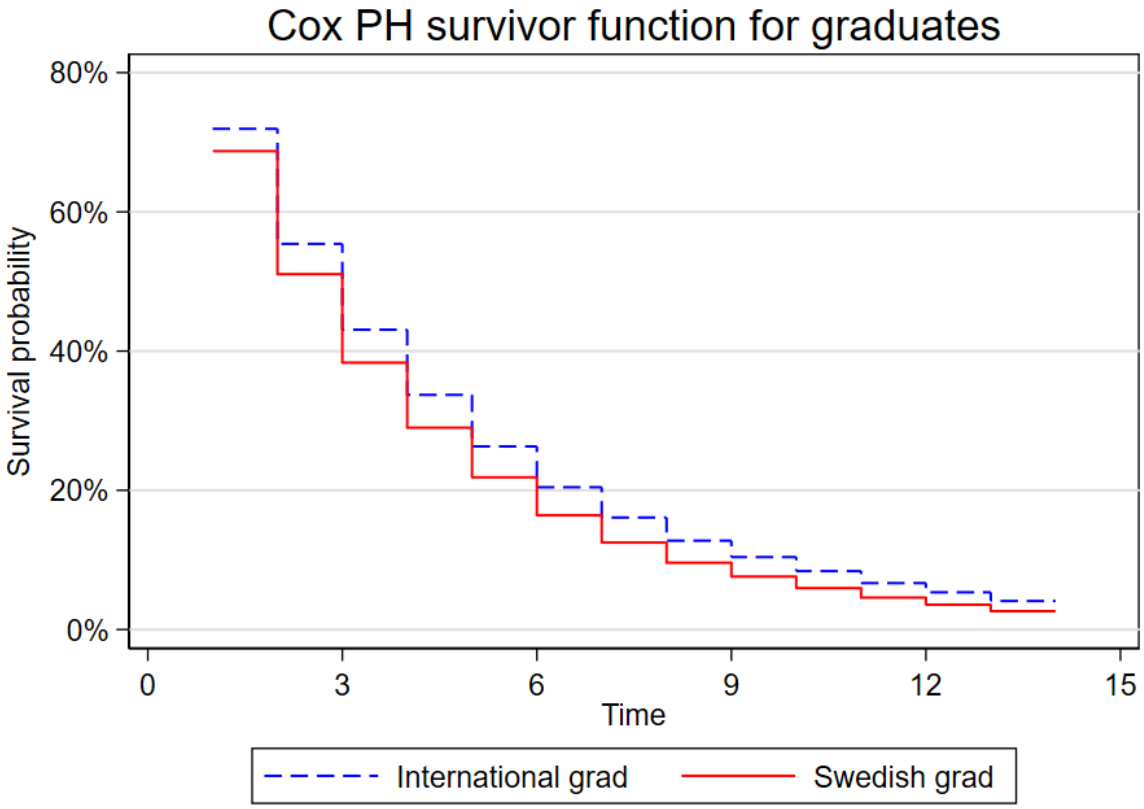

Figure 14

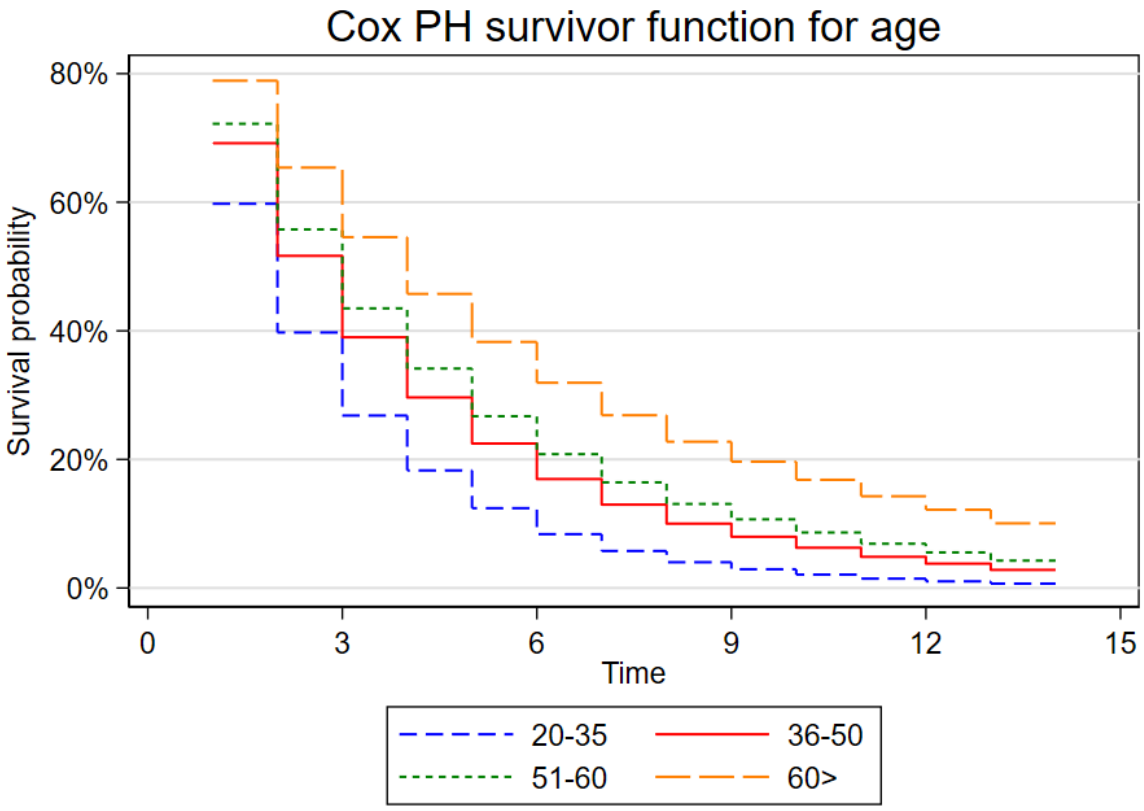

Figure 15

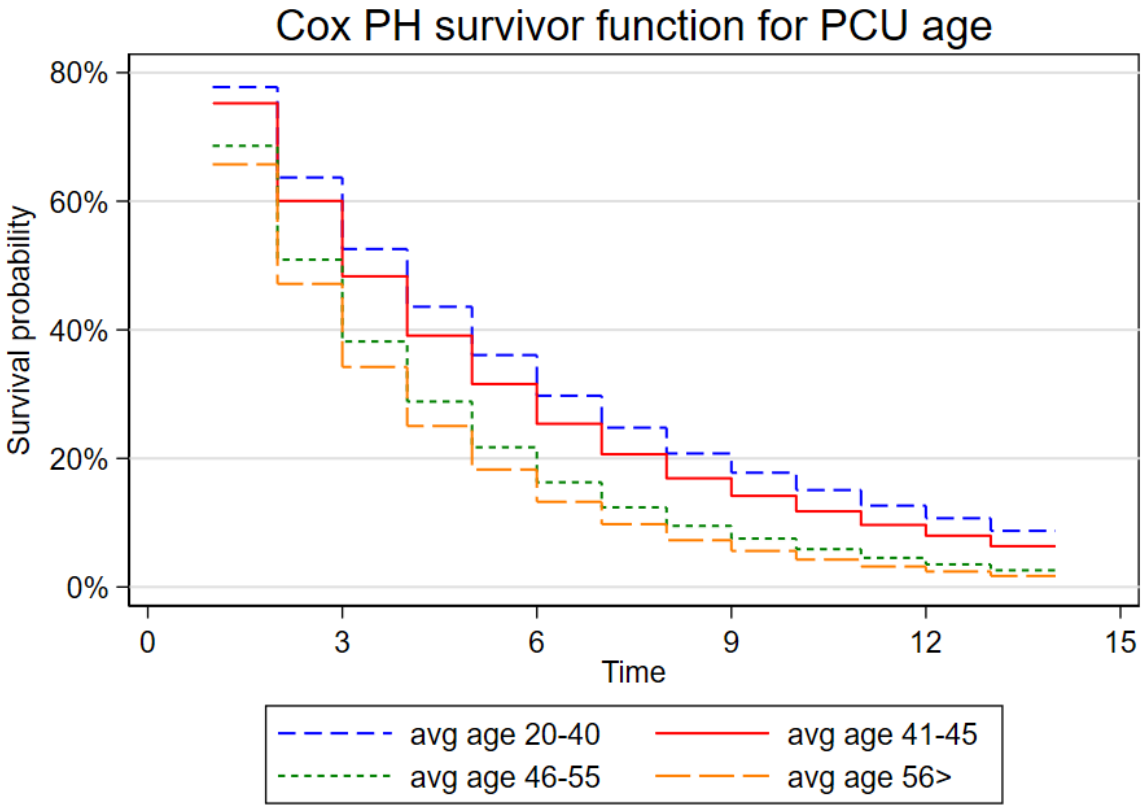

Figure 16

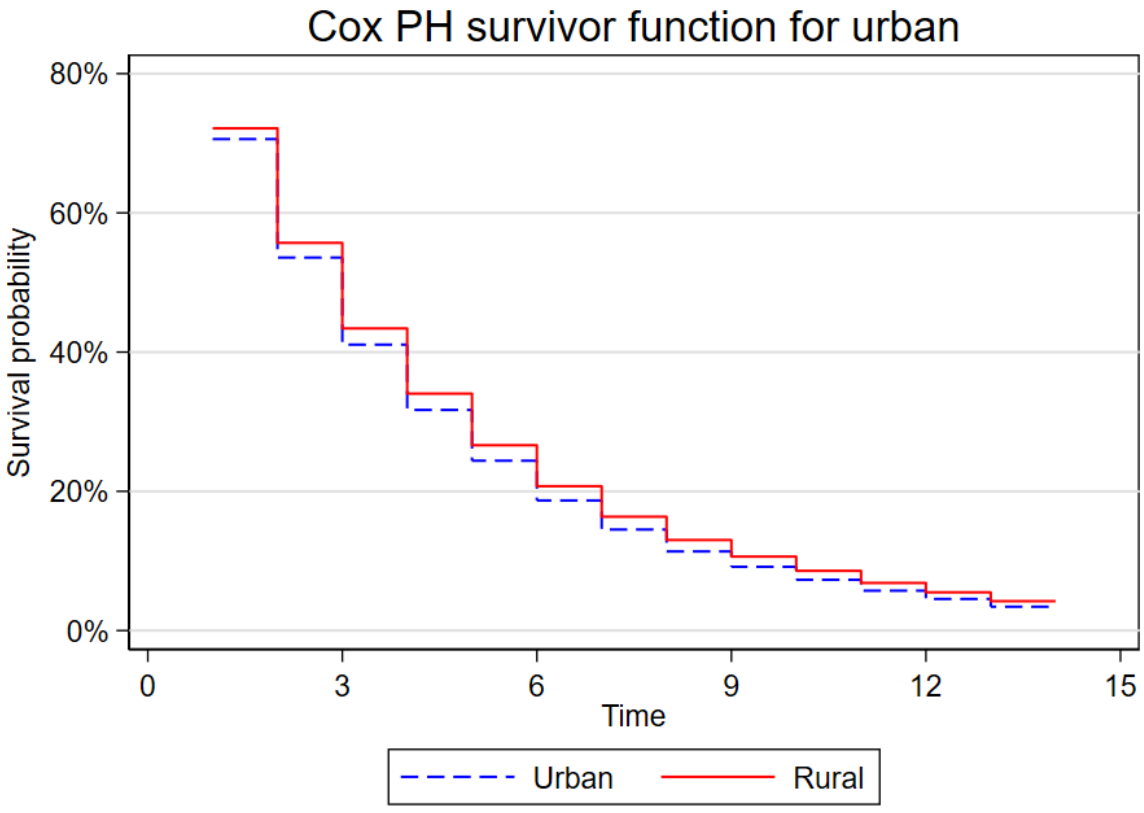

Figure 17

A.5 Appendix: Proportional Hazard Assumptions

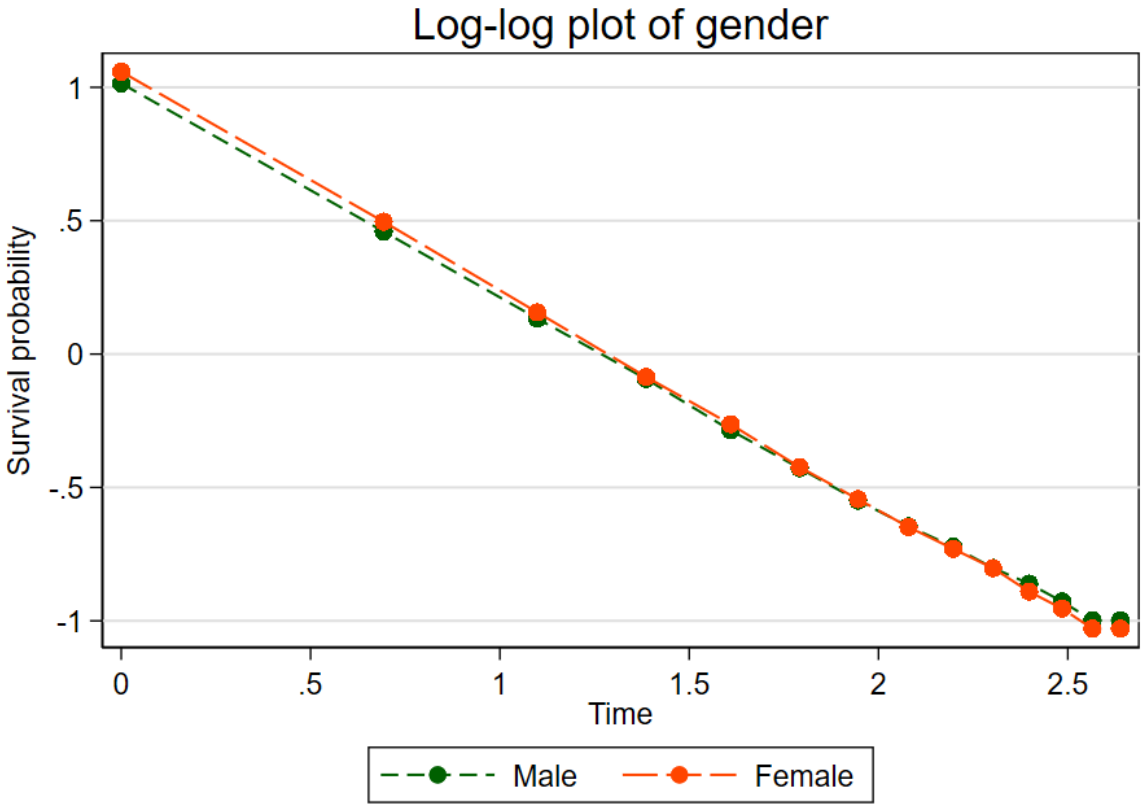

Figure 18

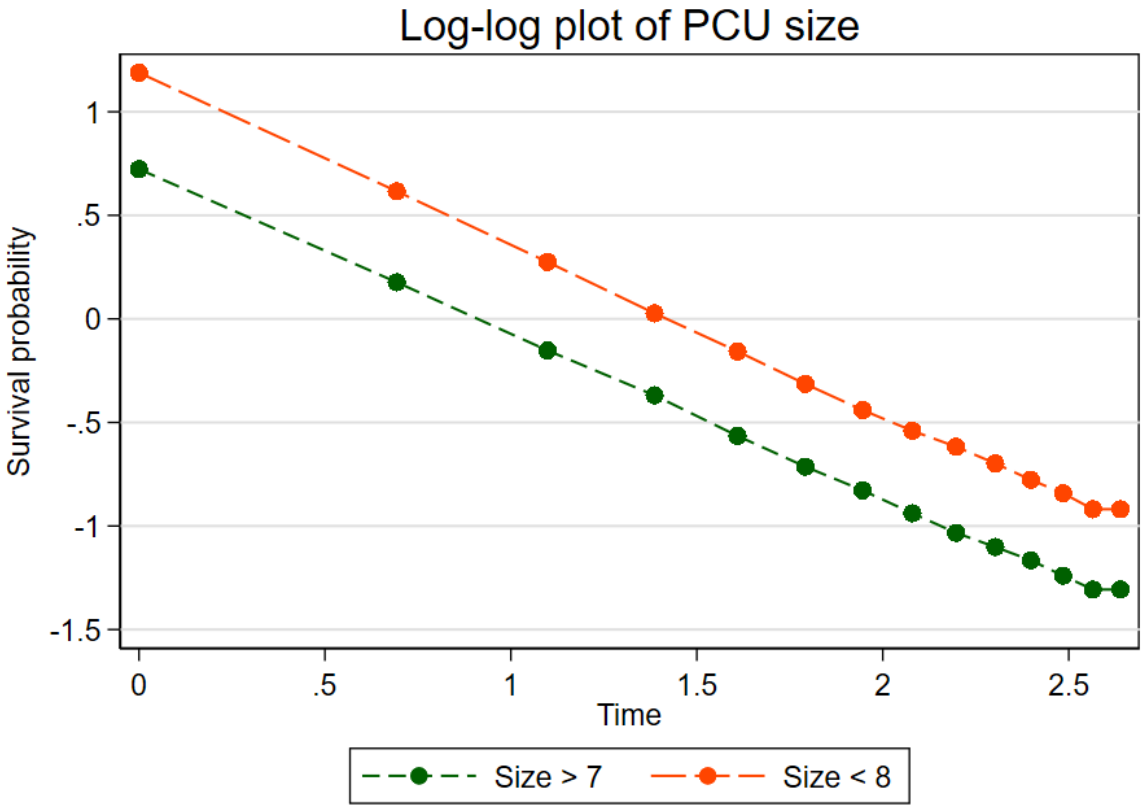

Figure 19

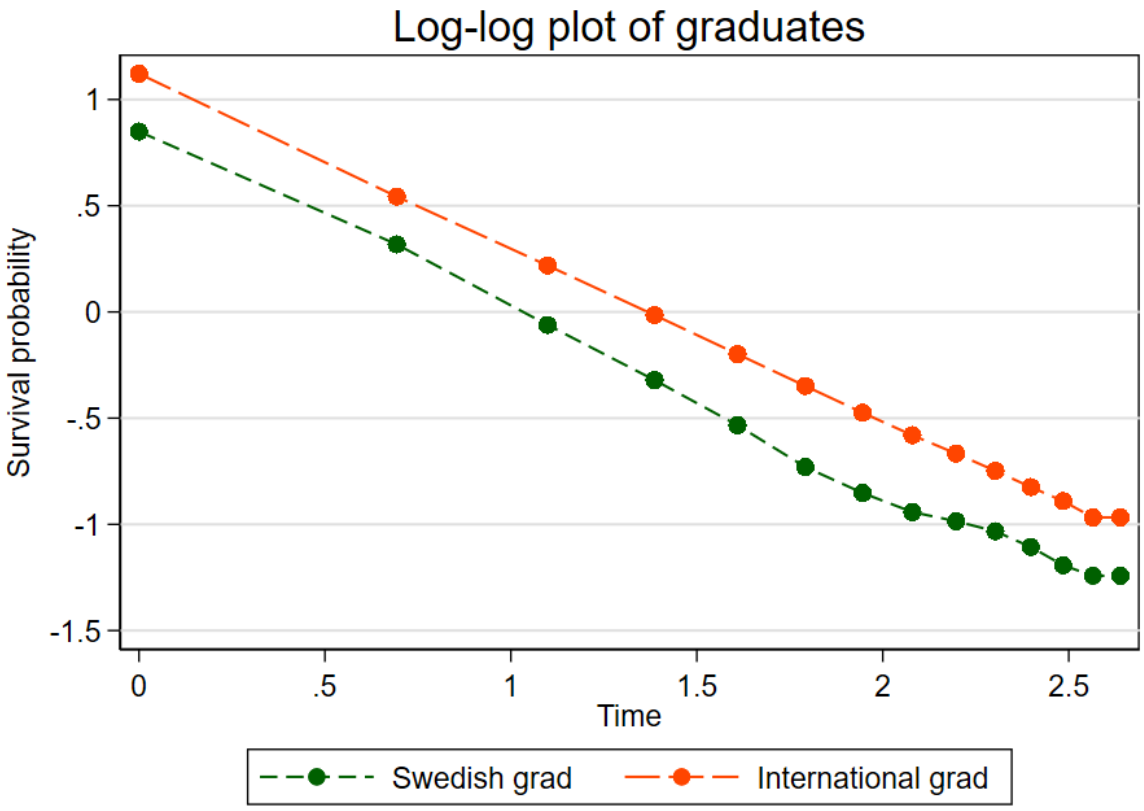

Figure 20

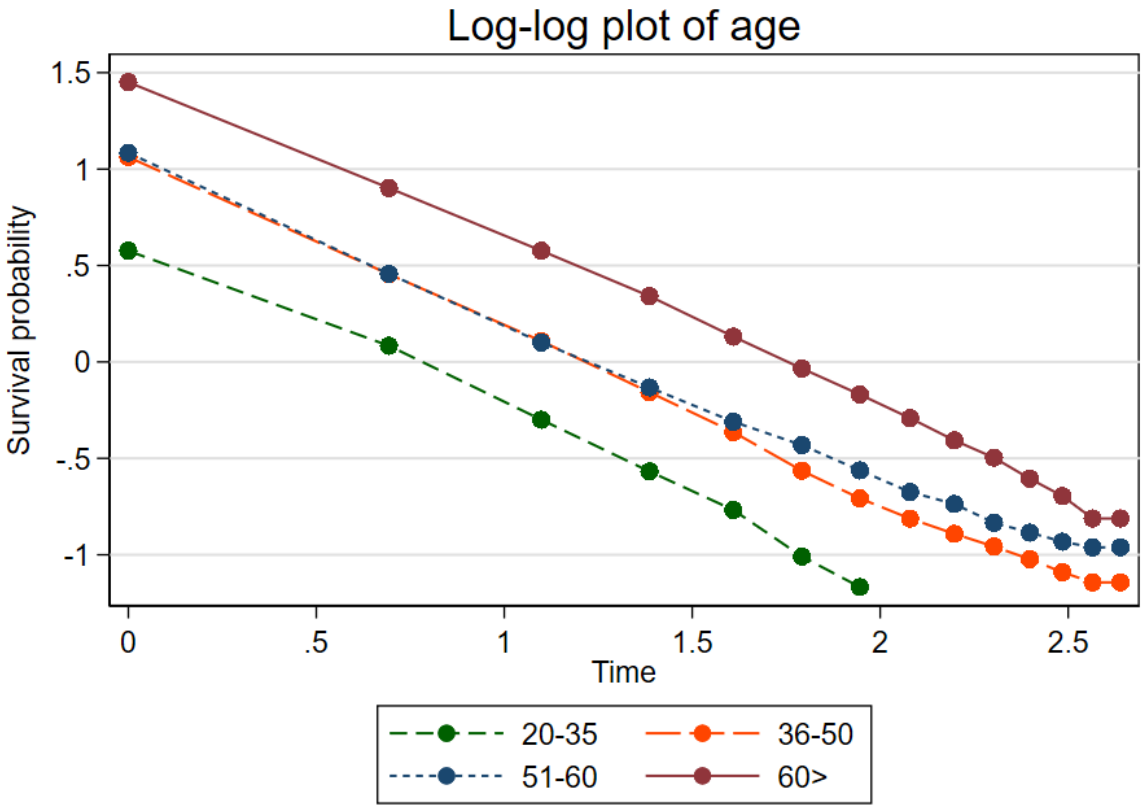

Figure 21

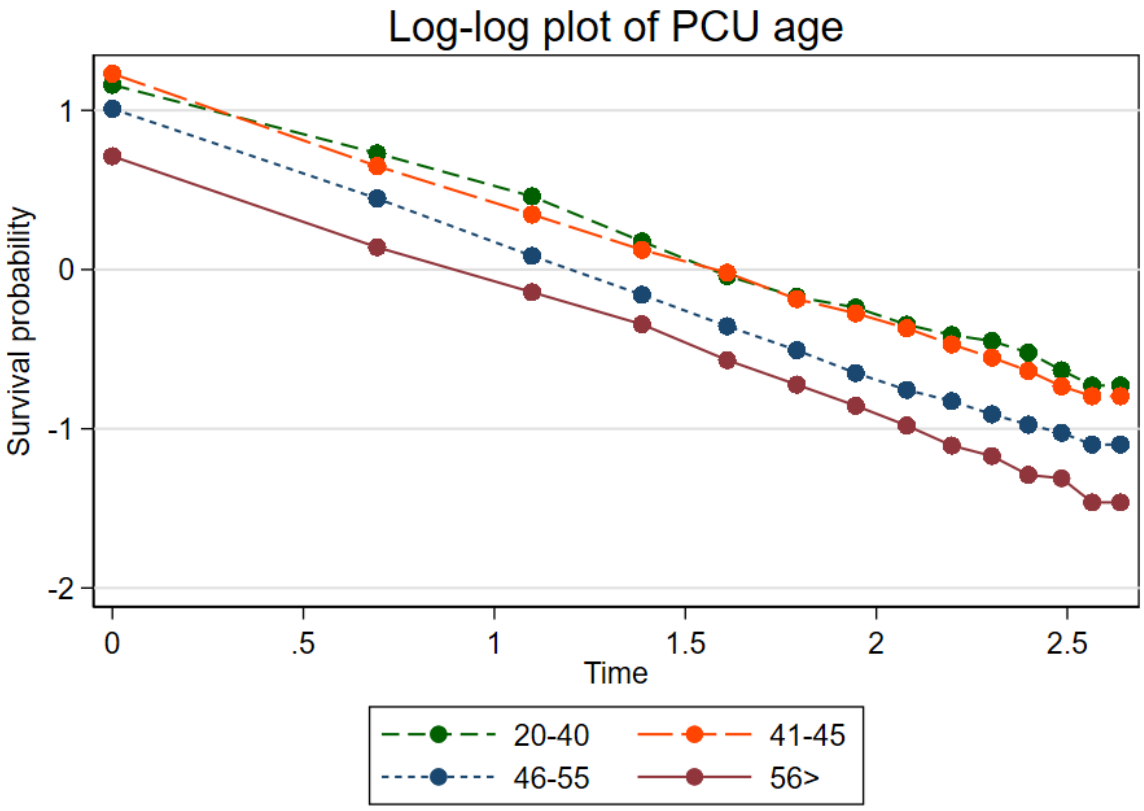

Figure 22

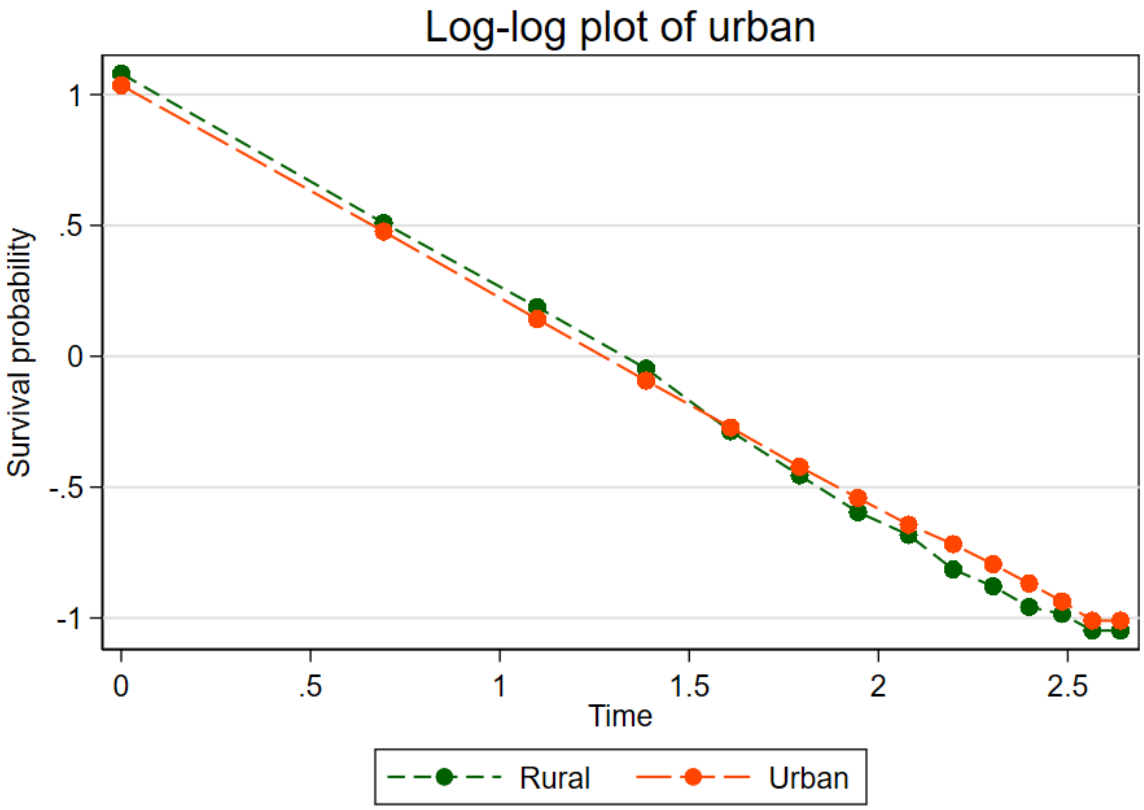
Log-log plot of urban
Survival probability
1
.5
0
-.5
-1
0
.5
1
1.5
2
2.5
Time
Rural
Urban

Figure 23

A.6 Appendix: Descriptive Statistics for physicians

Table 21 Descriptive Statistics for physicians by gender

	Males					Females				
Variables	Obs	Mean	St.d	Min	Max	Obs	Mean	St.d	Min	Max
Age	22,613	49.94	12.06	19	80	28,588	46.25	11.81	20	82
Quit	4,453	1.109	0.921	0	7	5,806	1.068	0.941	0	7
First age	4,453	43.20	12.66	19	80	5,806	39.82	11.61	20	79
Tenure PCU	6,405	3.392	3.265	1	15	8,370	3.272	3.103	1	15
Duration	4,453	5.078	4.302	1	15	5,806	4.924	4.225	1	15
Graduates										
Swedish	22,613	0.241	0.428	0	1	28,588	0.305	0.460	0	1
International	22,613	0.759	0.428	0	1	28,588	0.695	0.460	0	1
Work										
Work 1	20,743	0.622	0.485	0	1	25,853	0.692	0.462	0	1
Work 2	20,743	0.255	0.436	0	1	25,853	0.223	0.416	0	1
Work 3	20,743	0.124	0.329	0	1	25,853	0.0846	0.278	0	1

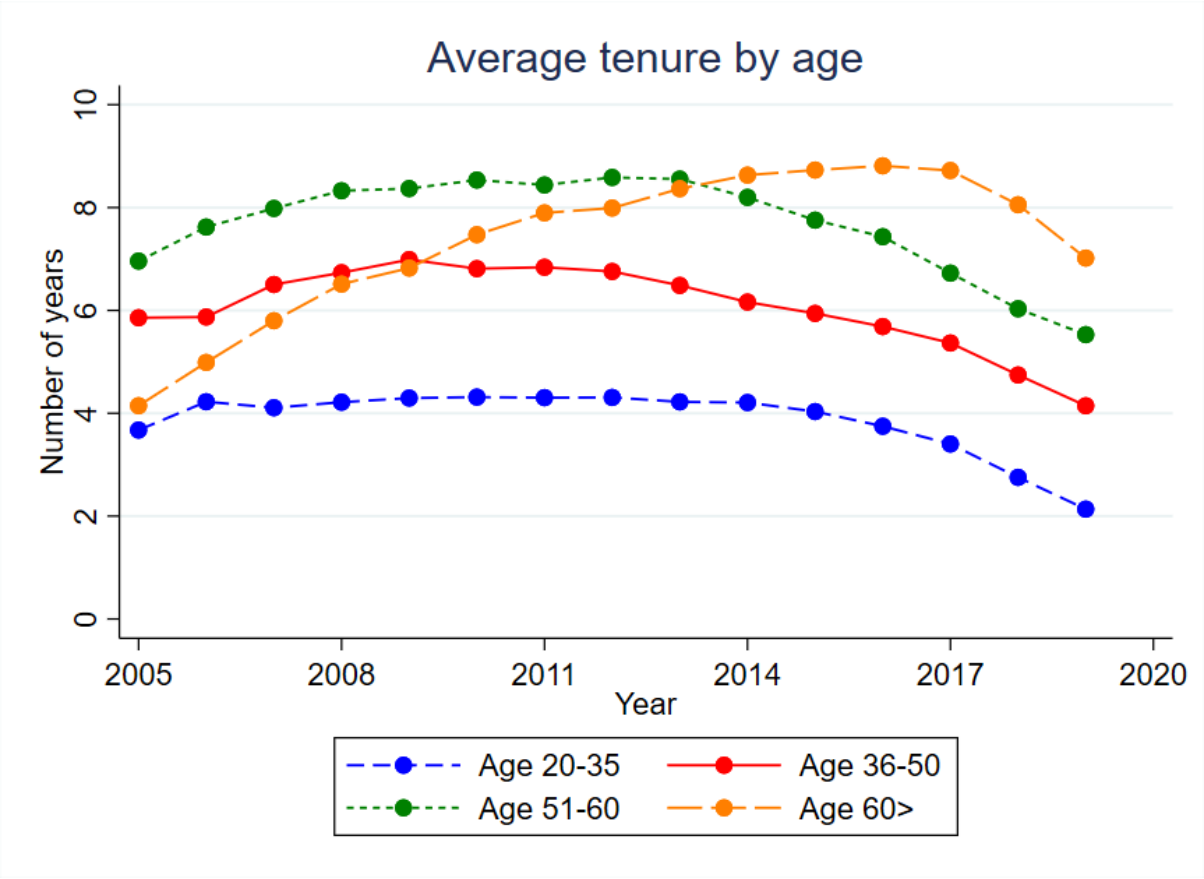

Figure 24

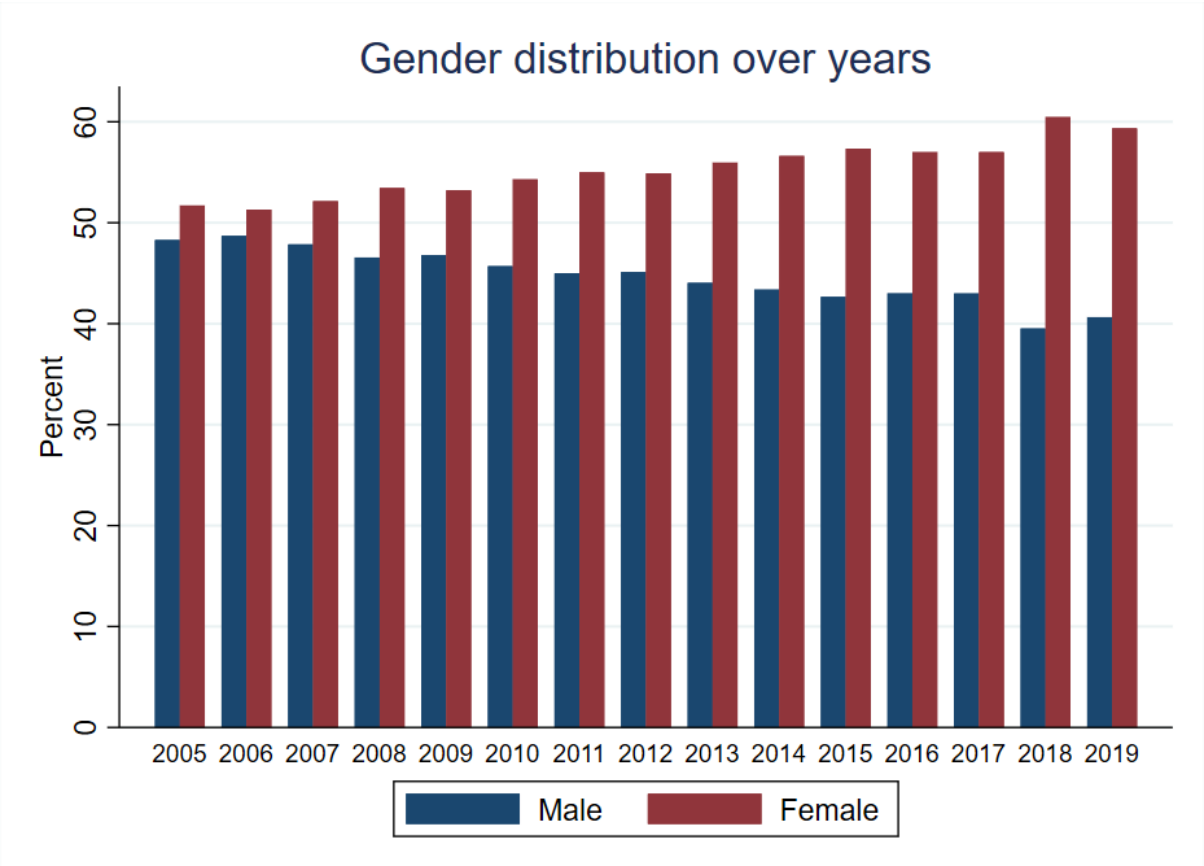

Figure 25

A.7 Appendix: Descriptive Statistics for Primary Care Units over years

Table 22 Descriptive statistics for primary care units year 2005

Variables	Obs	Mean	St.d	Min	Max
Phys count	340	7.065	4.545	1	28
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
PCU size					
Size <8	340	0.612	0.488	0	1
Size >7	340	0.388	0.488	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 23 Descriptive statistics for primary care units year 2006

Variables	Obs	Mean	St.d	Min	Max
Phys count	350	7.257	4.730	1	29
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
PCU size					
Size <8	350	0.594	0.492	0	1
Size >7	350	0.406	0.492	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 24 Descriptive statistics for primary care units year 2007

Variables	Obs	Mean	St.d	Min	Max
Phys count	363	7.270	5.062	1	32
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
PCU size					
Size <8	363	0.614	0.487	0	1
Size >7	363	0.386	0.487	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 25 Descriptive statistics for primary care units year 2008

Variables	Obs	Mean	St.d	Min	Max
Phys count	372	7.333	5.083	1	35
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	117	1	0	1	1
PCU size					
Size <8	372	0.597	0.491	0	1
Size >7	372	0.403	0.491	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 26 Descriptive statistics for primary care units year 2009

Variables	Obs	Mean	St.d	Min	Max
Phys count	425	6.734	5.257	1	36
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	139	1	0	1	1
PCU size					
Size <8	425	0.647	0.478	0	1
Size >7	425	0.353	0.478	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 27 Descriptive statistics for primary care units year 2010

Variables	Obs	Mean	St.d	Min	Max
Phys count	444	6.919	5.074	1	37
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	46	1	0	1	1
PCU size					
Size <8	444	0.633	0.483	0	1
Size >7	444	0.367	0.483	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 28 Descriptive statistics for primary care units year 2011

Variables	Obs	Mean	St.d	Min	Max
Phys count	446	7.150	5.101	1	34
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	25	1	0	1	1
PCU size					
Size <8	446	0.608	0.489	0	1
Size >7	446	0.392	0.489	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 29 Descriptive statistics for primary care units year 2012

Variables	Obs	Mean	St.d	Min	Max
Phys count	455	7.347	5.449	1	46
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	15	1	0	1	1
PCU size					
Size <8	455	0.620	0.486	0	1
Size >7	455	0.380	0.486	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 30 Descriptive statistics for primary care units year 2013

Variables	Obs	Mean	St.d	Min	Max
Phys count	464	7.496	5.476	1	46
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	16	1	0	1	1
PCU size					
Size <8	464	0.597	0.491	0	1
Size >7	464	0.403	0.491	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 31 Descriptive statistics for primary care units year 2014

Variables	Obs	Mean	St.d	Min	Max
Phys count	477	7.950	5.581	1	47
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	16	1	0	1	1
PCU size					
Size <8	477	0.564	0.496	0	1
Size >7	477	0.436	0.496	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 32 Descriptive statistics for primary care units year 2015

Variables	Obs	Mean	St.d	Min	Max
Phys count	477	8.310	5.628	1	43
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	10	1	0	1	1
PCU size					
Size <8	477	0.518	0.500	0	1
Size >7	477	0.482	0.500	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 33 Descriptive statistics for primary care units year 2016

Variables	Obs	Mean	St.d	Min	Max
Phys count	477	8.449	5.581	1	47
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	14	1	0	1	1
PCU size					
Size <8	477	0.478	0.500	0	1
Size >7	477	0.522	0.500	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 34 Descriptive statistics for primary care units year 2017

Variables	Obs	Mean	St.d	Min	Max
Phys count	482	8.541	5.482	1	42
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	9	1	0	1	1
PCU size					
Size <8	482	0.481	0.500	0	1
Size >7	482	0.519	0.500	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 35 Descriptive statistics for primary care units year 2018

Variables	Obs	Mean	St.d	Min	Max
Phys count	477	9.398	5.763	1	47
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	6	1	0	1	1
PCU size					
Size <8	477	0.392	0.489	0	1
Size >7	477	0.608	0.489	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

Table 36 Descriptive statistics for primary care units year 2019

Variables	Obs	Mean	St.d	Min	Max
Phys count	471	9.711	5.854	1	46
Open	546	11.94	4.014	2	15
Event cum. no	546	11.15	14.52	0	55
Event cum.	546	9.881	12.54	0	46
Event first	2	1	0	1	1
PCU size					
Size <8	471	0.384	0.487	0	1
Size >7	471	0.616	0.487	0	1
Treatment					
Untreated	546	0.240	0.427	0	1
Treated	546	0.760	0.427	0	1
Location					
Rural	546	0.125	0.331	0	1
Urban	546	0.875	0.331	0	1
Region					
Stockholm	546	0.375	0.485	0	1
Västra Götaland	546	0.350	0.477	0	1
Skåne	546	0.275	0.447	0	1

A.8 Appendix: Event Plot

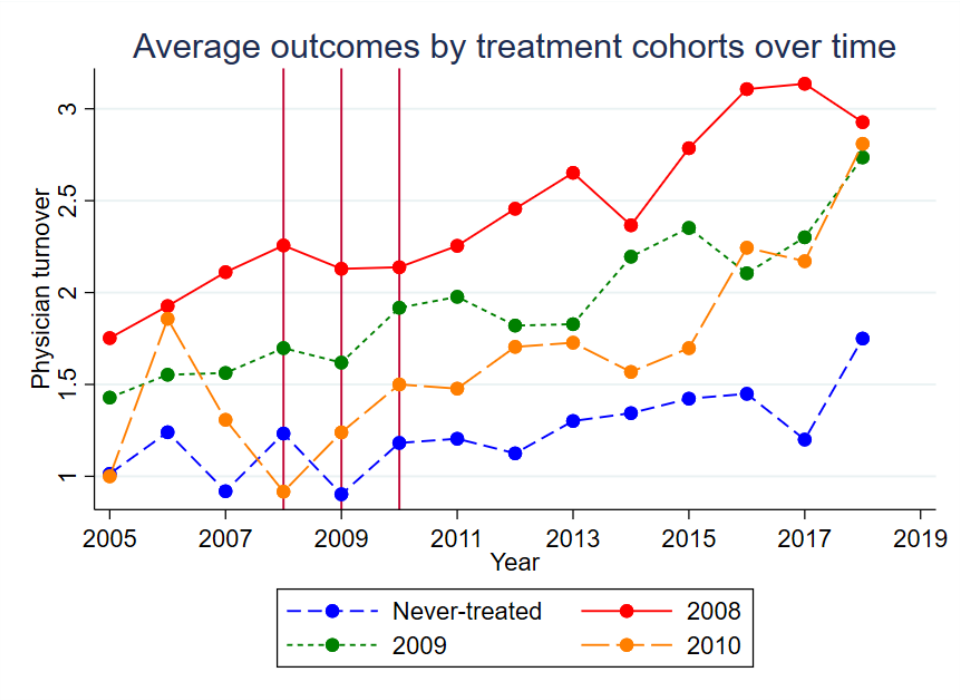

Figure 26