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Financial subsidies and the shortage of primary care physicians

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ABSTRACT

The shortage of primary care physicians is a global healthcare problem, especially in rural areas. In this paper, we analyse the choice of location of primary care physicians and estimate the causal effect of financial incentives on the supply of primary care physicians in underserved areas. Our analysis is based on a quasi-experimental setting from Hungary. After 2015, primary care physicians could receive financial subsidy if they filled such a primary care position which has been vacant for at least a year, the amount of the subsidy increasing with the duration of the vacancy. Our results suggest that targeted financial incentives can help fill long-time vacant primary care positions but cannot completely eliminate primary care shortages. We also provide evidence on the role of demographic characteristics and individual preferences in the location choice of primary care physicians.

JEL codes: H20; I11; I18

Keywords: primary care; physician shortage; financial subsidy; location choice; Hungary

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Pénzügyi támogatások és a háziorvoshiány

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ÖSSZEFOGLALÓ

A háziorvosok hiánya globális egészségügyi probléma, különösen a vidéki területeken. Ebben a tanulmányban elemezzük a háziorvosok területi elhelyezkedési döntését, és megbecsüljük az anyagi ösztönzők oksági hatását a háziorvosi ellátás biztosítására a rosszul ellátott területeken. Elemzésünk egy magyarországi kvázi kísérleten alapul. 2015 után az a háziorvos részesülhet pénzügyi támogatásban, aki egy legalább egy éve betöltetlen körzet betöltését vállalja. A támogatás mértéke a körzet betöltetlenségi időtartamával nő. Eredményeink arra utalnak, hogy a célzott pénzügyi ösztönzők segíthetnek betölteni a régóta betöltetlen háziorvosi körzeteket, de nem tudják teljesen megszüntetni a háziorvoshiányt. Tanulmányunkban továbbá elemezzük a demográfiai jellemzőknek és az egyéni preferenciáknak a szerepét a háziorvosok területi elhelyezkedési döntésében.

JEL: H20; I11; I18

Kulcsszavak: háziorvosi ellátás; orvoshiány; pénzügyi támogatás; területi elhelyezkedési döntés; Magyarország

Financial subsidies and the shortage of primary care physicians*

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May 25, 2022

Abstract

The shortage of primary care physicians is a global healthcare problem, especially in rural areas. In this paper, we analyse the choice of location of primary care physicians and estimate the causal effect of financial incentives on the supply of primary care physicians in underserved areas. Our analysis is based on a quasi-experimental setting from Hungary. After 2015, primary care physicians could receive financial subsidy if they filled such a primary care position which has been vacant for at least a year, the amount of the subsidy increasing with the duration of the vacancy. Our results suggest that targeted financial incentives can help fill long-time vacant primary care positions but cannot completely eliminate primary care shortages. We also provide evidence on the role of demographic characteristics and individual preferences in the location choice of primary care physicians.

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1 Introduction

Primary care is known to prevent illness and death and is associated with a more equitable distribution of health (Starfield et al., 2005; Chang et al., 2011). A higher number of primary care physicians is also associated with improved health outcomes and lower mortality rates (Macinko et al., 2007). The closure of primary care practices deteriorates the access to primary care and may lead to inefficient use of healthcare (Bischof and Kaiser, 2021). The shortage of primary care physicians is thus worrying for public policy. Simoens and Hurst (2006) pointed out the shortage of physicians in several OECD countries, while the shortage of physicians is generally a more pressing issue in rural areas (World Health Organization, 2010). The shortage of primary care physicians is a problem that is present also in the developed world to varying extent. In Australia, a major issue is the unequal distribution of physicians as the number of primary care services per capita in very remote areas is about half that of major cities (Ogden et al., 2020). In the US, there are large and persistent physician shortages. According to a recent report of the Association of American Medical Colleges, a primary care physician shortage of between 21,400 and 55,200 is projected by 2033 (AAMC, 2020). Looking at England, Majeed (2017) estimated that in 2016, around 6,5000 primary care physicians were missing from the English healthcare system, and the shortage was estimated to double by 2020. The shortage of primary care physicians is also a major issue in Central and Eastern Europe, which is exacerbated by the emigration of physicians (see, e.g., Sowada et al., 2019 for Poland and Vlădescu et al., 2016 for Romania).

In this paper, we estimate the effect of financial incentives on mitigating the shortage of primary care physicians, using a quasi-experiment from Hungary. Our identification strategy relies on the fact that only those primary care physicians could receive a subsidy who filled a primary care position that has been vacant for at least 12 months. Thus, we can use vacant positions of shorter time horizon (8-11 months) as a control group. Our main contribution to the literature is that we can identify the causal effects of the financial incentives on the supply of primary care in underserved areas. Our results suggest that a one-time subsidy of

around 35-55 thousand Euro (corresponding roughly to the annual budget of a primary care practice), increases the probability of a vacant position to be filled by around 6 percentage points. Thus, our results support the efficiency of financial incentives in mitigating the shortage of primary care physicians; at the same time, they also suggest that such incentives themselves are not sufficient to eliminate the shortages.

The literature lists four possible policies that could potentially increase the supply of primary care in underserved areas: (i) educational strategies, (ii) regulatory strategies, (iii) financial strategies, (iv) professional and personal support strategies (Grobler et al., 2015; World Health Organization, 2010). Our focus is on the impact of financial strategies, which aim at compensating for the opportunity costs associated with working in less preferred areas. Despite the wide usage of financial incentives, little is known about the effectiveness of this type of policy. According to the World Health Organization (2010), "well-designed and comprehensive evaluations of the effectiveness of financial incentives are rare, and the evidence that is available suggests mixed results". Systematic reviews of the literature also point out that there is limited evidence to what extent various interventions can reduce the inequitable distribution of healthcare professionals (see, e.g., Grobler et al., 2015 for a general overview of the literature and Buykx et al., 2010 for an overview of the literature on the effectiveness of various retention incentives for health workers in rural and remote areas). Bärnighausen and Bloom (2009) overview the literature on the effectiveness of financial incentives to alleviate health worker shortages. Mostly based on studies from the US they conclude that there is evidence for the effectiveness of the interventions, however, this evidence is based on studies that could not establish causal effects of the interventions. Bärnighausen and Bloom (2009) also call for studies that can eliminate selection bias in their analyses – our paper aims to fill this gap.

Our paper is also related to the literature that analyses the determinants of location choice of physicians. An early study by Cooper et al. (1975) and a more recent study by Hancock et al. (2009) show that a wide range of factors affect the choice of primary care

physicians between rural and urban areas in the US, including the place of birth, rural residency experience, distance to a medical centre, employment opportunities for the spouse and financial factors, among others. In a study from South Africa, Kotzee et al. (2006) claim that there is no one single factor that would have the clearly strongest impact on the choice between rural and urban location by healthcare workers. More recent papers (Falcettoni, 2018 and Costa et al., 2019) highlight the importance of home bias in physicians' location choice. We contribute to this strand of the literature by documenting how a rich set of area and practice characteristics influence the shortage of primary care physicians, confirming the earlier results of the joint influence of factors such as the income the practice can secure, the type and the ethnic composition of the settlement where the practice is located. We also extend this literature with survey based evidence for the role of demographic factors and individual preferences in the location choice of primary care physicians.

The rest of the paper is organised as follows. Section 2 provides details on the institutional background. Section 3 introduces the data. Section 4 provides evidence on the impact of the financial subsidy. Section 5 provides survey-based evidence for primary care physicians' location choice. Section 6 discusses the findings and concludes.

2 Background

2.1 Primary care

The following summary of primary care in Hungary is based on Bíró and Elek (2019); Gaal et al. (2011); Wilm et al. (2015).

The entire population of Hungary is fully insured for primary care services; there are no co-payments. For the majority of health problems, primary care physicians (PCPs) serve as the first point of contact, although some specialist care services can be accessed without the referral of a PCP (e.g., dermatology, gynaecology, traumatology). The municipalities are responsible for the provision of primary care. Local governments designate primary care

districts to the PCPs, who are not allowed to refuse patients from their district. On the other hand, patients have the right to choose their PCP.

To practice in primary care, a physician needs to be a specialists in family medicine or in internal medicine or should be in the process of completing a specialisation in family medicine. The overwhelming majority of PCPs are self-employed, while about 5–10% are salaried by national, regional or local authorities. PCPs have one contract with the governmental health insurance fund for financing and one contract with the local municipality to supply care. To work as a PCP, physicians must purchase a license. Thus, practices can be bought and sold, while local governments still keep a control over who serves as a PCP. PCPs' financing is mostly based on capitation, with some supplements depending for example on the age composition of the patients and the type of settlements covered.

A severe problem of the Hungarian primary care system is the shortage of physicians, especially in rural areas. Throughout our observation period, the average vacancy rate of primary care practices was around 5% (see Section 3.2 for further details). If a primary care practice is vacant then care is provided by the PCPs of neighbouring primary care districts. This implies fewer PCP contact hours in the affected settlements.

2.2 Subsidy

To alleviate the shortage of PCPs, the National Health Insurance Fund Management (Hungary) first announced a call for applications for a subsidy in 2014, payable to physicians who fill such primary care practices that have been vacant for at least 12 months. Each winner is required to provide care in the subsidised practice for at least 6 years (in the calls of years 2014-2016, this requirement was 4 years). The applicant has to possess the qualifications that are required by law to provide primary care, is not allowed to own a practice licence at the time of the application (or on the 1st of January, 2020, in the call of year 2020). The winner also has to sign a contract for the provision of care within three month after the announcement of the results. The subsidy amount is paid to the physician and there are no

restrictions on its usage.

The amount of the subsidy increases gradually with the duration of the vacancy (Table 1). The subsidy amounts were doubled from the call of 2016 to the call of 2017.

Table 1: Subsidy net amounts in (million HUF)

Year of receipt of subsidy	Duration of the vacancy in months				
	12-23	24-35	36-47	48-59	60-
2015	6	7	8	9	10
2016	6	7	8	9	10
2017	6	7	8	9	10
2018	12	14	16	18	20
2019	12	14	16	18	20
2020	12	14	16	18	20

Note: The table shows the net subsidy amounts by the year of the receipt of the subsidy and the duration of the vacancy in Hungarian Forints (HUF). 1 million HUF $\approx$ 3,320 USD or 2,991 EUR in 2020.

Each year, the list of winners is announced by the National Health Insurance Fund Management on its website, therefore this is a public information. The annual number of winners varied between 26 (in 2015) and 53 (in 2017) (National Health Insurance Fund Management, 2021c).

3 Data

3.1 Data sources

The quarterly list of primary care practices originates from the National Health Insurance Fund Management, Hungary (NHIFM). The list includes the unique identifier of each practice, the name of the primary care physician working in the practice (if the practice is not vacant), the name of the company or local government that is running the practice, the type of the practice (serving adults, children or both), the zip code and the settlement of the practice site. We use data from January 2012 to October 2020; that is, we have three years of observations prior to the first receipts of the subsidy in 2015 and six years of observations

after.

We also received the list of those primary care practices which had a vacancy for a primary care physician from the NHIFM. In what follows, we will refer to these practices as "vacant practices". The list of vacant practices includes the month when the practice became vacant and the month when the vacancy was filled (if ever). These data are linked to the list of primary care practices with the unique practice identifier.

The annual lists of primary care physicians who were awarded the financial subsidy are publicly available on the website of the NHIFM (National Health Insurance Fund Management, 2021b). The list includes the winner physician's name and the address of the practice where the vacancy is filled with the subsidy. The physician's name and the address allows us to match the list of winners to those practices where we observe a vacancy take-up.

The primary care practices are financed by the NHIFM. The annual amount of funding provided by the NHIFM is also publicly available on the website of the NHIFM (National Health Insurance Fund Management, 2021a). We merge the funding data to the list of primary care practices.[1]

Finally, we use several settlement level indicators from the T-STAR municipal statistical system of the Central Statistical Office of Hungary and from the National Regional Development and Spatial Planning Information System (TeIR). We merge the selected variables to the list of primary care practices using the settlement of the practice site.[2] We generate the following indicators for the empirical analysis: settlement type (town, village with at least 2000 inhabitants, village with 1000-2000 inhabitants, village with less than 1000 inhabitants); settlement level per capita taxable income (annual statistics); fraction of the

[1]To merge the two data sets, we use the name of the company or local government that is running the practice and the zip code of the settlement of the practice site, as these two variables are available in both data sets (although data cleaning is needed due to different spelling and abbreviations used for the company names).

[2]Note, that we consider the capital city (Budapest) as one settlement, even though some indicators are available separately for its districts. Also, the relation between the primary care practice sites and settlements is not a one-to-one relation. In the bigger settlements, there are several practices, while in the rural areas, a single practice might cover multiple settlements. In the latter case, we merge the settlement level indicators based on the practice site.

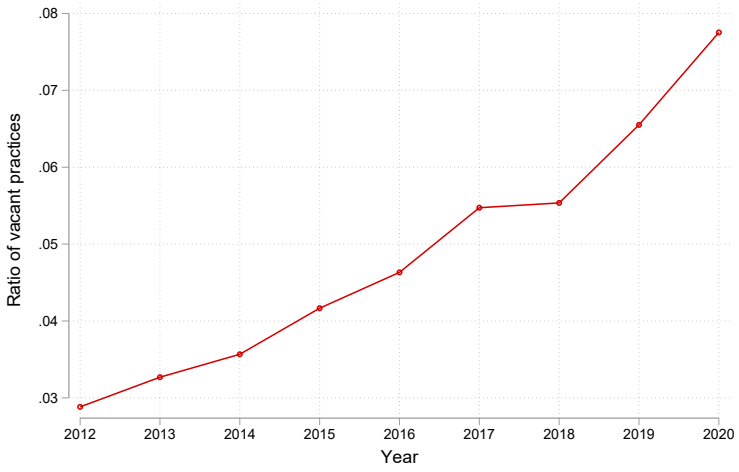
population aged 60 and above (annual statistics); fraction of Roma population (from the 2011 census as included in the TeIR data); fraction of disabled population (from the 2011 census as included in the TeIR data); outpatient specialist capacities (annual per capita specialist outpatient hours), the distance to the nearest hospital (in minutes) and the distance to the nearest county centre (in minutes). Here, we use the road distance measures included in the GEO database of the Centre for Economic and Regional Studies and set the distance to zero if a settlement has a hospital or is a county centre (Hungary has 20 counties).

We provide details of the survey data in Section 5.

3.2 Descriptive results

In 2012, there were 6,694 primary care practices in Hungary (both with and without a vacant position). This number decreased gradually to 6,514 by 2020 due to the merger of some practices. Figure 1 shows that the ratio of vacant practices increased from 2.9% in 2011 to 7.8% in 2020, mostly due to the ageing (and retirement) of primary care physicians. We also see that the increasing ratio of vacant practices halted between 2017 and 2018 but continued to increase afterwards.

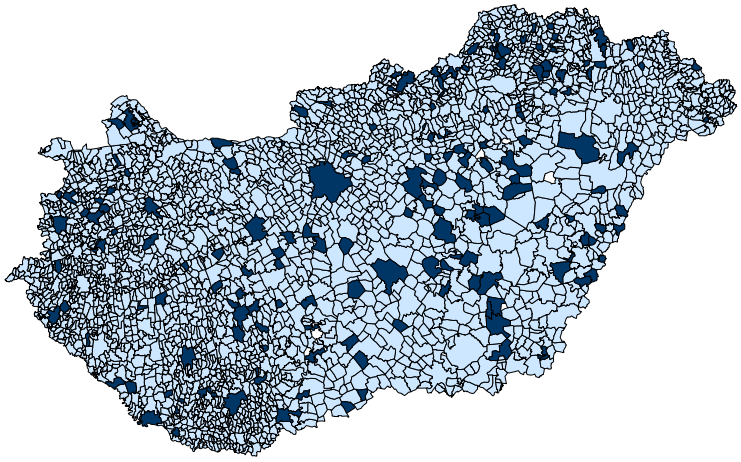
Figure 1: Ratio of vacant practices in January of each year



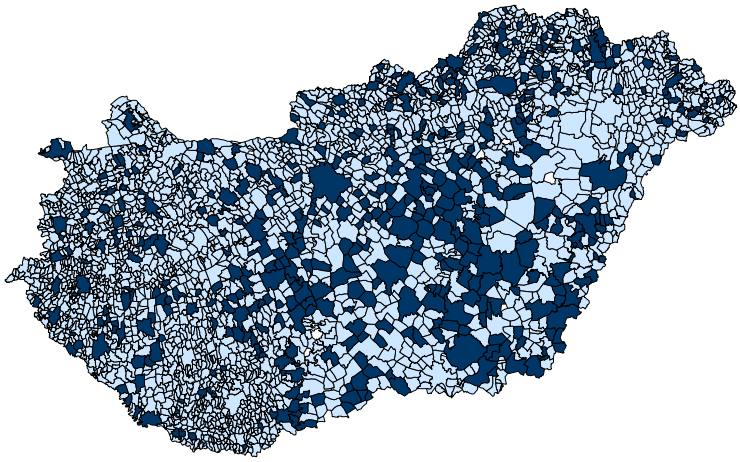
The maps in Figure 2 indicate that both at the beginning and the end of our observation period, the density of vacant practices was higher in the rural areas of Eastern Hungary, which are on average poorer and less developed.

Figure 2: Geographical location of vacant practices

(a) January 2012



(b) October 2020



Note: Dark blue areas indicate the settlements with at least one vacant practice.

The descriptive statistics of Table A1 reveal major differences between vacant and non-vacant practices and also by the duration of a practice being vacant. Vacant (especially the long-term vacant) practices are more likely to serve both adults and children, receive lower payments from the NHIFM, are more likely to be located in remote areas, small settlements, where there is lower availability of outpatient specialist care and where the ratio of Roma

population is higher.

The regression results of Table 2 confirm that worse paid practices, practices in remote locations and at locations with lower average income and with a higher fraction of older or Roma population are more likely to be vacant, ceteris paribus (Table 2 reports average marginal effects, while Table A2 in the Appendix reports estimated odds ratios). In general, the same indicators have a relation of the opposite sign with the probability of the filling of vacant practices. An exception is the financing indicator; however, it has moderate variation in the subsample of vacant practices (with 73% of the vacant practices belonging to the bottom tertile). Also, most settlement level indicators have the same relation to the probability of filling a vacant practice as to the probability of a transition between PCPs occurring without an in-between vacancy of three months or longer. When analysing the transitions, we restrict the sample to those non-vacant practices where the practice has a different PCP or is vacant three months later (third column of Table 2).

4 Impact of financial subsidies

4.1 Methods

We estimate year-specific effects of the financial subsidy on the probability of filling a vacant practice. Specifically, we estimate the linear probability model of equation (1):

$$fill_{it} = \alpha_0 + \delta_t + \sum_{t \neq 2014, c \neq 0} \beta_t year_t \times treated_{it} + X_{it}\alpha + \nu_{it}, \tag{1}$$

where i denotes the practice and t denotes time (year), α_0 is the constant term, δ_t is the year fixed effect and vector X_{it} includes practice level control variables. The regression is estimated on the sample of vacant practices and the $treated_{it}$ variable is a binary variable which equals zero for practices vacant for 8-11 months and one for vacancies of 12 months and above. The rationale for this categorisation is that practices which have been vacant for

Table 2: Logit models of practices being vacant, take-up and transition to new PCP without vacant period

	Logit marginal effects		
	vacant	fills	transition w\o vacancy
Practice type: children	0.027***	-0.047***	-0.153***
	[0.006]	[0.006]	[0.024]
Practice type: both adults and children	0.006	0.002	-0.061
	[0.006]	[0.011]	[0.038]
Annual payment from NHIFM, 2nd tertile	-0.094***	-0.001	-0.012
	[0.004]	[0.009]	[0.027]
Annual payment from NHIFM, 3rd tertile	-0.088***	-0.012**	-0.009
	[0.004]	[0.006]	[0.027]
Village, above 2,000 inhabitants	0.027***	-0.031***	-0.084**
	[0.006]	[0.012]	[0.036]
Village, 1-2 thousand inhabitants	0.043***	-0.060***	-0.103**
	[0.009]	[0.013]	[0.052]
Village, less than 1,000 inhabitants	0.072***	-0.079***	-0.183***
	[0.013]	[0.012]	[0.057]
Minutes to nearest hospital	0.000	0000	-0.006***
	[0.000]	[0.000]	[0.001]
Minutes to nearest county centre	0.001***	-0.000**	-0.005***
	[0.000]	[0.000]	[0.001]
Annual per capita specialist hours	-0.006***	0.003	-0.006
	[0.001]	[0.002]	[0.008]
Per capita taxable income, 2nd tertile	0.002	0.001	-0.049*
	[0.005]	[0.007]	[0.029]
Per capita taxable income, 3rd tertile	-0.015***	0.020*	-0.073**
	[0.005]	[0.011]	[0.035]
Fraction aged 60 and above	0.157***	-0.324***	-1.065***
	[0.045]	[0.087]	[0.386]
Fraction of Roma population	0.210***	-0.219***	-1.557***
	[0.028]	[0.051]	[0.481]
Fraction of disabled population	0.065	-0.146	-0.473
	[0.074]	[0.186]	[1.134]
Observations	229,154	11,738	1,988
Mean outcome	0.053	0.062	0.421

Note: Cluster robust standard errors in brackets, clustered at the practice level, *** p<0.01, ** p<0.05, * p<0.1. In the second column, the sample is restricted to vacant practices. In the third column, the sample is restricted to non-vacant practices where the practice has a different PCP or is vacant at the next observation point (i.e., 3 months later).

8-11 months are not eligible for the financial subsidy but are similar enough to the eligible vacant practices; therefore they can serve as a suitable control group. The coefficients of interest are β_t.

The X_{it} control variables are the following: duration of the vacancy (in years), practice type (serves adults, children or both), tertiles of annual payments from NHIFM, settlement type, minutes to nearest hospital and to nearest county centre, annual per capita specialist

hours, tertiles of per capita taxable income, fraction of individuals aged 60 and above in the settlement, fraction of Roma population in the settlement, fraction of disabled people in the settlement and the county of the settlement.

Next, we estimate the average impact of the subsidy in a difference-in-differences framework:

$$fill_{it} = \gamma_0 + after_t + \sum_{c \neq 0} \xi after_t \times treated_{it} + X_{it}\gamma + v_{it}, \tag{2}$$

where we follow the notation of equation (1), the $after$ binary indicator equals zero in years 2012-2014 and one in years 2015-2020. The coefficient of interest is ξ.

Then, we extend equation (2) with an interaction term between the *treated* variable and a binary indicator of after year 2018, i.e., after the subsidy amounts have been increased.

Finally, considering the nature of the outcome variable (vacancy take-up hazard), we estimate a Cox regression for vacant primary care practices getting filled, including the same regressors as in models (1) and (2).

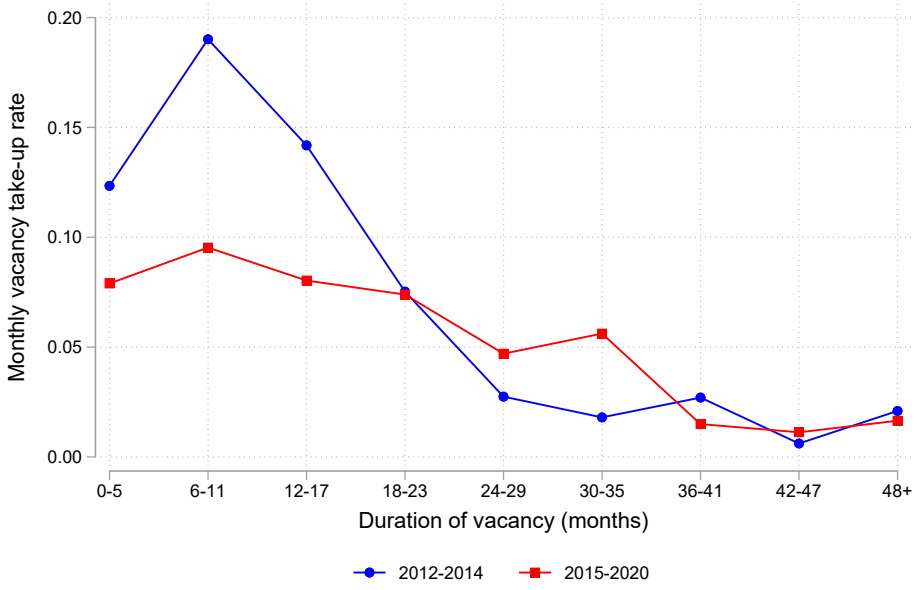
4.2 Results

Figure 3 indicates that among practices which have been vacant for less than one and a half years, the take-up rate dropped from 2012-2014 (before the introduction of the subsidy) to 2015-2020 (after the introduction of the subsidy). On the other hand, the take-up rate increased for those practices that have been vacant for 24-36 months. Figure 3 suggests a relative increase in the take-up rate of practices eligible for the subsidy.

Figure A1 indicates a decreasing time pattern in the take-up rate of those vacant practices which have been vacant for less than a year, i.e., which are not eligible for the subsidy. The decreasing time pattern of take-up rate is moderate for practices vacant for 12-47 months and practices vacant for 48 months or more.

Figure 4 displays the main results of equation (1). In panel (a) of the figure, we see positive effects on the take-up rate of practices vacant for 12 months and above. Compared

Figure 3: Take-up rate of vacant practices before and after the introduction of the subsidy



Note: Quarterly rate of take-up of vacant primary care practices, averages by the duration of the vacancy.

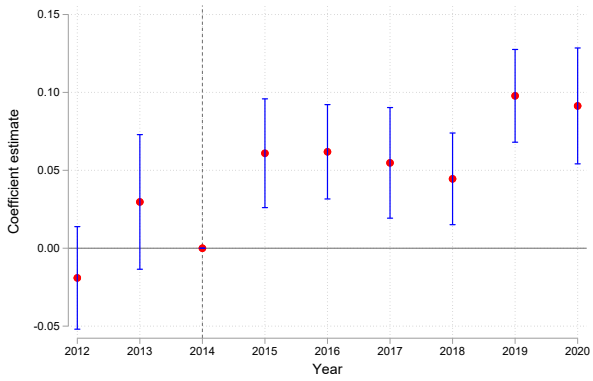
to year 2014 and relative to the reference category, the filling probability of a vacant practice is estimated to increase by about 4-10 percentage points. Panel (b) of the figure displays the Cox regression results, which also indicate increasing rates of vacancy take-up, even up to 3-fold increase. However, when estimating the Cox regression version of equation (2), we exclude year 2012 from the sample because the estimated hazard ratio of vacancy take-up is significantly less than one in year 2012.

Table 3 shows the estimation results of the difference-in-differences specifications (equation (2)). The linear probability model and the Cox regression model convey a similar message. According to the estimates reported in the first and third columns of the table, the subsidy increases the take-up probability of an eligible vacant practice by 6.6 percentage points or by 99.7%.

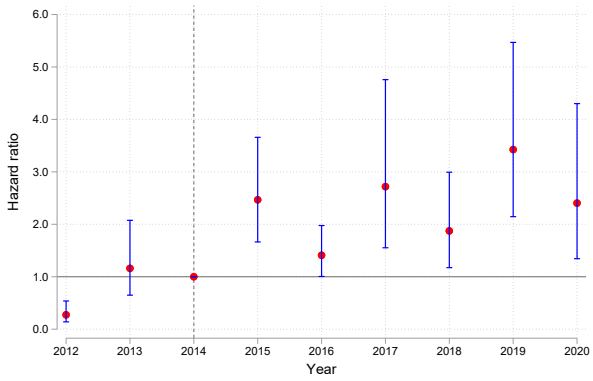
The second and fourth columns of Table 3 indicate that the increase in the subsidy amount in 2018 did not increase the impact of the policy statistically significantly. A possible explanation is that doubling the subsidy amount was not that substantial in real terms due

Figure 4: Year-specific impact of financial subsidy eligibility on the filling of vacant practices

(a) Linear probability model



(b) Cox regression, hazard ratio



Note: Equation (1), β coefficients with 95% confidence interval. Reference group: vacant practices with duration 8-11 months. Year effects and practice characteristics are netted out. See Section 4.1 for the list of control variables.

to wage inflation and increasing real estate prices. The annual increase of average net wages was around 10% and the annual increase of average real estate prices was between 10-20% in years 2017-2020 (Hungarian Central Statistical Office, 2021a,b).

The full estimation results reported in Appendix Tables A3 and A4 indicate that the inclusion of the control variables does not have a major effect on the results.[3] Appendix Figure A2 shows based on the Cox regression estimates that on average, the survival rate of a vacancy decreases to 0.4 over 10 years, however, it is around 0.1 for vacancies located in cities but close to 0.6 for vacancies located in the smallest villages.

[3]Further specification checks indicate that the effect of the subsidy on practices vacant for 48+ months was stronger, but the additional effect compared to the effect on practices vacant for 12+ months is statistically not significant (in the linear probability model, the additional effect is 0.025 with SE (standard error) 0.021). The linear probability average effects are also qualitatively robust to extending the control vacancies to 7-11 months (0.061 (SE 0.029) estimated treatment effect) or restricting the control vacancies to 9-11 months (0.073 (SE 0.019) estimated treatment effect).

Table 3: Effect of the subsidy on the take-up rate of vacant practices

	Linear probability model		Cox regression, hazard ratio	
Vacant for 12+ months × after 2015	0.066***	0.055***	1.997**	1.897***
	[0.020]	[0.017]	[0.591]	[0.439]
Vacant for 12+ months × after 2018		0.022		1.135
		[0.020]		[0.340]
Vacancy duration 12-23 months	-0.066***	-0.066***	0.728	0.718
	[0.017]	[0.016]	[0.184]	[0.179]
Vacancy duration 24-35 months	-0.099***	-0.098***	0.737	0.724
	[0.015]	[0.015]	[0.336]	[0.328]
Vacancy duration 36-47 months	-0.123***	-0.121***	0.722	0.725
	[0.014]	[0.013]	[0.519]	[0.500]
Vacancy duration 48-59 months	-0.107***	-0.106***	1.121	1.079
	[0.015]	[0.015]	[0.801]	[0.748]
Vacancy duration 60+ months	-0.112***	-0.109***	0.510	0.436
	[0.016]	[0.016]	[0.265]	[0.231]
After 2015	-0.080***	-0.056**	0.355***	0475***
	[0.016]	[0.012]	[0.089]	[0.086]
After 2018		-0.045**		0.517***
		[0.018]		[0.121]
Observations	8,834	8,834	8,313	8,313
Control variables	yes	yes	yes	yes

Note: Estimation results of equation (2). Standard errors in brackets, clustered at the calendar year × years of vacancy level. Under the Cox regression, the standard errors of the regression coefficient estimates are reported. *** p<0.01, ** p<0.05, * p<0.1. The sample is restricted to vacant practices. The reference group consists of practices vacant for 8-11 months. Analysis years: 2012-2020 in the linear probability model, 2013-2020 in the Cox regression. See Section 4.1 for the list of control variables.

5 Survey-based evidence

5.1 Location choice

To improve our understanding of the location choice of primary care physicians and to collect details on their demographic background, we conducted a survey. At the end of October 2022, we sent out a paper based survey to all PCPs in Hungary. While they could return the completed survey free of charge by post, they also had the option to fill in the same survey online (each PCP received a unique code to access the online survey). The majority of the PCPs opted for the paper-based survey. We received 1,599 responses, corresponding to 24.6% response rate. Out of the 1,599 respondents, 157 were subsidy recipients.[4]

[4]To incentivise the response among those PCPs who received the practice purchase subsidy, we offered them a grocery voucher of 5,000 HUF if they return the survey.

To investigate the representativeness of the survey, Table A6 compares the characteristics of the practice locations (settlements) in the administrative data (universe of practices) and the survey data. We split both data sets by subsidy recipiency. While we see statistically significant differences between the administrative and survey data, these differences are small in magnitude, therefore we conclude that the survey is reasonably representative for the location of primary care practices in Hungary. We also see that based on both the administrative and survey data, the subsidised practices are on average located in smaller and more disadvantaged settlements, which is in line with the results for vacancy in Tables A1 and 2.

Tables A5 and A7 provide further descriptive statistics based on the survey data. Table A5 indicates that the subsidy recipients are on average younger and, consequently, less experienced than the non-recipients.[5] Also, subsidy recipients were less likely born in the capital (Budapest), studied with lower probability in the capital, and are more likely to have work experience from abroad.

Our survey data also provides evidence for home bias (in line with Falcettoni, 2018 and Costa et al., 2019): 49% of the survey respondents have their primary care practice in the same county where they were born and 29% of the survey respondents have their primary care practice in the same county where they obtained their university degree.[6] Among those who were born in Budapest, 53% have their practice in Budapest and among those who studied in Budapest, 44% have their practice in Budapest.

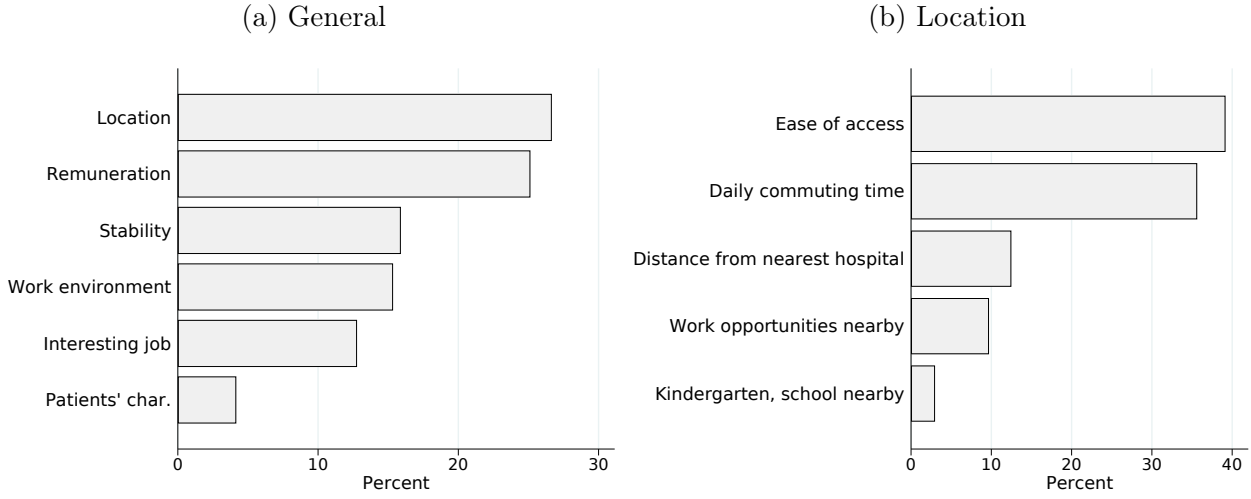
Figures 5 and 6 display summary plots. Figure 5 indicates that location (specifically the ease of access) and remuneration are the two most important attributes of the workplace generally. Within location, the ease of access and daily commuting time are the two most important factors. We show in Appendix Figure A3 that salary is the most important factor

[5]We do not observe the age of the PCPs in our administrative data. However, based on another administrative dataset of the Centre for Economic and Regional Studies ("admin3"), the average age of PCPs and occupational physicians was 51 in year 2017, suggesting that older PCPs were more likely to fill in our survey.

[6]Hungary has 20 counties, one of which is the capital, Budapest.

of remuneration and the patients' socioeconomic status and age are the most important factors of patients' characteristics. Figure 6 indicates that among the subsidy recipients, the socioeconomic status of the patients seem to be the most important negative aspect of the practice, followed by the daily commuting time. Finally, panel (b) of the same figure shows that more than 30% of the recipients spent the subsidy on real estate, while the purchase of durable goods and savings were also common usage options.

Figure 5: Preferences for workplace attributes, ranked as most important

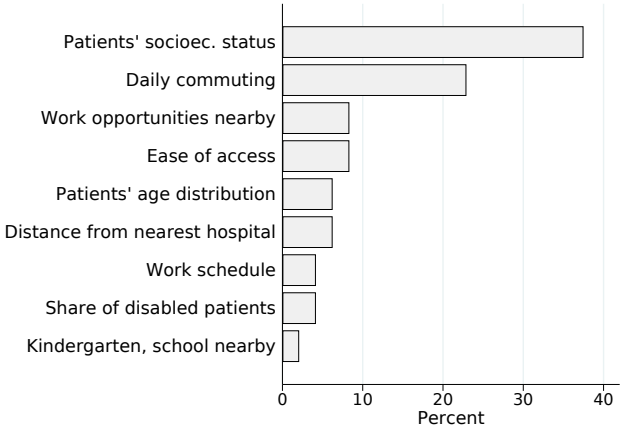


Notes: The figure displays the distribution of workplace attributes indicated as the most important. All respondents were asked these questions.

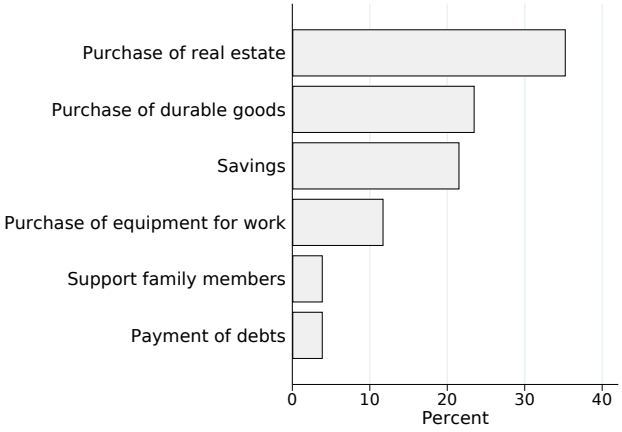
To understand the determinants of location choice of PCPs, we estimate discrete choice models. First, we define the choice set as the district level ratio of vacant practices being below or above its median, as observed in our administrative data (Hungary has 174 districts). Second, we define the choice set as the settlement of the location of the primary care practice being a city/town or a village. The settlement type also captures the living standards in the neighbourhood of the primary care practice, with villages having on average lower living standards. We estimate logit models of these two binary outcome variables. As alternative specifications, we consider further categories – tertiles of the district level ratio of vacant practices and four categories of settlement type –, and estimate multinomial logit models.

Figure 6: Survey based evidence: negative workplace attributes and the use of the subsidy

(a) Negative workplace attributes, most important



(b) Main use of the subsidy



Notes: The figure displays the distribution of negative workplace attributes indicated as the most important (panel (a)) and the most important spending category an individual spent the subsidy on (panel (b)). Only the subsidy recipients were asked these questions (52 observations).

The results of the binary choice models are reported in Table 4, the multinomial logit model results are reported in Tables A8 and A9. These results indicate that females, people born or studied in Budapest and who attach high importance to the accessibility of the location of the practice are less likely to work in practices which are based in districts that are characterised by above median ratio of vacant practices. On the other hand, older physicians and those who attach high importance to salary are more likely to work in practices which are based in districts that are characterised by above median ratio of vacant practices. Looking at the probability of working in a village (second column of Table 4), we observe that females and people born in Budapest are less likely to work in a village, whereas those who have more children are more likely to work in a village.

We also estimate a binary choice model of subsidy recipiency, the results are reported in the last column of Table 4, indicating a strong selectivity on age – younger physicians are more likely to be recipients.

5.2 Demographics and Stated Workplace Preferences

Data on workplace preferences may be immensely useful to a policy maker contemplating targeted incentives to attract physicians to vacant practices. Unfortunately, such data is seldom available, unlike data on demographics. A valuable use of our survey data, therefore, is to link demographics to stated workplace preferences. We estimate rank-ordered probit choice models[7] using data on the three most preferred attributes for each preference question and a a set of individual characteristics including sex, age group, marital status, the number of children (adults and minors), indicators for being born in and having studied in Budapest, and the number of years spent in the current job as a proxy for experience. We provide further details and report the corresponding marginal effects in Table A10 in the Appendix.

We find significant effects on the importance of various work attributes with respect to sex, age, being born in Budapest, and marital status. Regarding gender differences, we document that women attach higher importance to location and stability and less importance to remuneration. In line with recent studies in the labour economics literature (Le Barbanchon et al., 2020; Borghorst et al., 2021; Farré et al., 2020), our results also show that women care more about daily commuting time than men. Preference differences with respect to age are also significant: doctors aged 60 years or older attach less importance to daily commuting time, patients' socioeconomic status and the base salary, and more importance to patients' age distribution, equipment purchase subsidies and the provision of electronic devices as part of their remuneration package than younger doctors. Doctors born in Budapest care more about daily commuting time, and patients' socioeconomic status and less about work opportunities near their practice than those born outside of the capital. Finally, with respect to family status, married or partnered doctors attach higher importance to nearby work opportunities than their single counterparts, whereas those who have children care less about the job being interesting, and about the distance from the nearest hospital, but more about

[7] We prefer this model over logit specifications because it does not require the assumption of independence of irrelevant alternatives.

having a service car than childless doctors.

6 Discussion

In this paper, we documented the shortage of primary care physicians in Hungary. The geographical disparities in the availability of primary care are attributed to various factors, including economic factors and geographic disparities in the demographic composition of the population. Then, we investigated if financial incentives can reduce the shortage of primary care physicians in areas where there is a lack of primary care supply. Our results suggest that a one-time cash subsidy of around 35-55 thousand Euro increases the probability of a vacant primary care position to be filled by around 6 percentage points; however, such financial incentives are not sufficient to completely eliminate the shortage of primary care physicians. The subsidy amount was comparable in magnitude to the annual budget of a primary care practice (Table A1) and is about 2.5 as much as the average annual gross earnings of a physician (Health Care Registration and Education Center, 2015).

We also provided survey based evidence that females, younger physicians, those who were born or studied in the capital city and who attach high importance to the availability of the location of the practice are less likely to serve as a primary care physicians in areas characterised by a high ratio of vacant practices.

A limitation of our study is that we cannot estimate the general equilibrium effects of the subsidy. The positive effects we estimate might be a consequence of decreasing take-up rate of not subsidised vacant practices. Various factors affected the supply of primary care physicians at the same time period, such as the increasing rate of exit due to retirement, the decreasing supply of junior primary care physicians (partly due to emigration to countries where they can earn more) and a subsidy provided for physicians to purchase a primary care practice for the first time. We cannot separate the general equilibrium effects of the analysed policy from the effect of such other aggregate factors.

Overall, the results suggest that a one-time cash subsidy can partly compensate the primary care physicians for the disadvantaged location of the practice as the supply of primary care increases at such locations. However, such a subsidy policy is not sufficient on its own to eliminate the problem of the shortage of physicians in the primary care – the one-time subsidy should rather be considered only as an element of a complex policy package. Survey-based evidence on workplace preferences can be useful to design refinements of the subsidy scheme.

Table 4: Logit models of location choice and subsidy recipiency

	above median district level ratio of vacant practices	village	subsidy recipient
Female	-0.092***	-0.145***	-0.013
	[0.025]	[0.023]	[0.016]
Age category (baseline: -40)			
Age 41-60	0.123**	0.048	-0.128***
	[0.051]	[0.048]	[0.042]
Age 61-	0.105*	-0.009	-0.139***
	[0.055]	[0.052]	[0.047]
Born in Budapest	-0.211***	-0.099***	-0.037
	[0.038]	[0.037]	[0.026]
Studied in Budapest	-0.124***	-0.047	-0.013
	[0.031]	[0.030]	[0.020]
Number of children			
Aged 0-18	0.005	0.033**	0.034***
	[0.017]	[0.015]	[0.009]
Aged 19-	0.020	0.036***	-0.001
	[0.013]	[0.011]	[0.008]
Preference indicators – Location			
Ease of access	-0.036***	-0.009	0.008
	[0.011]	[0.011]	[0.007]
Daily commuting time	-0.040***	-0.003	-0.002
	[0.011]	[0.011]	[0.007]
Preference indicators – Patients			
Patients' age	0.001	0.004	0.003
	[0.013]	[0.012]	[0.008]
Patients' socioeconomic status	-0.001	0.019	-0.004
	[0.013]	[0.012]	[0.009]
Preference indicators – Remuneration			
Salary	0.024*	-0.007	-0.009
	[0.014]	[0.012]	[0.009]
Subsidies to buy equipment	-0.006	-0.020	0.004
	[0.013]	[0.012]	[0.008]
Observations	1,576	1,576	1,570

Note: Logit model average marginal effects, standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. The preference indicators range from 1 (not in the top 3 choice) to 4 (considered most important).

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Appendix

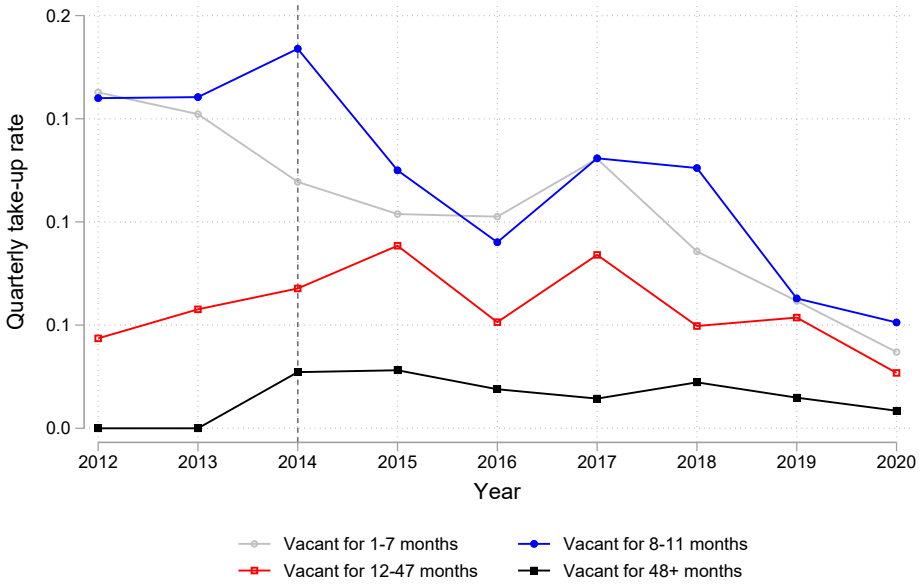
A Further Details of the Practices

Appendix Table A1: Descriptive statistics by status of the practice (2012-2020)

	Not vacant or vacant for 1-7 months		Vacant for 8-11 months		Vacant for 12-47 months		Vacant for at least 48 months	
	mean	sd	mean	sd	mean	sd	mean	sd
Practice type								
adult	0.567	0.495	0.348	0.477	0.230	0.421	0.137	0.344
children	0.239	0.426	0.210	0.407	0.216	0.411	0.202	0.402
both adults and children	0.194	0.396	0.442	0.497	0.554	0.497	0.660	0.474
Annual payment from NHIFM (1,000 HUF)	16,693	7,988	16,623	13,067	14,727	9,264	14,639	7,831
Settlement type								
town or city	0.745	0.436	0.447	0.497	0.322	0.467	0.208	0.406
village, above 2,000 inhabitants	0.134	0.341	0.223	0.416	0.216	0.412	0.186	0.389
village, 1-2 thousand inhabitants	0.076	0.264	0.193	0.395	0.224	0.417	0.223	0.416
village, less than 1,000 inhabitants	0.045	0.207	0.138	0.345	0.238	0.426	0.382	0.486
Minutes to nearest hospital	9.908	13.362	18.587	14.786	21.637	15.051	23.546	14.259
Minutes to nearest county centre	20.686	21.134	34.579	19.393	39.329	18.317	41.223	17.069
Annual per capita specialist hours	1.869	1.698	0.921	1.410	0.679	1.223	0.460	0.935
Per capita taxable income (1,000 HUF)	1,140	332	1,035	359	944	347	973	314
Fraction aged 60 and above	0.257	0.032	0.258	0.044	0.255	0.048	0.260	0.058
Fraction of Roma population	0.028	0.044	0.052	0.073	0.067	0.094	0.079	0.108
Fraction of disabled population	0.050	0.015	0.052	0.017	0.054	0.020	0.056	0.022
Number of observations over 2012-2020	220,030		996		4,938		3,198	
Mean number of practices over 2012-2020	6,112		28		137		89	

Note: 1,000 HUF $\approx$ 3.30 USD or 3.0 EUR in 2020.

Appendix Figure A1: Time pattern of vacancy take-up rate



Note: Annual averages of quarterly take-up rates of vacant primary care practices.

Appendix Table A2: Logit models of practices being vacant, getting filled and transition to new PCP without vacant period

	Logit OR		
	vacant	fills	transition w\o vacancy
practice type: children	1.805***	0.356***	0.454***
	[0.205]	[0.047]	[0.059]
practice type: both adults and children	1.160	1.034	0.734
	[0.182]	[0.164]	[0.139]
annual payment from NHIFM, 2nd tertile	0.124***	0.986	0.939
	[0.012]	[0.155]	[0.132]
annual payment from NHIFM, 3rd tertile	0.169***	0.795**	0.956
	[0.017]	[0.091]	[0.135]
village, above 2,000 inhabitants	1.945***	0.666***	0.659**
	[0.280]	[0.101]	[0.118]
village, 1-2 thousand inhabitants	2.612***	0.376***	0.597*
	[0.461]	[0.076]	[0.158]
village, less than 1,000 inhabitants	3.931***	0.196***	0.385***
	[0.728]	[0.045]	[0.121]
minutes to nearest hospital	1.004	1.003	0.971***
	[0.003]	[0.004]	[0.006]
minutes to nearest county centre	1.017***	0.993**	0.974***
	[0.003]	[0.003]	[0.004]
annual per capita specialist hours	0.867***	1.062	0.968
	[0.026]	[0.047]	[0.040]
per capita taxable income, 2nd tertile	1.036	1.023	0.769
	[0.112]	[0.132]	[0.125]
per capita taxable income, 3rd tertile	0.666***	1.396*	0.673**
	[0.091]	[0.241]	[0.135]
fraction aged 60 and above	43.059***	0.003***	0.004***
	[45.883]	[0.005]	[0.008]
fraction of Roma population	153.617***	0.019***	0.000***
	[102.789]	[0.018]	[0.001]
fraction of disabled population	4.712	0.072	0.086
	[8.354]	[0.239]	[0.508]
observations	229,154	11,738	1,988
mean outcome	0.053	0.062	0.421

Note: Cluster robust standard errors of the logistic regression coefficients in brackets, *** p<0.01, ** p<0.05, * p<0.1. In the second column, the sample is restricted to vacant practices. In the third column, the sample is restricted to non-vacant practices where the practice has a different PCP or is vacant at the next observation point (i.e., 3 months later).

B Further results on the effect of the subsidy

Appendix Table A3: Linear probability model of take-up of vacant practices

	Vacancy take-up			
vacant for 12+ months × after 2015	0.068***	0.057***	0.066***	0.055***
	[0.020]	[0.018]	[0.020]	[0.017]
vacant for 12+ months × after 2018		0.022		0.022
		[0.021]		[0.020]
vacant for 12-23 months	-0.078***	-0.078***	-0.066***	-0.066***
	[0.017]	[0.017]	[0.017]	[0.016]
vacant for 24-35 months	-0.120***	-0.120***	-0.099***	-0.098***
	[0.015]	[0.014]	[0.015]	[0.015]
vacant for 36-47 months	-0.148***	-0.148***	-0.123***	-0.121***
	[0.012]	[0.012]	[0.014]	[0.013]
vacant for 48-59 months	-0.138***	-0.138***	-0.107***	-0.106***
	[0.013]	[0.014]	[0.015]	[0.015]
vacant for 60+ months	-0.148***	-0.147***	-0.112***	-0.109***
	[0.014]	[0.014]	[0.016]	[0.016]
after 2015	-0.073***	-0.051***	-0.080***	-0.056***
	[0.016]	[0.013]	[0.016]	[0.012]
after 2018		-0.040**		-0.045**
		[0.019]		[0.018]
practice type: children			-0.058***	-0.058***
			[0.008]	[0.008]
practice type: both adults and children			-0.007	-0.007
			[0.009]	[0.009]
annual payment from NHIFM, 2nd tertile			-0.000	0.002
			[0.010]	[0.010]
annual payment from NHIFM, 3rd tertile			-0.011	-0.008
			[0.009]	[0.008]
village, above 2,000 inhabitants			-0.014	-0.013
			[0.012]	[0.012]
village, 1-2 thousand inhabitants			-0.040**	-0.038**
			[0.015]	[0.015]
village, less than 1,000 inhabitants			-0.064***	-0.063***
			[0.017]	[0.017]
minutes to nearest hospital			0.000	0.000
			[0.000]	[0.000]
minutes to nearest county centre			-0.000**	-0.001**
			[0.000]	[0.000]
annual per capita specialist hours			0.002	0.003
			[0.006]	[0.006]
per capita taxable income, 2nd tertile			0.005	0.004
			[0.009]	[0.009]
per capita taxable income, 3rd tertile			0.033**	0.034**
			[0.015]	[0.015]
fraction aged 60 and above			-0.054	-0.017
			[0.076]	[0.076]
fraction of Roma population			-0.038	-0.026
			[0.028]	[0.028]
fraction of disabled population			-0.049	-0.072
			[0.105]	[0.105]
constant	0.166***	0.166***	0.228***	0.217***
	[0.008]	[0.008]	[0.029]	[0.028]
county effects	no	no	yes	yes
observations	8,834	8,834	8,834	8,834

Note: Cluster robust standard errors in brackets, clustered at the calendar year × years of vacancy level, *** p<0.01, ** p<0.05, * p<0.1.

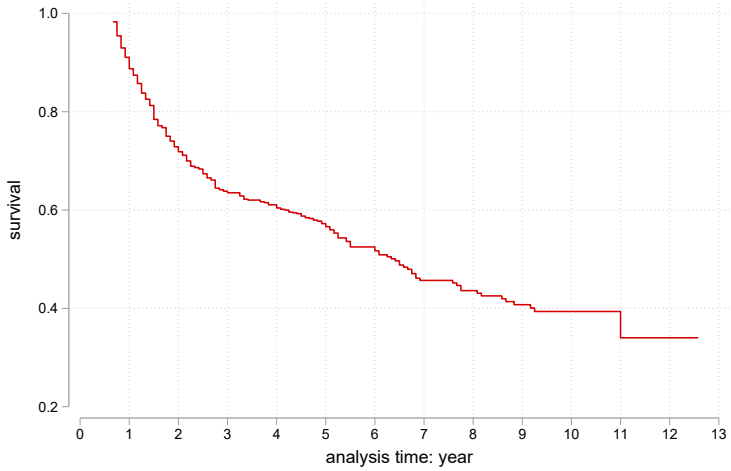
Appendix Table A4: Cox regression of take-up of vacant practices

	Hazard ratio of vacancy take-up			
vacant for 12+ months × after 2015	2.034***	1.909***	1.997**	1.897***
	[0.540]	[0.413]	[0.591]	[0.439]
vacant for 12+ months × after 2018		1.170		1.135
		[0.351]		[0.340]
vacant for 12-23 months	0.601**	0.594**	0.728	0.718
	[0.139]	[0.134]	[0.184]	[0.179]
vacant for 24-35 months	0.540	0.526	0.737	0.724
	[0.240]	[0.233]	[0.336]	[0.328]
vacant for 36-47 months	0.489	0.477	0.722	0.725
	[0.355]	[0.334]	[0.519]	[0.500]
vacant for 48-59 months	0.666	0.626	1.121	1.079
	[0.475]	[0.436]	[0.801]	[0.748]
vacant for 60+ months	0.310**	0.275**	0.510	0.436
	[0.162]	[0.145]	[0.265]	[0.231]
after 2015	0.380***	0.493***	0.355***	0.475***
	[0.075]	[0.057]	[0.089]	[0.086]
after 2018		0.575**		0.517***
		[0.133]		[0.121]
practice type: children			0.381***	0.383***
			[0.045]	[0.044]
practice type: both adults and children			0.977	1.000
			[0.145]	[0.142]
annual payment from NHIFM, 2nd tertile			1.139	1.218*
			[0.136]	[0.144]
annual payment from NHIFM, 3rd tertile			0.900	0.966
			[0.131]	[0.140]
village, above 2,000 inhabitants			0.870	0.914
			[0.156]	[0.161]
village, 1-2 thousand inhabitants			0.509***	0.528***
			[0.123]	[0.127]
village, less than 1,000 inhabitants			0.233***	0.235***
			[0.068]	[0.068]
minutes to nearest hospital			1.002	1.002
			[0.005]	[0.005]
minutes to nearest county centre			0.992*	0.991**
			[0.004]	[0.004]
annual per capita specialist hours			1.043	1.067
			[0.087]	[0.077]
per capita taxable income, 2nd tertile			1.035	1.038
			[0.173]	[0.170]
per capita taxable income, 3rd tertile			1.351	1.371
			[0.319]	[0.325]
fraction aged 60 and above			0.031	0.080
			[0.073]	[0.182]
fraction of Roma population			0.127**	0.181*
			[0.118]	[0.163]
fraction of disabled population			0.469	0.237
			[1.780]	[0.884]
county effects	no	no	yes	yes
observations	8,313	8,313	8,313	8,313

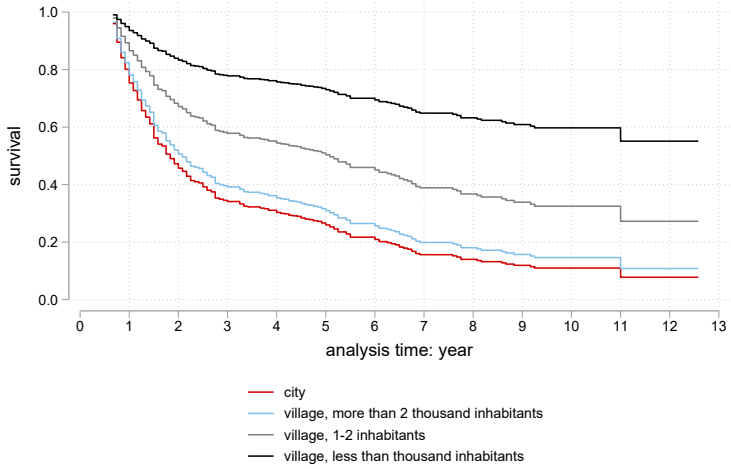
Note: Cluster robust standard errors in brackets, clustered at the calendar year × years of vacancy level, *** p<0.01, ** p<0.05, * p<0.1.

Appendix Figure A2: Cox regression results: survivor function of vacancy

(a) Survivor function



(b) Survivor function by settlement type



Note: The plots are based on the regression results reported in the third column of Table A4.

C Survey details

Appendix Table A5: Comparison of the subsidy recipients and non-recipients in the survey data

	Non-recipient of subsidy		Subsidy recipient			
Variable	Mean	Std dev	Mean	Std dev	Difference	p-value
Age	59.95	11.02	53.32	13.70	-6.63***	0.00
Total number of children	2.09	1.04	2.19	1.06	0.10	0.27
Number of children aged 0-5 years cohabiting	1.31	0.53	1.48	0.63	0.17	0.18
Number of children aged 6-14 years cohabiting	1.46	0.65	1.73	0.84	0.27**	0.02
Number of children aged 15-18 years cohabiting	1.14	0.52	1.09	0.42	-0.06	0.62
Number of children aged 19+ years cohabiting	0.62	0.81	0.93	0.81	0.31***	0.01
Number of specialist exams	1.85	0.83	1.60	0.78	-0.25***	0.00
Number of jobs held so far, not counting the current one	2.29	1.88	2.89	2.19	0.60***	0.00
Number of years since obtaining MD diploma	34.67	11.29	27.60	13.69	-7.07***	0.00
Number of years since start of first job	34.39	11.29	27.14	14.01	-7.25***	0.00
Number of years since start of current job	22.89	12.83	12.65	13.55	-10.24***	0.00
Observations	1,442		157		1,599	

Note: The last two columns test equality of means across groups,
*** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A6: Comparison of the administrative and the survey data

	(1) Admin data, no subsidy		(2) Admin data, subsidy		(3) Survey data, no subsidy		(4) Survey data, subsidy		(1)-(2)	(3)-(4)	(1)-(3)	(2)-(4)
	Mean	Std dev	Mean	Std dev	Mean	Std dev	Mean	Std dev	t-value	t-value	t-value	t-value
Town or city	0.711	0.453	0.463	0.500	0.754	0.431	0.561	0.498	6.271***	4.550***	-3.370***	-1.721
Village, above 2,000 inhabitants	0.141	0.348	0.232	0.423	0.129	0.335	0.216	0.413	-2.722***	-2.485**	1.204	0.327
Village, 1-2 thousand inhabitants	0.089	0.285	0.201	0.402	0.074	0.262	0.155	0.364	-3.545***	-2.660***	1.956*	1.057
Village, less than 1,000 inhabitants	0.059	0.235	0.104	0.306	0.043	0.203	0.068	0.252	-1.860*	-1.149	2.576***	1.142
Minutes to nearest hospital	10.626	13.674	20.024	16.366	9.614	12.828	15.365	14.208	-7.288***	-4.724***	2.634***	2.691***
Minutes to nearest county centre	21.598	21.244	37.495	18.893	20.413	20.883	28.755	20.033	-10.603***	-4.797***	1.912*	3.953***
Annual per capita specialist hours	2.029	1.715	0.975	1.400	2.191	1.789	1.327	1.581	9.461***	6.234***	-3.078***	-2.074**
Per capita taxable income (1,000 HUF)	1401	283	1222	309	1410	264	1332	305	7.354***	2.981***	-1.059	-3.166***
Fraction aged 60 and above	0.266	0.034	0.263	0.046	0.268	0.032	0.266	0.037	0.989	0.566	-1.534	-0.691
Fraction of Roma population	0.030	0.048	0.058	0.081	0.028	0.044	0.039	0.066	-4.355***	-2.023**	1.181	2.178**
Fraction of disabled population	0.050	0.016	0.051	0.016	0.050	0.013	0.051	0.014	-0.422	-0.713	0.514	-0.088
Sample size	6314		164		1396		148					

Note: The last four columns test equality of means across groups, *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A7: Further characteristics of the subsidy recipients and non-recipients in the survey data

		Non-recipient of subsidy		Subidy recipient		Total	
		N	Column %	N	Column %	N	Column %
Place of birth, country	Hungary	1,263	87.6%	125	79.6%	1,388	86.8%
	Other European country	149	10.3%	29	18.5%	178	11.1%
	Outside of Europe	28	1.9%	3	1.9%	31	1.9%
	Missing	2	0.1%	0	0.0%	2	0.1%
	Pearson chi2(3) =	9.6785	Pr =	0.022			
Born in Budapest	No	1,178	81.7%	137	87.3%	1,315	82.2%
	Yes	264	18.3%	20	12.7%	284	17.8%
	Pearson chi2(1) =	3.0063	Pr =	0.083			
Sex	Male	635	44.0%	74	47.1%	709	44.3%
	Female	804	55.8%	83	52.9%	887	55.5%
	Missing	3	0.2%	0	0.0%	3	0.2%
	Pearson chi2(2) =	0.8462	Pr =	0.655			
Highest education achieved	Master's degree (MA, MSc, MD)	1,406	97.5%	154	98.1%	1,560	97.6%
	Doctoral degree (PhD)	17	1.2%	1	0.6%	18	1.1%
	Missing	19	1.3%	2	1.3%	21	1.3%
	Pearson chi2(2) =	0.3765	Pr =	0.828			
Civil status	Single	56	3.9%	5	3.2%	61	3.8%
	Married	1,024	71.0%	116	73.9%	1,140	71.3%
	De facto or registered partner	98	6.8%	11	7.0%	109	6.8%
	Divorced	168	11.7%	18	11.5%	186	11.6%
	Widowed	88	6.1%	7	4.5%	95	5.9%
	Missing	8	0.6%	0	0.0%	8	0.5%
	Pearson chi2(5) =	1.8736	Pr =	0.866			
Region of medical school	Budapest	422	29.3%	38	24.2%	460	28.8%
	Baranya (Pécs)	276	19.1%	25	15.9%	301	18.8%
	Csongrád (Szeged)	280	19.4%	26	16.6%	306	19.1%
	Hajdú-Bihar (Debrecen)	324	22.5%	41	26.1%	365	22.8%
	Hungary, other	1	0.1%	0	0.0%	1	0.1%
	Romania	101	7.0%	19	12.1%	120	7.5%
	Russia/former USSR	7	0.5%	1	0.6%	8	0.5%
	Ukraine/former USSR	22	1.5%	3	1.9%	25	1.6%
	Southeast Europe/former Yugoslavia	3	0.2%	1	0.6%	4	0.3%
	Europe, other	0	0.0%	1	0.6%	1	0.1%
	Missing	6	0.4%	2	1.3%	8	0.5%
	Pearson chi2(10) =	20.9863	Pr =	0.021			
Worked abroad for more than 6 months	Yes	135	9.4%	28	17.8%	163	10.2%
	No	1,299	90.1%	126	80.3%	1,425	89.1%
	Missing 8	0.6%	3	1.9%	11	0.7%	
	Pearson chi2(2) =	15.2892	Pr =	0.000			
Recipient of purchase subsidy for current practice	Yes	136	9.4%	34	21.7%	170	10.6%
	No	1,300	90.2%	121	77.1%	1,421	88.9%
	Missing	6	0.4%	2	1.3%	8	0.5%
	Pearson chi2(2) =	24.7109	Pr =	0.000			
	Total	1,442	100.0%	157	100.0%	1,599	100.0%

Appendix Table A8: Multinomial logit models of location choice: ratio of vacant practices in district

	tertiles of district level ratio of vacant practices		
	1st	2nd	3rd
female	0.086***	-0.016	-0.070***
	[0.023]	[0.024]	[0.024]
age category (baseline: -40)			
age 41-60	-0.117**	0.023	0.094**
	[0.050]	[0.051]	[0.044]
age 61-	-0.078	-0.054	0.132***
	[0.055]	[0.055]	[0.048]
born Bp	0.243***	-0.106***	-0.137***
	[0.032]	[0.040]	[0.042]
studied Bp	0.108***	0.007	-0.115***
	[0.028]	[0.031]	[0.031]
number of children			
age 0-18	-0.007	0.004	0.004
	[0.015]	[0.016]	[0.016]
age 19-	-0.033***	0.035***	-0.003
	[0.012]	[0.012]	[0.012]
preference indicators			
ease of access	0.031***	-0.020*	-0.011
	[0.011]	[0.011]	[0.011]
commuting time	0.030***	-0.002	-0.028***
	[0.011]	[0.011]	[0.011]
patients' age	0.006	-0.011	0.006
	[0.012]	[0.012]	[0.012]
patients' socioeconomic	0	0.002	-0.002
status	[0.012]	[0.013]	[0.013]
salary	-0.02	0.022*	-0.003
	[0.013]	[0.013]	[0.013]
subsidies to buy equipment	0.012	0.006	-0.018
	[0.012]	[0.013]	[0.012]
observations	1,576	1,576	1,576

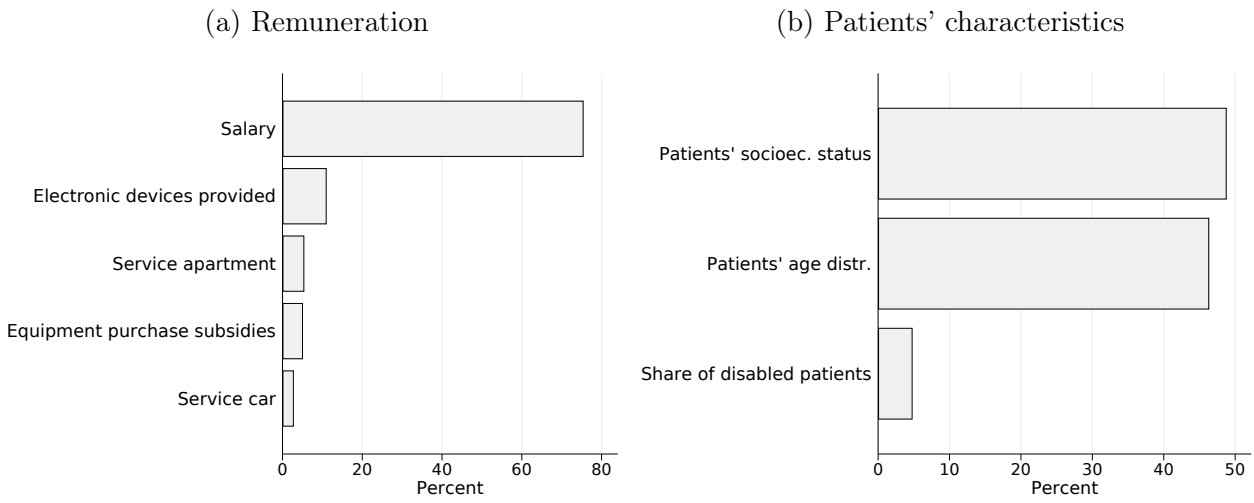
Note: Multinomial logit model average marginal effects, standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. The preference indicators range from 1 (not in the top 3 choice) to 4 (considered most important).

Appendix Table A9: Multinomial logit models of location choice: settlement type

	settlement type			
	town or city	village, 2,000+	village, 1,000-2,000	village, less than 1000
female	0.145***	-0.049***	-0.061***	-0.035***
	[0.023]	[0.018]	[0.015]	[0.011]
age category (baseline: -40)				
age 41-60	-0.049	0.021	-0.003	0.031*
	[0.046]	[0.035]	[0.033]	[0.016]
age 61-	-0.002	0.006	-0.036	0.032*
	[0.050]	[0.039]	[0.035]	[0.017]
born Bp	0.094**	0.002	-0.074***	-0.022
	[0.038]	[0.028]	[0.029]	[0.021]
studied Bp	0.052*	-0.026	-0.005	-0.021
	[0.030]	[0.024]	[0.019]	[0.016]
number of children				
age 0-18	-0.037***	0.028**	0.009	0.001
	[0.014]	[0.011]	[0.008]	[0.008]
age 19-	-0.032***	0.017*	0.006	0.009*
	[0.011]	[0.009]	[0.007]	[0.005]
preference indicators				
ease of access	0.005	-0.006	0.002	-0.001
	[0.011]	[0.008]	[0.007]	[0.005]
commuting time	0.001	0.004	-0.008	0.003
	[0.010]	[0.008]	[0.007]	[0.005]
patients' age	0.003	0	0.003	-0.006
	[0.012]	[0.009]	[0.008]	[0.005]
patients' socioeconomic	-0.018	0	0.017**	0.001
status	[0.012]	[0.010]	[0.008]	[0.006]
salary	0.005	0.006	-0.011	0
	[0.012]	[0.010]	[0.008]	[0.006]
subsidies to buy equipment	0.020*	-0.005	-0.006	-0.009
	[0.012]	[0.010]	[0.008]	[0.006]
observations	1,525	1,525	1,525	1,525

Note: Multinomial logit model average marginal effects, standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. The preference indicators range from 1 (not in the top 3 choice) to 4 (considered most important).

Appendix Figure A3: Preferences for further workplace attributes, ranked as most important



Notes: The figure displays the distribution of workplace attributes indicated as the most important. All respondents were asked these questions.

D Rank-Ordered Probit Choice Model Marginal Effects

Formally, assume that there are $j = 1 \ldots, J$ alternatives ranked by decision maker i (ties are allowed) with utilities (latent variables):

$$\eta_{ij} = z_i \alpha_j + \varepsilon_{ij}$$

where z_i are the individual-specific variables and $\varepsilon_{ij} \sim N(0, \Sigma)$.[8] The decision maker ranks the alternatives according to the underlying utilities. The α_j coefficients are not all identifiable, nor are the elements of the variance-covariance matrix. The model requires normalisation, both for location and scale. While the estimated coefficients are sensitive to which alternatives were chosen for location and scale baselines, the predicted probabilities and marginal effects are not. We report the estimated marginal effects below.

[8] A more general form of the model is $\eta_{ij} = x_{ij}\beta + z_i \alpha_j + \varepsilon_{ij}$; however, we do not have alternative-specific characteristics x_{ij} in our data, therefore we omit the corresponding term.

Appendix Table A10: Marginal effects from rank-ordered probit choice models

	Female	Age: 60+ years	Born in Budapest	Married or partnered	Number of years in current job	Number of children 0-18 years	Number of children 19+ years
General workplace characteristics							
Location	0.0373*	0.00503	-0.00549	0.0312	0.00194*	0.0149	0.0138
	(0.0190)	(0.0262)	(0.0237)	(0.0235)	(0.00100)	(0.0125)	(0.00981)
Remuneration	-0.0758***	-0.0444*	-0.0376	-0.00988	-0.000720	0.0105	-0.00951
	(0.0198)	(0.0264)	(0.0246)	(0.0248)	(0.00104)	(0.0131)	(0.0102)
Work environment	0.0217	0.00735	0.0101	-0.00415	0.000253	-0.00357	0.0135*
	(0.0152)	(0.0203)	(0.0201)	(0.0192)	(0.000781)	(0.0102)	(0.00773)
Patients' attributes	0.000691	0.0131	-0.00122	-0.0120	-0.000225	0.00509	0.00102
	(0.00869)	(0.0123)	(0.0107)	(0.0124)	(0.000448)	(0.00556)	(0.00466)
Stability	0.0272**	0.0109	-0.00654	0.00887	-0.000758	-0.00341	-0.00157
	(0.0139)	(0.0180)	(0.0168)	(0.0164)	(0.000703)	(0.00955)	(0.00640)
Interesting job	-0.0169	0.00622	0.0235	-0.0195	-0.000131	-0.0190**	-0.0147**
	(0.0128)	(0.0173)	(0.0149)	(0.0165)	(0.000616)	(0.00863)	(0.00651)
Observations	4105						
Location characteristics							
Ease of access	-0.0279	0.0417	-0.00474	-0.0131	0.00311***	0.0168	0.0182
	(0.0222)	(0.0300)	(0.0265)	(0.0264)	(0.00114)	(0.0145)	(0.0113)
Daily commuting time	0.0449**	-0.0661**	0.0577**	-0.0000498	-0.00170	0.0130	-0.00200
	(0.0223)	(0.0297)	(0.0268)	(0.0266)	(0.00116)	(0.0145)	(0.0112)
Kindergarten, school nearby	-0.00631	-0.00263	-0.00867	-0.00519	-0.000187	0.00275	0.00259
	(0.00704)	(0.0105)	(0.00821)	(0.0104)	(0.000355)	(0.00423)	(0.00361)
Work opportunities nearby	-0.00767	-0.00378	-0.0371***	0.0429***	-0.000728	-0.0175**	-0.00369
	(0.0115)	(0.0151)	(0.0135)	(0.0134)	(0.000603)	(0.00775)	(0.00598)
Distance from nearest hospital	0.00346	0.0305*	-0.0118	-0.0154	-0.000149	-0.0163*	-0.0169***
	(0.0117)	(0.0155)	(0.0140)	(0.0147)	(0.000578)	(0.00877)	(0.00605)
Observations	4063						
Patients' characteristics							
Patients' age distribution	0.0594**	0.134***	-0.0920***	-0.00254	0.000798	-0.0152	0.0127
	(0.0251)	(0.0345)	(0.0303)	(0.0317)	(0.00130)	(0.0164)	(0.0127)
Share of disabled patients	-0.0186*	0.0102	-0.00301	0.00451	-0.000135	0.00355	-0.0000849
	(0.0103)	(0.0140)	(0.0128)	(0.0124)	(0.000534)	(0.00652)	(0.00520)
Patients' socioeconomic status	-0.0274	-0.146***	0.0733**	0.00354	0.000552	0.00939	-0.00657
	(0.0256)	(0.0347)	(0.0321)	(0.0320)	(0.00131)	(0.0170)	(0.0129)
Observations	3785						
Remuneration elements							
Salary	-0.0183	-0.0694***	0.0187	-0.0258	-0.000494	-0.00570	-0.0165*
	(0.0184)	(0.0250)	(0.0229)	(0.0221)	(0.000940)	(0.0129)	(0.00958)
Service apartment	-0.00487	0.0206	0.00165	0.0154	0.00119**	0.00249	-0.00211
	(0.0108)	(0.0141)	(0.0149)	(0.0127)	(0.000553)	(0.00730)	(0.00533)
Service car	0.00746	-0.00230	0.00169	-0.000162	0.000405	0.00885**	0.00671**
	(0.00637)	(0.00858)	(0.00793)	(0.00810)	(0.000345)	(0.00409)	(0.00340)
Subsidies to buy equipment	0.00461	0.0303***	-0.0162*	0.00368	-0.000459	0.00370	0.00389
	(0.00780)	(0.0111)	(0.00838)	(0.00955)	(0.000403)	(0.00567)	(0.00406)
Electronic devices	0.0135*	0.0239**	-0.0136*	0.00783	-0.000632*	-0.0115**	0.00487
	(0.00745)	(0.00986)	(0.00822)	(0.00869)	(0.000380)	(0.00535)	(0.00376)
Observations	4016						

Note: Each row corresponds to a separate regression, with the preference indicator (listed in the first column) as the dependent variable. Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1. The marginal effects on the "Other" option have been omitted.