Do men avoid seeking medical advice? Gender-specific changes in primary healthcare use after first hospitalization at ages 60+ in Denmark

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Background

Women have lower mortality rates than men following most adverse health conditions, including hospitalizations. [1-3] To explain women's mortality advantage, the literature points towards the interaction of biological and behavioral factors. [4, 5] One observation among the behavioral factors is that women, on average, utilize primary healthcare more than men. [6, 7] Primary healthcare is among the main means of prevention, [8, 9] while timely diagnosis can be crucial for effective treatment and prolonging an individual's life. [9, 10]

Seeking medical help is a complex process, shaped by demographic, structural and individual factors such as age, sex, access to healthcare, socioeconomic inequalities, cultural norms, gender-roles, and education. [11-14] Most quantitative research documenting patterns in primary healthcare use is based on cross-sectional analysis of aggregated-level data. These findings have consistently shown that women utilize primary healthcare services more often than same-aged men – even when excluding consultations for child-bearing and birth control. [7, 15] One major limitation of these population-level studies has been the inability to account for underlying morbidity levels.

In contrast to population-level studies, individual-level studies have yielded mixed findings. Some studies report small or non-significant differences when comparing men and women, who face a similar conditions, such as headache, back pain, and prior major cancers. [16-18] Other studies have found a consistent female surplus in primary healthcare use when controlling for morbidity levels. [19-22] It therefore remains unclear whether higher rates of primary healthcare use among women are due to women's health disadvantage or whether they are due to a lower threshold to seek medical help. [16, 23] In addition, studies did not distinguish between users and non-users of primary healthcare. This distinction is important because there may be no or small differences in treatment-seeking behavior between those men and women, who are willing to engage with healthcare, while differences may be more pronounced among non-users.

We investigate trajectories of primary healthcare use and levels of non-use surrounding a health shock, measured as the first hospital admission at age 60 and older. We examine primary healthcare use patterns before and after hospitalization for four major causes of admission: stroke, myocardial infarction (MI), chronic obstructive pulmonary disease (COPD), and gastrointestinal cancers (GIC). We expect the frequency of contacts with primary healthcare to be higher in the period after admission to hospital. As women have greater somatic awareness, [24, 25] we assume women to be more likely to engage with primary healthcare services – before and after admission. If men are more reluctant to see medical advice until hospital admission, we may see a greater change in primary healthcare use among men than among women after the health shock. Finally, we anticipate patterns of primary healthcare use to be more similar across the two genders for GIC and COPD than for stroke and MI as the formers are slowly progressing chronic conditions which would require an individual to be exposed to primary healthcare already before hospital admission.

Methods

Data

We utilized routinely collected, population-based register data on hospital admissions and contacts with primary healthcare covering the entire Danish population. Using the unique personal identification number (CPR–Number), we linked records from the Central Population Registry (CPR), the National Patient Register (NPR), and the National Health Service Register (NHSR). While the CPR contains information on each resident's vital status, sex, and date of birth, [26, 27] the NPR contains information on hospital treatments since 1977, including dates of admission and discharge, and the causes of admission. [28] The NHSR, established in 1990, contains data on the primary healthcare use and includes information on the provider and a code for the provided services. [29] Since treatments of under 16-year-olds were reported with the CPR–Number of one parent until 31 December 1995, it was therefore not possible to distinguish whether a visit was for a parent or a child before 1996 and restricted our study period from 1996 to 2014.

Study Population

Over one million men and women were aged 60 or older in Denmark by 1 January, 1999 (N=1,056,733). We focused on healthcare use after age 60 to remove obstetrics-related contacts with healthcare, which otherwise would have biased patterns observed among women of reproductive ages. We applied a 7-year washout-period to increase the likelihood that the observed admission is not a re-admission. Washout-periods of 7 years are recommended by the Swedish National Board of Health and Welfare in order to capture first events of MI, [30] and have been widely used in register-based studies. [31, 32] We excluded 433,352 individuals who were admitted to hospital within the previous 7-year period, lasting from 1 January 1992 to 31 December 1998.

Among the remaining individuals (N=623,381), we identified those who were admitted to a Danish hospital between 1 January, 1999 and 31 December, 2011 (N=414,839). We defined an admission to hospital as the first inpatient hospital stay at age 60 or older lasting three days (equivalent to two overnight stays) or longer, distinguishing whether the underlying cause for the hospitalization was stroke, MI, CRC, and COPD (N=65,622). We linked admissions with data on contacts with primary healthcare, covering the 33 months before and after hospitalization that would capture short and long-term changes in primary healthcare use before and after hospital admission.

The study population includes individuals who survived and who died within the 33-month period after hospitalization. To account for a potential bias emerging from an increased healthcare use in close proximity to death [33, 34] we conducted a sensitivity check by restricting our analysis to those who survived the 33 months after admission.

Study Design and Statistical Modeling

The study design is illustrated in Figure 1. For each individual in the study population, we recorded the number of contacts with primary healthcare in five 6-month periods spanning 30 months before and after the hospitalization event. Varying lengths of stay in hospital are likely to influence the use of outpatient healthcare services, since intensified primary healthcare use can occur in preparation for admission or due to treatment following hospital admission in outpatient settings. Additionally, intensified primary healthcare use is needed to ensure continuity of care after hospital discharge, and might be reinforced by GPs rather than initiated by patients themselves. To account for these factors and to ensure that all intervals are of 6-month length, we specified an additional interval surrounding admission to hospital. This interval covers three months before and after hospitalization. We omitted this period from our analysis, and thus analyzed the frequency of contacts with primary healthcare in the five 6-month intervals preceding and following the 6-month admission period. Consequently, the analysis intervals start 33 months before hospital admission and end 33 months thereafter.

[Figure 1: Overview on the study design and the modelling of time before and after hospital admission using a linear spline]

We investigated how the number of contacts with primary healthcare changes with temporal distance to hospital admission (*Temporal Distance*, see Figure 1) and with other covariates. As different temporal patterns before and after hospitalization are likely, we introduced a binary variable (*After Admission*) that could, via interaction with temporal distance, capture potential differences in the trajectories of healthcare use before and after hospital admission.

In this longitudinal cohort study, the responses are repeated observations of counts. Furthermore, the distribution of the number of contacts with primary healthcare shows a stark change after hospitalization. As shown in Figure 2, the marked zero-inflation present before hospital admission largely disappears thereafter. We utilized a hurdle model to account for the special properties of our data. [35]

[Figure 2: Distribution of contacts with primary healthcare within the 3- to 9-month period before and after admission to hospital]

Hurdle models have been increasingly used in the social and medical sciences, including applications in healthcare utilization and substance-abuse research. [36-40] A hurdle model is a two-part model which combines a regression model for the probability of zero-counts with a regression model for the positive counts. The first is a binomial logistic regression, which in our application captures non-users of primary healthcare. The second models the frequency of healthcare use for individuals who are in the user group. Both regression models can, but do not need to share the same covariates. An individual random effect was incorporated to account for repeated observations. Positive counts were modelled by a truncated negative binomial regression with a log-link to account for overdispersion not captured by the observed covariates. As shown in Table 1, we performed model selection for both parts of the model step-wise and hierarchically, separately for each cause of admission. The covariates are *Sex*, *Age* and the variable *After Admission*, which discriminates between the period before and after hospital admission.

Temporal distance to hospitalization was included in two ways: either with a single linear effect (log-scale) or as a linear spline (piecewise-linear function) with a knot at *Temporal Distance = 2*. The linear spline allowed the slope to be different for the 6-month intervals next to the admission period as, for example, the frequency of contacts with primary healthcare might have changed more rapidly within the period close to admission. Based on Akaike's Information Criterion (AIC) we selected Model 5 as the final model. The merging of registers was carried out with Stata (Version 14). Statistical models were estimated using the *glmmTMB* package for R (Version 3.5.1). [41]

[Table 1: Overview of the stepwise model development process; models were developed separately by cause of admission]

Results

Descriptive Statistics

As shown in Table 2, we studied 65,622 individuals, of which 48% were women and 52% were men. The mean age at first admission was significantly higher ($p < 0.001$) among women (77.25 years) than men (75.17 years). More women were admitted for COPD and stroke, while men more were admitted for MI and GIC.

[Table 2: The number and percentages of hospital admissions by gender and cause of admission to hospital.]

Regression Model

Table 3 presents exponentiated beta-coefficients for both parts of the hurdle model. The upper section of Table 3 shows the logistic zero-inflation part of the model for being in the non-user group. We found that men have higher odds of being in the non-user group than women for all causes of admission. For men and women and across all causes, the odds of being in the non-user group were consistently smaller in the period after admission than in the period before admission. A significant interaction between gender and the period of hospital admission for all causes, apart from stroke, suggests that the decline in the probability of being a non-user after hospital admission is larger among men than women. This results in smaller gender differences in the probabilities of being a non-user after hospital admission. For example, a man aged 60-69, who was admitted for MI had a 25% probability of being in the non-user group before admission, while the probability among women was 15%. After admission for MI, the corresponding probabilities of non-use were 2% among men and 1% among women.

The probabilities of being in the non-user group varied largely by cause of admission within the period before admission. For example, a man aged 60-69, who was admitted for stroke had a probability of 24% of being in the non-user group before admission, while the equivalent probability for a man with COPD was 6%. After hospitalization, the corresponding probabilities of being a non-user were 2% for stroke and 1% for COPD, indicating a substantial decline in the levels of non-use after hospital admission.

[Table 3: Results of hurdle regression models]

The lower section of Table 3 shows the regression results for the positive counts model. Across all causes of admission, we found that the average number of contacts with primary healthcare to steadily increase within the period before admission but were between 14% and 20% lower among men, depending on cause. The average number of contacts with primary healthcare increased substantially directly after hospitalization. Levels decreased thereafter for stroke, MI, and GIC, but remained stable for COPD. The significant interaction between gender and the period of hospital admission suggests that the increase in the average number of contacts with primary healthcare after admission was larger among men than among women. This resulted in a smaller gender gap in the number of contacts in the period after hospital admission, varying from 5% to 12% across the four causes. The post-hospitalization increase was higher among the acute conditions stroke (73%) and MI (64%) than among the slowly-progressing conditions COPD (29%) and GIC (35%). For example, before admission for MI, men had 20% fewer contacts with primary healthcare than women, and in the period after 9% fewer contacts.

[Figure 3: Estimated, average number of contacts with primary healthcare before and after admission to hospital for MI]

The trajectories of contacts with primary healthcare before and after hospitalization among men and women admitted for MI are shown in Figure 2. Visualizations for COPD , stroke, and GIC can be found in the supplementary material (Figures: 4-S, 5-S, 6-S).

Sensitivity Analysis

To examine the impact of mortality selection following hospitalization on primary healthcare use patterns, we re-ran the analysis excluding individuals who died during the 33-month period after hospital admission. This reduced the study population by 36% to 42,683 individuals, of which 22,423 were men (53%) and 20,260 were women (47%). We observed only marginal changes in the parameters of the hurdle models, underlining the robustness of our presented main findings. However, gender differences increased in both parts of the model: the probability of being a non-user, and the expected number of contacts with primary healthcare. This points towards the fact that women's surplus in primary health care use is linked to their survival advantage, albeit likely in poor health. Results of this sensitivity check are shown in the supplementary material (Table 1-S, Table 2-S, Table 3-S).

DISCUSSION

Principal Findings

We investigated the number of contacts with primary healthcare among men and women before and after the first hospital admission at age 60 and older. Across all studied causes, men had lower levels of primary healthcare use before and after hospitalization. In addition, men had a higher probability of being a non-user before hospital admission. However, after experiencing a health shock, we found substantial decline in the probability of being a non-user and increase in the levels of healthcare use among both, men and women. In absolute terms, these changes were stronger among men than among women.

Strengths and Limitations

We utilized high-quality register data, which covered the entire Danish population over 23 years, ranging from 1992 to 2014. Working with population-based registers reduces challenges of longitudinal surveys: losses to follow-up, recall bias, and non-responses. These issues have significant impact on the generalizability of results and often systematically differ between men and women. [16, 42]

This study uses individual-level data on four causes of hospital admission to examine changes in treatment-seeking behavior after a health shock by comparing men and women of similar morbidity levels. Unfortunately, our data did not allow us to investigate the severity of the underlying conditions. Systematic gender differences in the severity of the studied conditions could influence gender-specific patterns of primary healthcare use before and after admission. Furthermore, the data on primary healthcare did not allow to distinguish whether a contact was directly related to the cause of admission to hospital, and whether it was a preventative visit or for continuing treatment. In addition, our findings may be limited to the Danish healthcare context in which there are no out-of-pocket expenses for GP visits and may not be generalizable to other welfare state contexts. Despite these limitations, our study makes an important contribution to the literature by examining gender differences in the levels of primary healthcare use across four major conditions and distinguishing between users and non-users of primary healthcare.

Interpretations and Implications

Using a hurdle model enabled us to distinguish between two features: first, the probability that individuals are users of primary healthcare, and second, the number of contacts given that an individual is a user of primary healthcare. Differentiating by cause of hospitalization allowed us to investigate whether consultation patterns differed by acute and slowly-progressing conditions. For MI and stroke, symptoms might not be present before disease onset or already present symptoms might be overlooked. Contrastingly, patients with COPD are likely to have noticeable symptoms before admission. While we found probabilities of non-use before admission to hospital to be highest among the acute conditions MI and stroke, probabilities were lowest for the slowly progressing condition COPD.

Before admission to hospital, and consistently across all four causes of admission, men were less likely to be users of primary healthcare than women. This finding appears to be in line with early qualitative work on differentials in treatment-seeking behavior, which reported that the postponement of treatment-seeking is gender patterned. [25, 43-45] In the past, the over-generalization of these findings has contributed to over-simplified, stereotypical expectations about gender and treatment-seeking behavior: men are more reluctant to seek medical advice while women are over-users of the healthcare system, being more willing to consult a doctor even with less-serious complaints. [46, 47] However, we found a remarkable share of women to be non-users before admission to hospital. This is consistent with more recent work, which has demonstrated that neglecting symptoms and postponing treatment-seeking exist among women, too. [46] Therefore, treatment-seeking behavior cannot be separated into binary gender patterns. Men and women may face similar psycho-social obstacles in using primary healthcare services. [48] For example, both may postpone seeing a doctor when no urgency is perceived. [16] At the same time, when experiencing signs of a severe disease, such as lung cancer, fear of the diagnosis' implications may be a reason for not seeking medical advice. [49-51] In our study, the probabilities of being a non-user of primary healthcare were equally low after admission to hospital among men and women. This may partly reflect the impact of established treatment schemes after hospitalization for a specific condition which are fixed irrespective of the patient's gender. Nevertheless, gender differences in contacts with primary healthcare did not disappear after hospitalization. Instead, women used primary healthcare services more often than men across all four causes. This may be due to higher mortality selection in men following hospitalization: women are more likely to survive in disabling conditions. [3] Supporting this assumption, we found greater gender differences when restricting the analysis to individuals who survived the 33-month period following admission.

Conclusion

Although men were more responsive to a health shock with respect to primary healthcare use, our findings indicate a lower threshold for treatment-seeking among women. However, higher levels of primary health care use among women may be underpinned by the fact that women are more likely to survive in disabling conditions, while men experience higher levels of mortality following hospitalization. Increasing men's and women's usage of primary healthcare services, long before hospitalization should be given attention to prevent or postpone the ultimate health deterioration.

Ethics Approval

The study involves secondary data analysis of existing register data. The project was approved by the ethical committee assigned through the Danish National Committee on Biomedical Research and the Danish Data Protection Agency.

Funding

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FIGURES

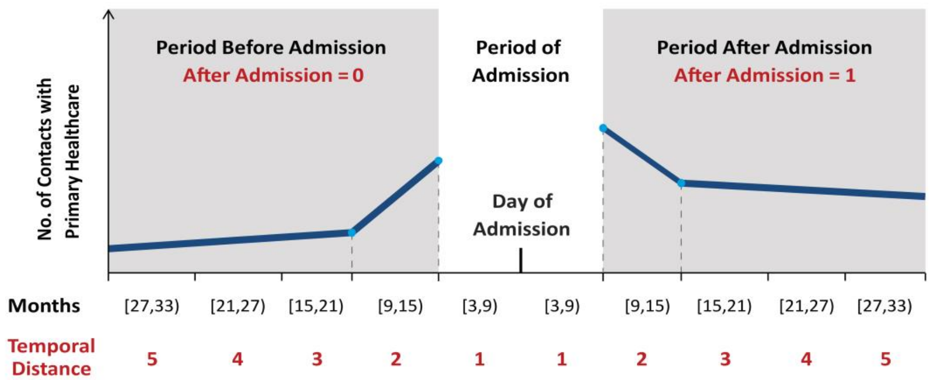

Figure 1: Overview on the study design and the modelling of time before and after hospital admission using a linear spline

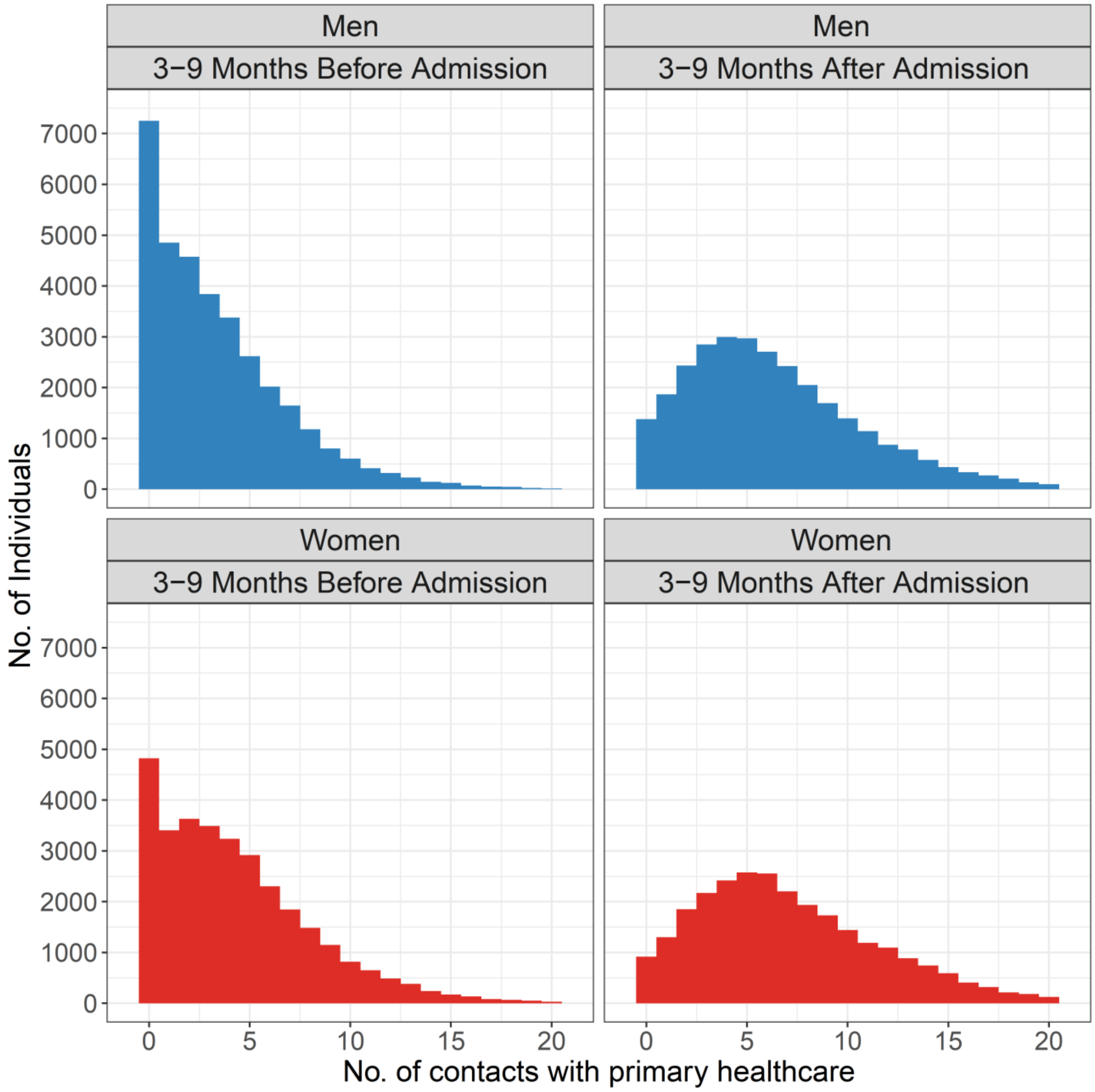

Figure 2: Distribution of contacts with primary healthcare within the 3- to 9-month period before and after admission to hospital

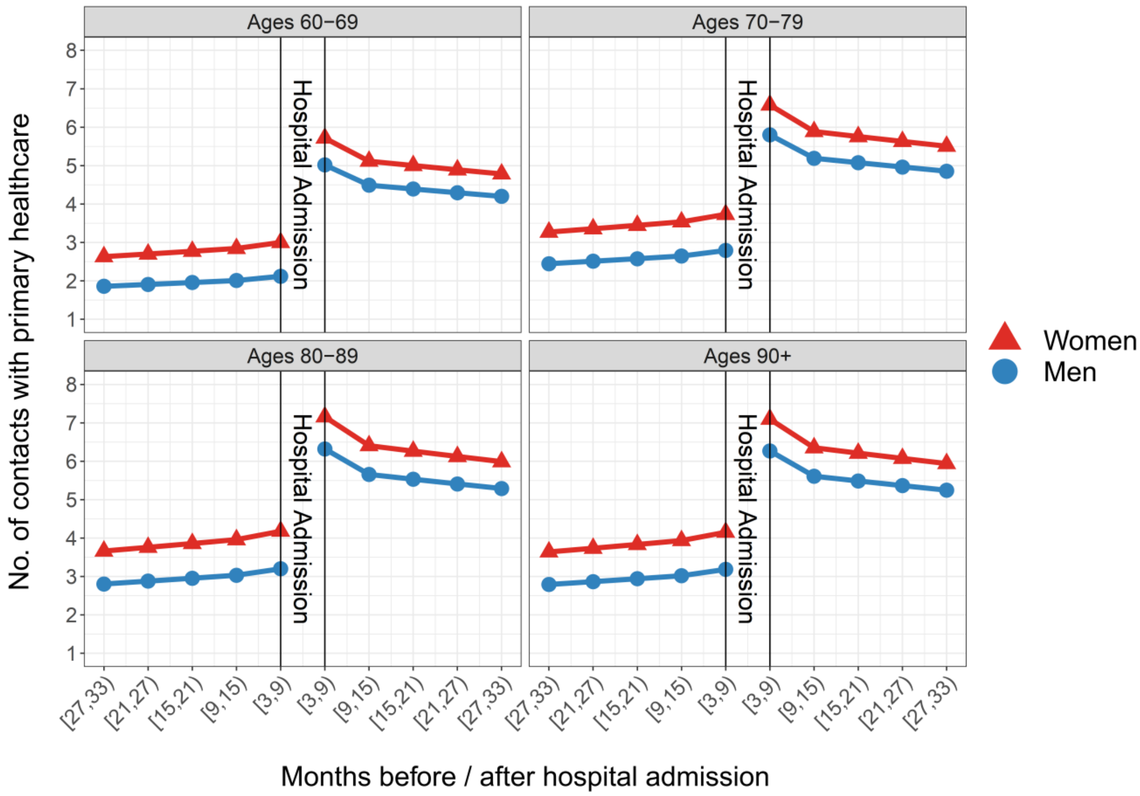

Figure 3: Estimated average number of contacts with primary healthcare before and after admission to hospital for MI

TABLES

Table 1: Overview of the stepwise model development process; models were developed separately by cause of admission

Cause	Model	Model for zero-counts	Model for positive counts	AIC	dAIC	DF
Stroke	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	1,014,319	753	17
Stroke	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	1,013,961	395	18
Stroke	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	1,013,925	359	19
Stroke	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	1,013,566	0	20
Stroke	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	1,013,567	1	21
MI	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	719,204	468	17
MI	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	718,932	195	18
MI	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	719,012	275	19
MI	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	718,739	2	20
MI	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	718,737	0	21
COPD	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	447,466	176	17
COPD	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	447,368	79	18
COPD	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	447,399	110	19
COPD	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	447,302	12	20
COPD	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	447,289	0	21
GIC	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	513,393	274	17
GIC	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	513,289	169	18
GIC	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	513,228	109	19
GIC	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	513,123	3	20
GIC	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	513,119	0	21

Note: (1|D) stands for individual random effect

Table 2: Number and percentage of hospital admissions by gender and cause of admission to hospital

Cause of Admission	ICD-10 Chapter	Men		Women	
		No.	in %	No.	in %
Stroke	I.61 – I.64	11,919	34.8	12,227	38.9
MI	I.21 – I.22	10,482	30.6	6,736	21.4
COPD	J.40 – J.47	4,335	12.7	5,530	17.6
GIC	C.15 – C.26	7,465	21.8	6,928	22
Total	-	**34,201**	**100.0**	**31,421**	**100.0**

Table 3: Results of hurdle regression models

Logistic Model: Zero Counts [exp(b)]	Stroke	MI	COPD	GIC
Intercept	0.17 ***	0.18 ***	0.03***	0.22 ***
After Admission	0.06 ***	0.07 ***	0.19 ***	0.23 ***
Men	1.80 ***	1.84 ***	2.16 ***	1.60 ***
Men * After Admission	0.96	0.89 *	0.75 ***	0.89 *
Age 70-79	0.53 ***	0.46 ***	0.60 ***	0.46 ***
Age 80-89	0.35 ***	0.28 ***	0.43 ***	0.29 ***
Age 90+	0.32 ***	0.26 ***	0.66	0.23 ***
No. of Observations	216,700	157,680	88,712	114,961
No. of Groups	24,146	17,218	9,865	14,393
VAR Individual Random Effect	4.60	3.90	6.05	3.87

Negative Binomial Model: Positive Counts [exp(b)]	Stroke	MI	COPD	GIC
Intercept	3.63 ***	3.54 ***	5.13 ***	3.46 ***
lin.spline(Temporal Distance) 1	0.94 ***	0.95 ***	0.91 ***	0.87 ***
lin.spline(Temporal Distance) 2	0.87 ***	0.88 ***	0.80 ***	0.79 ***
After Admission	1.73 ***	1.64 ***	1.29 ***	1.35 ***
lin.spline(Temporal Distance)1 * After Admission	0.94 ***	0.94 ***	1.06 ***	1.06 ***
lin.spline(Temporal Distance)2 * After Admission	0.98 *	0.95 ***	1.24 ***	1.17 ***
Men	0.82 ***	0.80 ***	0.86 ***	0.86 ***
Men * After Admission	1.11 ***	1.11 ***	1.08 ***	1.10 ***
Age 70-79	1.12 ***	1.14 ***	1.08 ***	1.13 ***
Age 80-89	1.16 ***	1.24 ***	1.10 ***	1.22 ***
Age 90+	1.13 ***	1.23 ***	1.07	1.28 ***
No. of Observations	216,700	157,680	88,712	114,961
No. of Groups	24,146	17,218	9,865	14,393
Overdispersion Parameter	11.20	15.50	13.90	8.55
VAR Individual Random Effect	0.23	0.24	0.25	0.28

Significance codes: "***" : 0.001 "**" : 0.01 "*" : 0.05 "." : 0.1

SUPPLEMENTARY MATERIAL: TABLES

Table 1-S: Overview of the stepwise model development process; survivors of the 33-month study period

Cause	Model	Model for zero-counts	Model for positive counts	AIC	dAIC	DF
Stroke	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	783,611	753	17
Stroke	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	783,310	395	18
Stroke	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	783,224	359	19
Stroke	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	782,922	0	20
Stroke	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	782,923	1	21
MI	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	585,568	452	17
MI	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	585,347	231	18
MI	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	585,342	225	19
MI	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	585,120	4	20
MI	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	585,116	0	21
COPD	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	320,473	131	17
COPD	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	320,395	53	18
COPD	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	320,426	84	19
COPD	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	320,349	6	20
COPD	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	320,342	0	21
GIC	1	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex + Age + (1|ID)	287,754	171	17
GIC	2	After + Sex + Age + (1|ID)	Temporal Distance * After + Sex * After + Age + (1|ID)	287,685	101	18
GIC	3	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex + Age + (1|ID)	287,656	72	19
GIC	4	After + Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	287,586	2	20
GIC	5	After * Sex + Age + (1|ID)	lin.spline(Temporal Distance) * After + Sex * After + Age + (1|ID)	287,584	0	21

Note: (1|D) stands for individual random effect

Table 2-S: Number and percentage of hospital admissions by gender and cause of admission; survivors of the 33-month study period

Cause of Admission	ICD-10 Chapter	Men		Women	
		No.	in %	No.	in %
Stroke	I.61 – I.64	8,388	37.4	8,432	41.6
MI	I.21 – I.22	8,065	36.0	4,873	24.1
COPD	J.40 – J.47	2,651	11.8	3,778	18.6
GIC	C.15 – C.26	3,319	14.8	3,177	15.7
Total	**-**	**22,423**	**100.0**	**20,260**	**100.0**

Table 3-S: Results of hurdle regression models: survivors of the 33-month study period

Logistic Model: Zero Counts [exp(b)]	Stroke	MI	COPD	GIC
Intercept	0.18 ***	0.18 ***	0.03***	0.19 ***
After Admission	0.07 ***	0.08 ***	0.19 ***	0.30 ***
Men	1.87 ***	2.01 ***	2.31 ***	1.86 ***
Men * After Admission	0.94	0.89 *	0.79 **	0.89 *
Age 70-79	0.57 ***	0.49 ***	0.61 ***	0.43 ***
Age 80-89	0.39 ***	0.32 ***	0.45 ***	0.27 ***
Age 90+	0.36 ***	0.33 ***	0.92	0.15 ***
No. of Observations	168,200	129,389	64,290	64,960
No. of Groups	16,820	12,938	6,429	6,496
VAR Individual Random Effect	4.19	3.59	5.44	3.56

Negative Binomial Model: Positive Counts [exp(b)]	Stroke	MI	COPD	GIC
Intercept	3.60 ***	3.51 ***	4.87 ***	3.31 ***
lin.spline(Temporal Distance) 1	0.95 ***	0.96 ***	0.92 ***	0.89 ***
lin.spline(Temporal Distance) 2	0.89 ***	0.89 ***	0.82 ***	0.80 ***
After Admission	1.73 ***	1.68 ***	1.29 ***	1.22 ***
lin.spline(Temporal Distance)1 * After Admission	0.92 ***	0.92 ***	1.04 ***	1.04 **
lin.spline(Temporal Distance)2 * After Admission	0.98 **	0.94 ***	1.25 ***	1.19 ***
Men	0.80 ***	0.78 ***	0.85 ***	0.82 ***
Men * After Admission	1.11 ***	1.11 ***	1.08 ***	1.09 ***
Age 70-79	1.10 ***	1.13 ***	1.08 ***	1.18 ***
Age 80-89	1.13 ***	1.19 ***	1.11 ***	1.27 ***
Age 90+	1.09 **	1.15 ***	0.99	1.35 ***
No. of Observations	168,200	127,370	64,290	64,960
No. of Groups	16,820	12,737	6,429	6,496
Overdispersion Parameter	12.80	17.50	16.60	11.30
VAR Individual Random Effect	0.22	0.22	0.25	0.28

Significance codes: "***" : 0.001 "**" : 0.01 "*" : 0.05 "." : 0.1

SUPPLEMENTARY MATERIAL: FIGURES

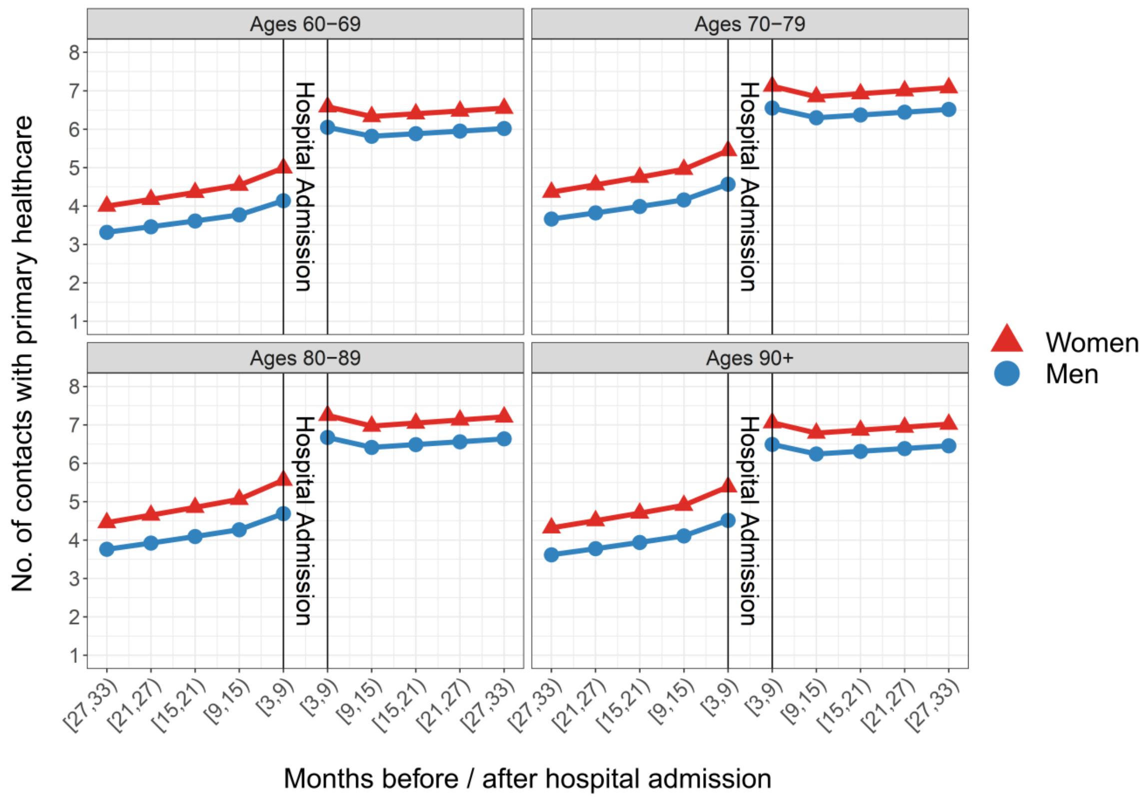

Figure 4-S: Estimated, average number of contacts with primary healthcare before and after admission to hospital for chronic obstructive pulmonary disease

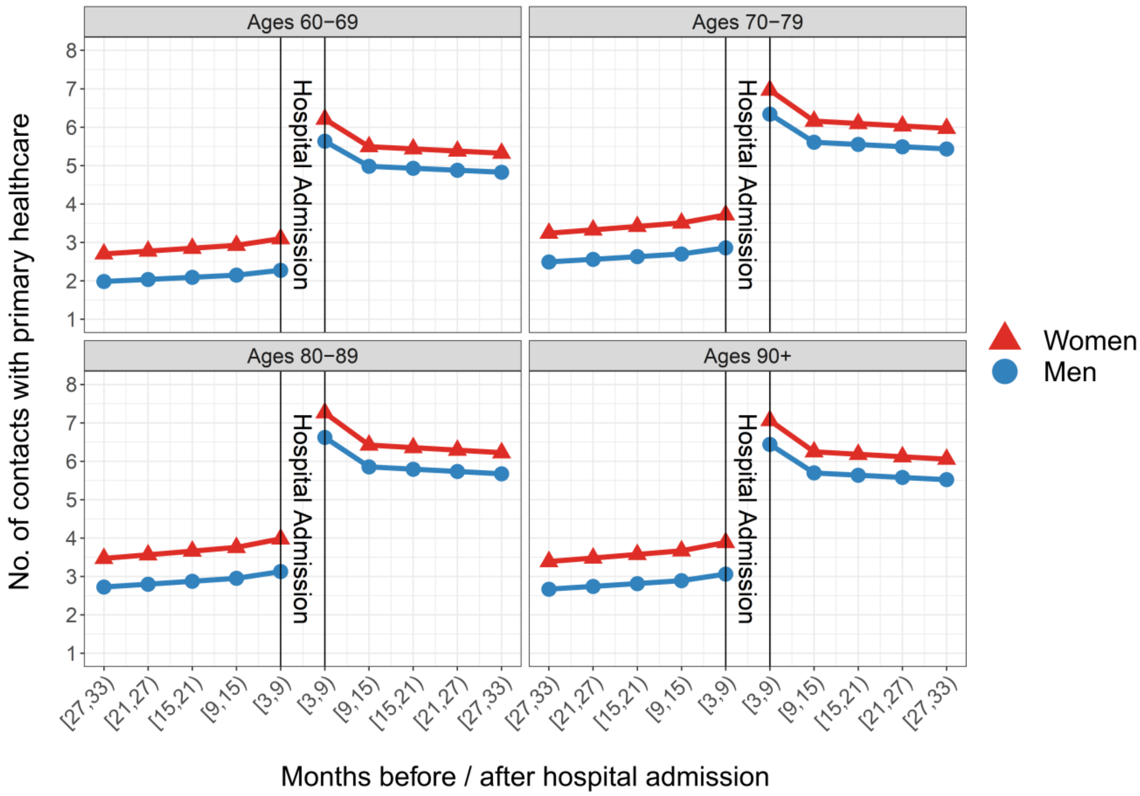

Figure 5-S: Estimated, average number of contacts with primary healthcare before and after admission to hospital for stroke

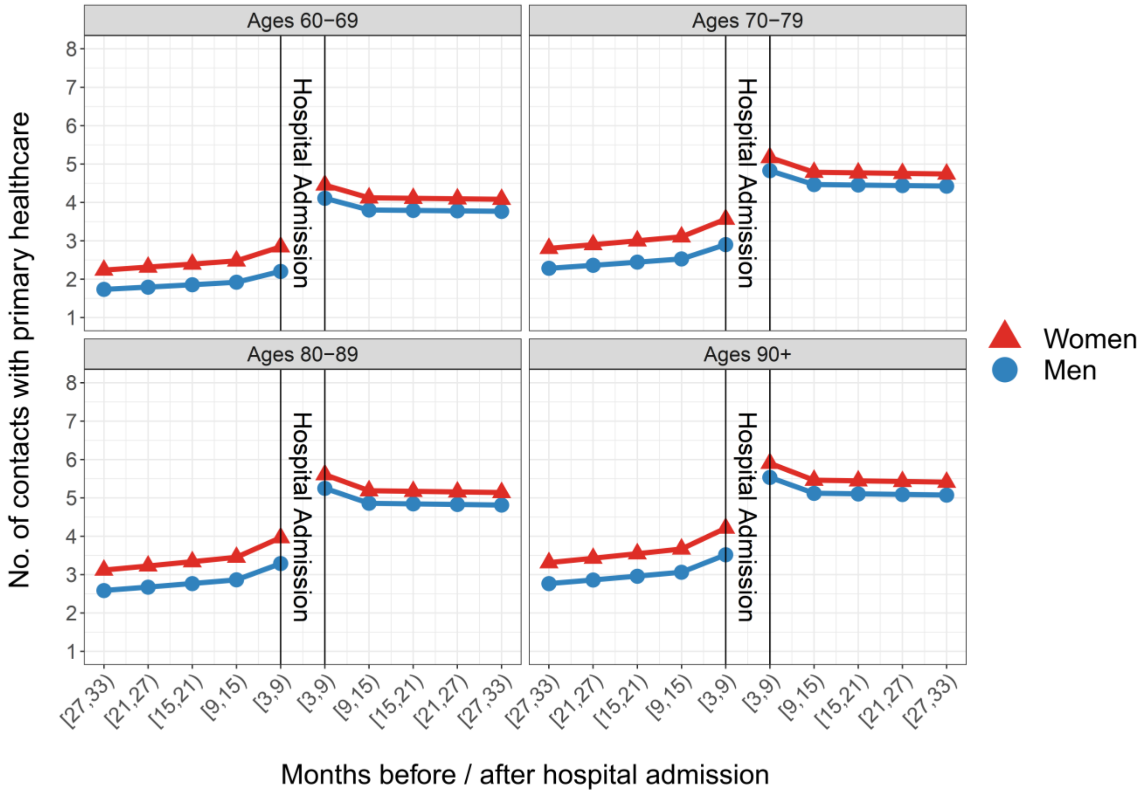

Figure 6-S: Estimated, average number of contacts with primary healthcare before and after admission to hospital for gastrointestinal cancers

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