What factors affect doctors' work decisions: Comparing a discrete choice structural approach to a reduced-form approach*

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Abstract

The World Health Organisation predicts that most OECD countries will face a substantial shortage of physicians in the next years, yet little research exists about the pecuniary and non-pecuniary determinants of doctors' labour supply. We address this gap using a unique data set on Australian physicians. Applying both a reduced-form and a structural discrete choice approach, we examine the policy implications of different modelling approaches in terms of wage elasticities at the intensive margin. We contribute to the literature on doctors' labour supply in a number of ways. First, we show that the estimated wage elasticities are very similar on average in the two approaches. However, whereas the reduced-form approach hides a substantial amount of variation, the structural model reveals heterogeneous wage elasticities, ranging from -1 to +1. Second, we examine these heterogeneous responses but do not find strong responses concentrated amongst particular groups that could be targeted by wage policies. Finally, we use the structural approach to calculate the labour supply responses of doctors in response to 5 and 10% wage increases. The results show that such wage increases lead to a substantial decline in labour supply by male, but not female doctors, suggesting important implications for the design of effective workforce policies.

Keywords: labour supply, discrete choice model, wage elasticity, MABEL.

1 Introduction

A number of developed countries, including the US, UK, Canada, New Zealand, and Australia, have been concerned about the supply of medical services for several years (World Health Organisation, 2013). The WHO estimates global shortages of about 12.9 million health workers, i.e., medical doctors, midwives, nurses, by 2035. To a substantial extent, this deficit is driven by the shortage of general practitioners (GPs) and specialists, especially in remote and rural regions of a country. Preventing a shortage of health workers in general, and GPs in particular, remains a critical task for health care policy to ensure the long-term supply of medical services for an ageing population (including an ageing health work force) that exhibits an increasing demand for medical care.

We examine the labour supply of Australian doctors for whom average working hours have fallen by 11.4% from 48.2 to 42.7 hours per week between 1998 and 2008 (AIHW, 2010). A number of factors contribute to the observed decrease in working hours. First, the share of female doctors has increased substantially as women account for only 18 per cent of older cohorts (doctors aged 55 and over) compared with almost 50 per cent of the new generation of doctors (aged 35 and under) (AIHW, 2010). These changes in the gender composition of the workforce have an impact on labour supply, since female doctors work 37.7 hours per week on average compared to 45.4 hours for males (AIHW, 2010). Second, at the same time men have also reduced their working hours, and relatively more so than women over time so that the gender differential in working hours has decreased (AIHW, 2010). This has further reduced labour supply. Third, the age profile of doctors is changing as the proportion of older doctors has increased over the past ten years which resulted in a significant drop in average working hours as older doctors tend to work fewer hours. Fourth, Markwell and Wainer (2009) and Shrestha and Joyce (2011) document the changing work/life balance expectations amongst doctors. For instance, both younger and older doctors, male and female, have reduced their working hours compared to a decade ago, amplifying the reductions in hours worked caused by the increased proportion of women and older doctors. In addition, studies of retirement intentions suggest that one third of GPs plan to retire before age 65, and that job satisfaction is a key factor in this decision (Brett et al., 2009).

Despite a vast general labour supply literature (see e.g., Blundell and MaCurdy, 1999; Blundell, MaCurdy, and Meghir, 2007) and despite the concern over shortages of GPs in many developed countries, the labour supply of doctors has received surprisingly little attention as evidence exists basically only for two (very different) countries, the US and Norway. However, given the decline in working hours, designing effective workforce policies requires a better understanding of the determinants of doctors' labour supply, and the potential differences in determinants between groups. The few studies that do examine doctors' labour supply mostly apply a reduced-form approach that uses a linear specification of the logarithm of hours worked derived from the theory of utility maximisation, which includes the logarithm of the wage rate as one of the explanatory variables (Sloan, 1974; Rizzo and Blumenthal, 1994; Showalter and Thurston, 1997; Thornton, 1998; Ikenwilo and Scott, 2007).[1] However, this popular specification imposes a constant wage elasticity for all doctors and ignores potential heterogeneities. Because wage elasticities are expected to decline at higher hours of work due to an increased marginal utility of leisure relative to utility of income, imposing a constant wage elasticity ap-

[1]Baltagi, Bratberg, and Holmås (2005) also use a reduced form but they have applied a panel approach on the repeated observations of hospital physicians in Norway.

pears particularly problematic.

We contribute to the literature on doctors' labour supply in three main ways. First, we estimate a discrete choice structural labour supply model which has gained increasing popularity in the general labour economics literature and which directly estimates the underlying utility function. A few studies, e.g., Cheng, Kalb, and Scott (2013), Andreassen, Di Tommaso, and Strøm (2013), and Sæther (2005), apply a structural labour supply model but these studies mainly examine choices between different types of jobs (such as public versus private). The discrete choice approach offers a number of advantages compared to the reduced-form approach, including the flexibility of the functional form, the ease with which the model can incorporate the tax and transfer systems, and the broader range of utility functions to base the labour supply model on. Second, we explore heterogeneous responses by providing a detailed analysis for different subgroups. Whereas previous studies have relied on small samples and estimated models for male and female doctors combined, or models for male doctors only (see Section 2), our large sample allows us to estimate separate models by gender. Given an increasing proportion of female doctors and the fact that women are likely to have different determinants of labour supply compared to men, understanding the determinants of female doctors' labour supply is important for workforce policy. Finally, the discrete choice approach allows the simulation of policy changes, e.g., to Medicare rebates or other changes to the financial remuneration of (specific) doctors taking into account the non-linearity of the tax schedule. We simulate labour supply responses at the intensive margin in response to nominal wage increases in the order of 5 and 10%.

Using data from a unique Australian study of doctors, "Medicine in Australia: Balancing Employment and Life" (MABEL), we estimate a reduced-form and a structural model and compare the estimated wage elasticity from both models for doctors with different characteristics. We focus on GPs and specialists, and estimate separate models for men and women in both groups. We find negative wage elasticities for male and female doctors, GPs and specialists, and show that the wage elasticities are very similar on average in the two approaches. However, the reduced-form approach hides a substantial amount of variation across individuals because of the restrictive underlying assumption of a constant elasticity that is independent of hours worked. The structural discrete choice approach, in contrast, reveals heterogeneous responses to financial incentives which could help policy makers target specific groups. Our policy simulation shows that nominal wage increases of 5 or 10% lead to a substantial reduction in the labour supply of male doctors at the intensive margin. The results are robust to different definitions of non-labour and other household income, different specifications of the discrete sets of working hours, and including random variation in preferences.

The paper proceeds as follows. Section 2 presents a brief literature review on physicians' labour supply and summarises the reported wage elasticities. Section 3 outlines the two types of labour supply models and the associated estimation approaches. In section 4 we describe the data and discuss some descriptive statistics. Section 5 presents the empirical results, followed by a policy simulation in section 6. We conclude the paper with a discussion of the implications in Section 7.

2 Literature review

In this section we briefly review the main studies and their estimated wage elasticities, which differ as the studies use different data sources and examine specific doctor types. The earliest studies on the determinants of doctors' labour supply, e.g. Feldstein (1970), Fuchs and Kramer (1972), Brown and Lapan (1972), run OLS regressions of the quantity of services provided by a GP on different control variables and a fee measure. Using different data sources from the US, these studies generally find small negative wage elasticities that are measured imprecisely due to the small sample sizes. Sloan (1974) estimates the wage elasticities on weekly hours worked (and weeks worked per year) using US census data from 1960 and 1970. He finds small positive wage elasticities (< 0.1) on average as well as evidence in favour of a backward-bending labour supply curve for a minority of doctors at the top of the income distribution.

More recently, Rizzo and Blumenthal (1994) use a sample of young self-employed physicians from the 1987 Practice Patterns of Young Physicians Survey. They model labour supply and the wage rate jointly and instrument the wage rate using professional experience. The study estimates the model for men and women combined, and finds a positive wage elasticity of 0.23 which they decompose into an income (-0.26) and a substitution effect (0.49). Showalter and

Thurston (1997) study the effect of changes in state marginal tax rates on labour supply using data from the 1983-1985 Physicians' Practice Costs and Income Survey (PPCIS). Focusing on physicians, the study finds significant positive wage elasticities for self-employed physicians (0.33), but small (0.10) and insignificant wage elasticities for doctors on wages or salaries. Thornton (1998) also uses the PPCIS and estimates wage elasticities for male, self-employed, solo-practice physicians. He finds very small positive wage elasticities of around 0.06 and concludes that reductions in medical fees are unlikely to decrease the supply of medical services. He also finds very little evidence for a backward-bending labour supply curve.

For Norway, Baltagi et al. (2005) use administrative data from 1993 to 1997 for male hospital physicians and apply different estimators to their labour supply model. The data covers a period where some doctors received a 15 per cent wage increase while others did not receive this wage increase. This variation over time facilitates estimation of the wage elasticity. Estimating the labour supply model by GMM, they find significant positive wage elasticities of around 0.3.

The studies discussed all use a reduced-form approach, which imposes some strong assumptions including a constant wage elasticity although Showalter and Thurston (1997), for example, allows the wage elasticity to depend on age. Only a small number of studies use a discrete-choice approach that allows a more flexible modelling of labour supply. Using administrative data for Norwegian residents in 1995 and 1997, Sæther (2005) estimates a discrete choice labour supply model for doctors aged 28-66, both employed and self-employed. He finds wage elasticities for hospital physicians ranging broadly from 0.1 to 0.2. He also shows that although private sector wage increases lead to stronger changes in hours worked in the relevant sector than public sector wage increases, the wage elasticity for overall hours is slightly smaller at 0.08 than the wage elasticity of 0.10 for overall hours associated with a public sector wage increase.

Most recently, Andreassen et al. (2013) use Norwegian administrative data from 1996-2000 to estimate a labour supply model that allows doctors to choose between 10 different job packages which derive from a combination of attributes: part- or full-time work, hospital or primary care, public or private sector, with 'working in other sectors' and 'not working' representing the 9th and 10th package. The study focuses on all employed married physicians and finds an average wage elasticity of 0.04. The paper demonstrates the flexibility of the discrete choice approach by presenting estimated wage elasticities, and sectoral employment changes, that result from simulated changes to the taxation schedule.

3 Methods

In this section we briefly describe the two approaches used in this paper: a discrete choice labour supply model in Section 3.1 and a reduced-form linear regression model in Section 3.2.

3.1 A structural labour supply model

Our central analyses use a structural model of individual labour supply, based on a utility function, to obtain estimates of labour supply preferences and elasticities with respect to income and wages. We treat labour supply as a discrete choice problem rather than a continuous choice, similar to the approach by Van Soest (1995).

As in standard labour supply models, we assume that doctors choose a combination of hours worked and household net income (assumed to be equal to household consumption) that maximises their utility. Following Keane and Moffitt (1998), we use a quadratic specification for the utility function. The quadratic specification is straightforward to implement and quite flexible as leisure and consumption of each doctor can be either substitutes or complements. The quadratic model can thus represent complex interactions without imposing too many restrictions a priori.[2] Furthermore, unlike many other utility functions, the quadratic utility function can be expressed as a function of working hours rather than leisure. Thus, we do not have to choose an arbitrary value for the total endowment of time. These advantages make the quadratic utility function a good choice, even though it is not automatically quasi-concave. We can, however, easily check this property post-estimation: if utility U is increasing in income at the observed income and leisure time, and the matrix of second order derivatives of income with respect to leisure along the indifference surface is positive at the observed income and leisure time, then U is quasi-concave at that point (Varian, 1992, pp.96-97).

[2] Van Soest et al. (2002) show that utility functions including fifth-order polynomials yield almost identical wage elasticities compared with models using lower-order polynomials, thus indicating that a second-order polynomial, or quadratic, function performs adequately.

We depart from the continuous labour supply model by assuming that each doctor i can choose between j alternatives from a limited set of m combinations of income and working hours, $\{(y_{ij}, h_{ij}); j = 1, 2, ..., m\}$, where y_{ij} is the household's net income associated with the doctor's working hours h_{ij}. We specify the following quadratic utility function:

$$U_{ij} = \beta_1 y_{ij} + \beta_2 y_{ij}^2 + \beta_3 h_{ij} + \beta_4 h_{ij}^2 + \beta_5 h_{ij} y_{ij} + \epsilon_{ij} \tag{1}$$

We assume that the random error ϵ_{ij} follows a type I Extreme Value distribution and estimate the parameters of the resulting multinomial logit model by maximum likelihood (see Maddala, 1983). Due to the tractability of the multinomial logit model, this choice has been popular in discrete choice labour supply modelling. Furthermore, we allow the vector of linear preference parameters β to differ by family status and some individual characteristics, e.g., the number of children, the doctor's age and health status.

The discrete choice approach has the major advantage that we can easily calculate the level of utility for each possible combination of working hours and net income. Given the above model and assuming that individuals choose the alternative that leads to the highest utility, we can easily calculate the probability that individual i chooses alternative j (from the m alternatives) as:

$$Pr(U_{ij} > U_{ik}, k \neq j) = \frac{exp(U_{ij})}{\sum_{k=1}^{m} exp(U_{ik})} \tag{2}$$

To estimate these probabilities we need to determine the utility level (and thus the household net income) associated with each choice j. To generate household net income, we first compute gross hourly wages either directly from observed information (on income and hours worked) or by imputing gross wages using wage regressions. Using gross hourly wages, we can calculate gross labour income associated with each choice of working hours. We then add non-labour income and the spouse's gross income to generate gross household income. Finally, we apply the Australian 2008 tax and transfer system, which accounts for the household's tax liabilities and eligibility for family payments, to generate the amount of net household income associated with each level of working hours.[3]

Choosing a discrete choice approach has a number of major advantages. First, the model is able to incorporate non-linearities in the taxation system, other household income, and family payments. Second, the labour supply literature has shown that a discrete representation of continuous labour supply is adequate, and perhaps even preferred, since workers often have a limited number of working hours to choose from.[4] The discretisation of working hours may be particularly appropriate for GPs who are likely to face institutional constraints that affect their labour supply (Sæther, 2005). Despite these potential constraints, the observed distribution of hours worked suggests that both part-time and full-time hours ranges are reasonably well covered (see Figure 1). Thus, a broad range of working hours is on offer to doctors, facilitating the supply of preferred hours without facing major demand side constraints.[5] For our analysis, we choose discrete labour supply points that cover the observed labour supply as well as possible. Hence, our main model offers ten different choices of working hours: 16, 20, 30, 40, 45, 50, 55, 60, 65 or 70 hours per week.[6] Third, the direct estimation of the preference parameters in the utility function allows the simulation of labour supply responses to policy changes affecting net income.[7] Fourth, as opposed to the continuous model, we do not need to impose quasi-concavity

[3]We include individual income tax payments and income tax rebates, as well as the Medicare Levy and Government payments to families with children.

[4]For instance, Van Soest, Woittiez, and Kapteyn (1990) and Tummers and Woittiez (1991) show that a discrete specification of labour supply can improve the representation of actual labour supply compared with a continuous specification.

[5]Individuals who are most likely to face demand side factors that lead to sub-optimal working hours are those for whom observed hours are not equal to preferred hours. This may potentially lead to bias in the estimation of the model's parameters due to measurement error. Therefore, in the empirical section of the paper, we follow Ribeiro (2001) who uses information from the sample (whether workers were looking for another job) to exclude individuals from the analysis, and estimate an alternative version of the model, excluding all observations who are not working at their preferred hours. This provides an indication of the bias of the estimated elasticities due to sub-optimal labour supply reported in the data. Unfortunately, the question in MABEL is not ideal since it is not asked conditional on income changing with a change in hours worked, but the results provide some indication to the sensitivity of our elasticity to leaving out doctors who state they would like to change hours worked. The estimation results show that the results are robust to dropping these individuals from the analysis, available upon request.

[6]The corresponding hours intervals are: [0 -18); [18 -25); [25 -35); [35 -42.5); [42.5-47.5); [47.5-52.5); [52.5-57.5); [57.5-62.5); [62.5-67.5); [67.5-80). We also examine the sensitivity of results to choosing a smaller and larger number of labour supply points: five (allowing 20, 40, 50, 60 or 70 hours per week) and thirteen (allowing 8, 16, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65 or 70 hours per week), instead of ten. Models with 5 or 13 labour supply points do not differ much in estimated elasticities. Results are presented in Table 3.

[7]As a robustness check, we allow for random preference parameters by adding error terms to the income and working hours parameters in equation 1, similar to the approach by (Van Soest, 1995). The results are very similar and show that allowing for random preferences does not change the estimated wage elasticities.

conditions a priori to guarantee coherency but can calculate these post-estimation.

[Insert Figure 1 about here]

Ideally, we would like to jointly model the labour supply of both spouses for couple families. Unfortunately, the data available does not provide information on partners' working hours. Hence, a limitation of our study is to treat the partner's labour supply and non-labour income as exogenous. We have this limiting assumption in common with most of the literature on doctors' labour supply who face the same data issue (e.g. Sæther (2005); or Andreassen et al. (2013)). A recent exception is Wang and Sweetman (2013), who use Canadian Census data (from 1991 to 2006) to investigate the labour supply of physicians and their spouses jointly. They are particularly interested in the association of family status with labour supply and find that male physicians are not much affected by family status, which does not change much over time. For female physicians, being married decreases hours worked while having children decreases it further and more substantially. Over time the former association became less important whereas the latter association became stronger. However, these results are based on reduced-form equations, estimated using SUR, which do not include any financial variables. Given that we are only interested in the doctor's labour supply in response to financial incentives and the doctor's characteristics, we only vary policy parameters that affect the doctors and have less need to understand their partners' labour supply choices which remain exogenous in our modelling.

3.2 A reduced-form labour supply model

Starting from the same economic framework of utility maximisation, and a few simplifying assumptions, we can derive a reduced-form static labour supply model as in equation 3:

$$ln(H_i) = \alpha_1 ln(W_i) + \alpha_2 ln(Y_i) + \mathbf{X}'\beta + \epsilon_i \tag{3}$$

where the natural logarithm of hours worked (H_i) is regressed on (the log of) the gross wage rate (W_i), gross other non-labour income (Y_i), and a range of individual characteristics $\mathbf{X}$, e.g., the age of the doctor, number of children, age of the children. The parameter α_1 thus yields the uncompensated substitution elasticity (Blundell and MaCurdy, 1999, p.1599).

Although the first generation of labour supply models used this reduced-form approach frequently (Killingsworth, 1984), it imposes a number of restrictive assumptions that the structural discrete choice model does not require. First, the model assumes a constant wage elasticity as estimated by the coefficient α_1. The linear specification is fairly restrictive as the wage elasticity may vary over the hours distribution or depend on non-labour income or other demographic characteristics. Second, the reduced-form model also assumes quasi-homothetic preferences (through the linear income term) which have typically been rejected by empirical studies on consumer behaviour (Blundell and MaCurdy, 1999). Third, the model needs to impose quasi-concavity conditions a priori to guarantee coherency. Finally, the reduced-form specification cannot easily take into account the non-linearity of the income tax and transfer system when translating gross income into net income. Instead, gross wage is included as a linear term without allowing for the non-linearity of the wage after applying the rules of the tax and transfer system. The model nevertheless provides an interesting benchmark against which to compare the average wage elasticity derived from the structural model. In addition, it allows for a comparison to the literature using the reduced-form approach.

4 Data and summary statistics

4.1 MABEL survey

This paper uses a unique longitudinal survey of doctors, MABEL, which is a prospective cohort study of workforce participation, labour supply and its determinants among Australian doctors. The survey covers many topics related to labour supply, e.g. job satisfaction and attitudes to work, characteristics of the work setting, workload, income, geographic location, demographic characteristics, and family circumstances. Joyce et al. (2010) provide a detailed discussion of the study design and baseline characteristics and show that the cohort is nationally representative with respect to age, gender, geographic location and hours worked. We use data from the first wave of the MABEL survey on qualified GPs and specialists working in clinical practice. This means that we can only examine labour supply responses at the intensive margin and not analyse the decision to work in clinical practice.[8,9]

4.2 Construction of income variables

A key argument in the utility function is net income at all hours points in the doctor's choice set. To obtain this, we first need to compute total gross income at different values of hours worked. Therefore we need information on i) the gross hourly wage earned in medical practice and ii) gross other household income. The MABEL survey collects information on gross or net income per fortnight or annually, and separately asks for income from the medical practice and for total household income.[10] If doctors provide weekly or fortnightly income figures, we assume that this income was the same over all weeks/fortnights worked to impute an annual income value. We divide annual medical income by annual hours worked in the medical practice to compute the gross hourly wage earned in medical practice. We compute gross other household income by subtracting the income from medical practice from total household income. Other household income thus includes the doctors' income from other sources (e.g. income from other business interests, dividends, interest) and, for cohabiting doctors, the partner's labour and non-labour income, or a mix of these sources. Unfortunately, we cannot distinguish between these easily, due to a lack of information about the partner's income.

Using the tax and family support rules that were in place at the time of the interview in the second half of 2008, we compute net income from gross income. Because of individual taxation, we ideally need information about the partner's earnings which the survey does not provide. We are therefore required to make a few assumptions about the split of other household income. First, if the partner is working (either full- or part-time), we allocate all other income

[8] However, given the high investment in human capital required in terms of time and money to become a doctor, relatively few qualified doctors do not work in their profession. The AIHW (2012) reports that about 7% of all registered medical practitioners do not work in the medical workforce. Note that this figure includes non-GPs and specialists, for whom the non-participation rate may be higher than for GPs and specialists. Furthermore, women may take time off to raise children, and older doctors may decide to retire earlier rather than later, but these groups are relatively small and specific. These issues would need to be studied in a separate paper so factors relevant to these decisions can be fully taken into account.

[9] Although labour supply as measured by hours of work is important, effort and services provided per unit of time are alternative ways to increase the medical services supplied by doctors. As shown by Fortin et al. (2010) these can be important as well, but insufficient data are available on these outputs. Therefore, we ignore these two alternative pathways to increase services provided and focus on hours of work.

[10] Although the response rate for the financial variables is lower than for some of the other questions (Kuehnle et al., 2010), the large majority of GPs and specialists (85.3%) provide either gross or net income by one of the specified time periods.

entirely to the doctor's partner. Second, if the partner is not working, then we split the other household income equally between both spouses. We argue that in this case it is reasonable to assume that couples will split other income to maximise tax benefits (e.g., to use the tax-free income threshold).

To address measurement error and the potential endogeneity of wages, we also use predicted wages from four separate wage regressions; that is, separately for specialists and GPs and by gender. We follow a similar specification to Cheng et al. (2012) and use additional exclusion restrictions, such as median local house prices, that we argue belong in the wage equation but not in the model for hours.[11] Based on the parameter estimates from the wage equation, we predict hourly wage rates that we use to calculate gross earnings from medical practice associated with each level of working hours. We compute other income in the same way as for the observed wage approach.

To address the sensitivity of results with respect to measurement error in the partner's income or other household income, we also apply alternative approaches to construct these two measures of income both when using observed wages and imputed wages. First, the survey asks doctors about the proportion of income they earned through medical practice and through other sources. We use this to impute the division of other household income between the doctor's other income and the income of the doctor's partner.[12]

The second alternative approach additionally uses observations for which we only observe net income. We can use the taxation and family income support rules to compute the corresponding gross income. We assign other net household income to the doctor and his/her partner (if present) in the same way as described under the first approach for gross income. We only use the imputed gross income if the observed gross income is not available. This allows us to include an additional 282 doctors.

The third alternative approach combines the previous two approaches. First, we impute gross incomes from the net figures. We then apply the given proportions of other net income and net medical practice income from the doctor's total income to imputed gross total income.

[11] Coefficients are reported in Table A.1 in the Appendix.

[12] This approach reduces the estimation sample compared to the first approach since the information on the proportions is missing for about 25 per cent of doctors.

In the results section, we only present results using the base case approach with observed and predicted wages. The estimated wage elasticities from the alternative approaches 1 to 3 are very similar to those from the base case approach.[13] This indicates that the results are robust to the different approaches taken to compute the doctor's medical earnings and household income, and the different assumptions made regarding the division between the partner's earnings and other household income.

4.3 Summary statistics

We present descriptive statistics for our estimation sample on average hours worked by gender, doctor type, and age in Figure 2, together with the proportions of women in each age group. The figure shows patterns consistent with the national patterns of recent years discussed in Section 1.

[Insert Figure 2 about here]

First, the proportion of women decreases over the age cohorts and is largest amongst the younger cohorts, reaching between 62 and 65 per cent amongst GPs aged less than 40. Second, men and women differ markedly in their labour supply over the life-cycle. For instance, women in their prime child-rearing ages (30-49) work the lowest average hours. Conversely, women aged 50-59 work the longest hours amongst women, which is likely to be due to children having grown up by this stage. The table shows clearly that men and women aged over 60 reduce their labour supply with men reducing their hours worked more sharply than women.

Additionally, we refer back to Figure 1 which presents kernel density estimates for the distribution of observed working hours by gender and doctor type. The figure clearly reveals two findings: first, women work fewer hours than men with the female distribution being located to the left of the male distribution. For GPs and specialists, women represent the majority of the part-time doctors (e.g. less than 40 hours). Second, specialists are more likely to work long hours than GPs.

Table 1 contains the summary statistics for all variables used in the analysis and reveals several differences in socio-economic characteristics between the four groups of doctors. As

[13] Results are available upon request.

expected, specialists earn more per hour than GPs, and in both groups women earn less per hour than men. Female doctors are about 6 years younger and therefore more likely to have young children than male doctors. Female doctors are more likely to be single, but if they have a partner, their partner is more likely to be employed than for male doctors.

[Insert Table 1 about here]

5 Results

5.1 Labour supply estimates and marginal effects

This section discusses the results from the structural labour supply model with 10 discrete hours points. We present the simulated marginal effects and their 90% confidence intervals in Table 2 because the coefficients do not allow a direct interpretation of the associations between personal characteristics and hours worked.[14,15]

[Insert Table 2 about here]

Table 2 reveals interesting similarities and differences between the four doctor groups. As expected, young children reduce working hours for all groups; this reduction is largest for female GPs, and then female specialists. Somewhat unusually, compared to the general male population, we also observe a reduction of working hours by male GPs with young children. Young children do not affect the labour supply of male specialists substantially. Female specialists no longer significantly reduce their labour supply once their youngest child is 10 or older.

For women, the effect for the total number of children compounds the negative effect of the youngest child. For men, the effect of family size is more ambiguous. Male specialists with children work on average slightly longer hours than male specialists without children. For male

[14] We present the coefficients from the multinomial logit model with 10 discrete hours points in Appendix Table A.3

[15] Using observed wages instead of imputed wages in estimating the discrete choice model, the marginal effects for the individual characteristics only change slightly. The direction and magnitude of the estimated effects remain quite similar, see Table A.4. Estimating a reduced-form specification using the same individual and household characteristics as in the structural specification, Table A.5 shows that the marginal effects for the individual characteristics are very similar to those obtained from the structural model.

GPs, the combined effect remains negative if there is one child only and the child is younger than 10 years. For male GPs with two children or more, or with older children only, the combined effect is always positive indicating that this type of GP tends to work longer hours than a GP without children. Our results are consistent with the findings by Wang and Sweetman (2013) who, using Canadian census data, find that children do not influence male physicians' labour supply much unless a doctor has at least three children which leads to an increase in working hours. For female physicians, the presence of children reduces working hours substantially, especially when the children are at pre-school age.

Reflecting the observed decline in working hours across the age distribution, increasing age by one year decreases labour supply for all doctor types, except for female specialists, and is slightly stronger for male doctors than female doctors. We attribute this finding partly to the age distribution within the four populations, as male doctors are on average 6 years older than female doctors. Health status appears important for GPs but not for specialists. Worse health reduces the expected hours of work, especially for female GPs.

The marginal effects of having a partner reveal some interesting patterns. If the partner is not employed or in part-time employment, female doctors tend to work more hours than single female doctors, while it makes no difference to male partnered doctors compared to single male doctors. Men generally seem not to respond to their partner's working status, apart from male partnered GPs working slightly more hours than their single counterparts. If the partner is in full-time employment, female specialists and GPs work slightly fewer hours compared to single women.

5.2 Wage elasticity

In this section we simulate total labour supply responses to a 1% increase in individual wages. Using the estimated parameters in the different specifications, we simulate individual doctors' wage elasticities which reflect each doctor's expected responsiveness to financial incentives. Table 3 reports average elasticities for each of the specifications.

[Insert Table 3 about here]

A number of important points stand out. First, we observe negative wage elasticities for male and female doctors, GPs and specialists, reflecting that Australian doctors are located on the backward bending parts of their labour supply curves. The elasticities are relatively modest and range in value between -0.07 and -0.17. The negative wage elasticities are mostly significant for both men and women, except for the estimates using imputed wages for female doctors. However, this is to be expected given the lower precision of the estimated coefficients when using imputed wages. Second, the negative wage elasticities are not driven by the choice of the number of discrete labour supply points allowed in the specification of the discrete choice model. Five, ten or thirteen mid-points yield very similar results.[16] The largest change we observe is for female GPs where the model with 5 mid-points appears to introduce substantial measurement error by not covering the observed distribution of labour supply well. Third, the estimated negative wage elasticities are quite robust on average against using observed or imputed wages. The point estimates are never significantly different from each other, although some of the estimates using imputed wages are not significantly different from zero due to the loss of precision. Fourth, the table shows that structural and reduced form approaches produce strikingly similar wage elasticities on average for each of the four subgroups. The similarity indicates that the constant wage elasticity estimated in the reduced-form approach is consistent with the average elasticity in the structural discrete choice approach. The specifications using 10 or 13 mid-points appear to be slightly closer to the reduced form coefficients than the specification with 5 mid-points.[17][18] However, the advantage of the structural approach becomes clear

[16]The results for specialists are also similar to the overall wage elasticities reported by Cheng et al. (2013) using a model distinguishing hours worked in the public and private sector.

[17]Similar to Van Soest (1995), we also estimate the model taking into account errors in wage rate predictions by drawing 100 wages for each individual, taking into account the standard deviation of the wage regressions. The results show that the estimated wage elasticities are robust against wage rate prediction error. Results available upon request.

[18]These results are, however, opposite to what Mu and Maruyama (2013) find using the MABEL data. They find relatively large negative wage elasticities for women (-0.24 for self-employed female GPs and -0.34 for employee female GPs) and even larger positive wage elasticities for men (0.47 for male self-employed GPs and 0.57 for male employee GPs). The latter is particularly surprising given the large number of hours already worked by this group. There appear to be a number of possible reasons for the difference with our results on GPs. First, the hours equation has hours worked per year as the dependent variable which is by definition a positive number. Nevertheless, no account is taken of this feature of the dependent variable: the equation is estimated using a linear regression. Second, a combined wage equation is estimated for male and female GPs which is based on relatively few explanatory variables (including age and experience which are correlated to a large extent). As a result, predicted wages are unlikely to vary to a great extent between GPs, which explains the low significance level of the estimated wage coefficient.

when we present the variation in estimated wage elasticities of individual doctors graphically as in Figure 3.

[Insert Figure 3 about here]

Figure 3 uses our preferred specification based on imputed wages and 10 discrete labour supply points. The figure clearly shows the heterogeneous distribution of wage elasticities across different doctors. While the probability mass is mostly to the left of zero, reflecting negative wage elasticities on average, a substantial proportion of doctors are estimated to have positive wage elasticities.

This shows that wage increases are expected to lead to heterogeneous responses which cannot be incorporated in the reduced form model, but can be reflected through the structural model. In addition to determining how a 1% increase in wages affects total labour supply which is important for aggregate policy considerations, we want to reveal the heterogeneous effects for sub-populations which health authorities could potentially target specifically. Therefore, Figure 4 presents the estimated wage elasticities for a number of selected subgroups.

[Insert Figure 4 about here]

Generally, we do not observe significant differences in wage elasticities for these selected subgroups. Hence, these groupings do not clearly identify particular groups that would respond more strongly to wage increases than other groups. In particular, the subgroup analysis shows that the labour supply of male and female specialists does not respond much to wage increases. The only group that stands out are female GPs in inner regional areas who respond positively to a 1% increase in wages.

Further, we investigate whether the average wage elasticities differ by family status and working hours in Table 4. We would expect that doctors with very young children (less than 5) have more time constraints compared to single doctors or doctors with older children and thus be the group most responsive to wage rate changes. While Specialists with young children are largely unaffected, apart from female Specialists working more than 50 hours per week, the data shows that almost all doctors with young children (0-4) have negative wage elasticities. GPs with young children exhibit fairly negative wage elasticities, women (ranging from

-0.377 to -0.556) more so than men (ranging from -0.239 to -0.285). For Specialists, on average we find that those with older children (10-15) and doctors with no children have very similar wage elasticities. Another interesting result is that the wage elasticities for female doctors with a youngest child aged 5 to 9 are positive, which may indicate the importance of the child's transition to start attending school.

6 Policy simulations

We use the structural model to simulate doctors' labour supply responses to different increases in the nominal wage rate: 1%, 5%, and 10%. Unlike the reduced form model, the structural model is capable of taking the non-linearity of the tax schedule into account when calculating the labour supply responses. We calculate the labour supply responses in relative terms and in absolute terms (hours per week). The latter measure is particularly useful as it allows us to calculate labour supply responses for the population of doctors in terms of full-time equivalent (FTE) doctors. FTE is a meaningful measure of supply because it takes into account both those working full-time and those working part-time. We calculate the FTE measure by multiplying the number of medical practitioners in the population by the average change in weekly hours worked, and dividing the result by the number of hours in a standard full-time working week.[19,20]

[Insert Table 5 about here]

The simulation results are shown in Table 5. We first examine the results presented in panel A which displays the relative labour supply responses. For the current population of doctors, the model predicts non-linear relative changes in response to different wage increases. For female GPs, for instance, a 1% wage increase results in almost the same relative change as a 10% wage increase. However, we observe a large increase in the variability of the 90% confidence intervals

[19] Although the Australian Bureau of Statistics defines full-time work as working at least 35 hours per week, this figure may be less appropriate for doctors who tend to work more hours (42.6 hours per week on average). For this reason, we use 40 hours for a standard full-time week that is consistent with the measure used by the National Healthcare Agreement reporting.

[20] According to the AIHW (2012), there were 9,222 female and 14,793 male GPs in 2008, and 6,019 female and 16,439 male specialists in Australia in 2008.

for the 10% wage increase. For female specialists, we also observe a non-linear relationship where the relative response seems to flatten out at higher wage increases. Despite the large magnitudes, none of these estimates are statistically significant due to the loss of precision.[21] For men, the results are quite different as we observe large relative changes in response to the 5% and 10% wage increases. For instance, a 10% increase is predicted to decrease working hours for male GP's by 1.39% and for male specialists by about 0.95%.

The table also contains labour supply estimates for a projected future population of doctors which is expected to consist of a larger proportion of women. To calculate these estimates, we still use the labour supply estimates presented in Table A.3 to calculate the average wage elasticity. We then adjust the average wage elasticities by weighting each observation to make the proportion of female doctors in the older age groups the same as in the youngest age group (those aged less than 39 years). Our projection therefore assume that future older women will behave in the same way as the current older women, which we argue to be reasonable assumption given changes in work preferences over an individual's life-cycle. Applying weights to approximate a changed gender composition in the future workforce produces some minor changes for men, but stronger changes for women. For female GPs, for instance, the estimated changes become more positive. Given that the weighting structure gives more weight to older cohorts (which currently contain fewer women than are expected to be present in the future workforce) this means that older cohorts of female GPs must have more positive wage responses than younger GPs. Reassuringly, this is exactly what we observe in Figure 4 which shows that older female GPs have more positive wage elasticities. The results imply that the future workforce representing more women in the older cohorts may respond more strongly to wage increases than the current population, whereas the results for the male population remain largely unchanged.

Finally, Panel B presents the absolute change in weekly hours worked and in terms of FTE for the current population. Consistent with the modest relative wage responses by female doctors, the model predicts that nominal wage increases in the order of 5% or 10% reduce the

[21] Using observed wages, the coefficients for female doctors are all significant at the 10% level. Moreover, the relationship between changes in wages and changes in hours is almost completely linear for all doctor types. However, we prefer the specification using imputed wages due to the endogeneity issues associated with observed wages.

supply of female doctors by a modest amount. A 5% wage increase is associated with a reduction of 21 FTE for female GPs, and a reduction of about 18 FTE for female specialists. Given the total population of female doctors in 2008, the 5% wage increases are predicted to reduce the total labour supply of female GPs by about 0.2%, and for female specialists by about 0.3%. For male GPs, a 5% (10%) increase in wages is predicted to reduce the labour supply by about 140 (241) FTE doctors. These wage changes lead to a decrease of 85.4 (174) FTE doctors for male specialists. This represents a reduction in total labour supply by about 1% (1.6%) for male GPs, and for male specialists by about 0.5% (1%). That male GPs and specialists respond more strongly than women is consistent with the theory of a backward bending labour supply curve and the summary statistics presented in section 4 which showed that male doctors earn higher incomes and work longer hours than female doctors. The policy simulations therefore provide evidence that wage increases in the order of 5-10% are likely to reduce labour supply in the short-run, more so for male than female doctors.

In the longer term, increased wage rates may draw in additional doctors, but given the long qualification period of doctors it is likely to take several years before any effect will be observed. There are relatively few qualified doctors who are currently not working in the medical workforce. The most notable exceptions are probably female doctors on maternity leave and recently retired doctors. These groups might respond to some extent to increased wage rates, but again the net effect is ambiguous. Higher wages may allow doctors to finance a comfortable retirement more quickly or it may incentivise doctors to stay in the workforce longer because the opportunity cost of their hours worked as a doctor are high. This needs to be determined empirically. Being a survey collecting data from doctors in clinical practice, MABEL is not particularly suitable for this.[22]

[22]However, we can still provide some descriptive statistics on the relevant group that is at risk of retirement. 28.9% of all doctors in our sample are aged 55 and over. Of these, 25% signal high or moderate dissatisfaction for either hours of work or financial remuneration. Furthermore, 38.7% respond they are very likely to leave medical practice within the next five years, and another 20% respond they are likely to leave within five years.

7 Conclusion

Although the World Health Organisation has projected that most OECD countries will face a substantial shortage of physicians in the next years, little research exists about doctors' labour supply. We analyse the pecuniary and non-pecuniary determinants of doctors' labour supply and examine the policy implications derived from different modelling approaches for predicted wage elasticities. We apply a reduced-form approach, frequently used in the literature on physicians' labour supply, as well as a discrete choice approach, which has seen an increase in popularity in the general labour economic literature of the past two decades.

Using a recently collected and unique data set on Australian physicians, "Medicine in Australia: Balancing Employment and Life" (MABEL), we make three main contributions to the literature on doctors' labour supply. First, we show that both modelling approaches predict negative wage elasticities for male and female doctors, GPs and specialists. While the estimated wage elasticities are very similar on average in the two approaches, the reduced-form approach assumes a constant wage elasticity across individuals thereby hiding a substantial amount of variation across individuals. Assuming a constant wage elasticity may hide potential differences in responses to financial incentives, for example, differences due to decreasing marginal utility of leisure with decreasing labour supply. Our second contribution addresses this shortcoming as the rich data allow us to perform a detailed subgroup analysis that no other study on doctors' labour supply has done before. Although such differences may be potentially important to enable policy makers to target financial incentives on particular groups, our subgroup analysis does not reveal particularly strong responses to wage increases by any specific group.

Finally, we can use the structural model to predict relative and absolute labour supply changes in response to different wage increases. Unlike the reduced-form approach, the structural model allows researchers interested in ex ante policy analysis to perform these policy simulations that explicitly take into account the non-linear taxation schedule or financial subsidies. Our policy simulations show that male doctors respond strongly to wage increases in the order of 5-10%. A 5% increase in wages is predicted to reduce the labour supply of male GPs by about 140 full-time equivalent (FTE) doctors, and by about 85.4 FTE doctors for male specialists. That male GPs and specialists respond more strongly than women is consistent with the theory of a backward bending labour supply curve and the fact that male doctors earn relatively high incomes and work long hours. Our results imply that nominal wage increases aimed at increasing the supply of medical doctors at the intensive margin are likely to reduce labour supply in the short-run, especially by men. Methodologically, our study exploits the advantages of the structural model and shows that the reduced-form model, in contrast, is much less suited to make predictions about the effects of changing government policies affecting financial incentives of physicians.

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Table 1: Summary statistics by gender and doctor type

	Female				Male			
	GPs		Specialists		GPs		Specialists	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Weekly net income in $	1755.4	(830.4)	2843.1	(1625.6)	2668.4	(1179.1)	4178.5	(2261)
Weekly hours	32.5	(13)	36.8	(13.4)	45.1	(12.7)	47.1	(11.8)
Hourly wage in $	76.6	(32.4)	122.5	(69.4)	91.2	(41.4)	146.8	(81.4)
Age	4.6	(0.9)	4.6	(0.8)	5.2	(1)	5.1	(1)
No children/youngest child over 15	0.283	(0.5)	0.299	(0.5)	0.346	(0.5)	0.320	(0.5)
Number of dependent children (under 25)	1.6	(1.3)	1.493	(1.2)	1.509	(1.4)	1.629	(1.4)
Youngest child 0-4	0.174	(0.4)	0.252	(0.4)	0.117	(0.3)	0.167	(0.4)
Youngest child 5-9	0.154	(0.4)	0.160	(0.4)	0.113	(0.3)	0.146	(0.4)
Youngest child 10-15	0.206	(0.4)	0.161	(0.4)	0.169	(0.4)	0.176	(0.4)
No partner	0.133	(0.3)	0.178	(0.4)	0.072	(0.3)	0.051	(0.2)
Partner	0.867	(0.3)	0.822	(0.4)	0.928	(0.3)	0.949	(0.2)
Partner works	0.769	(0.4)	0.730	(0.4)	0.624	(0.5)	0.647	(0.5)
Partner works full-time	0.657	(0.5)	0.576	(0.5)	0.226	(0.4)	0.205	(0.4)
Partner works part-time	0.112	(0.3)	0.153	(0.4)	0.398	(0.5)	0.442	(0.5)
Partner does not work	0.097	(0.3)	0.092	(0.3)	0.304	(0.5)	0.302	(0.5)
Self-employed	0.296	(0.5)	0.273	(0.4)	0.570	(0.5)	0.468	(0.5)
Employed	0.704	(0.5)	0.727	(0.4)	0.430	(0.5)	0.532	(0.5)
Self-assessed health[a]	2.03	(0.9)	2.02	(0.9)	1.86	(1)	2.00	(0.9)
City	0.705	(0.5)	0.882	(0.3)	0.636	(0.5)	0.824	(0.4)
Outer city	0.180	(0.4)	0.090	(0.3)	0.226	(0.4)	0.140	(0.3)
Remote	0.115	(0.3)	0.029	(0.2)	0.138	(0.3)	0.036	(0.2)
ACT	0.026	(0.2)	0.013	(0.1)	0.013	(0.1)	0.017	(0.1)
NT	0.007	(0.1)	0.007	(0.1)	0.011	(0.1)	0.007	(0.1)
QLD	0.205	(0.4)	0.169	(0.4)	0.192	(0.4)	0.169	(0.4)
SA	0.071	(0.3)	0.113	(0.3)	0.100	(0.3)	0.084	(0.3)
TAS	0.043	(0.2)	0.029	(0.2)	0.035	(0.2)	0.027	(0.2)
VIC	0.283	(0.5)	0.319	(0.5)	0.279	(0.4)	0.317	(0.5)
WA	0.106	(0.3)	0.069	(0.3)	0.107	(0.3)	0.081	(0.3)
N	1067		769		1128		1908	

Notes: a) Values for self-assessed health range from 1 (excellent) to 5 (poor).

Table 2: Marginal effects on hours worked for labour supply model with 10 discrete points, imputed wages

Panel A: Women				
	GPs		Specialists	
	Point est.	90% CIs	Point est.	90% CIs
Age of youngest child (ref. group: no dependent children)				
0-4	-12.07	[-13.79, -10.15]	-11.11	[-13.14, -8.75]
5-9	-9.32	[-11.04, -7.5]	-6.49	[-9.11, -3.98]
10-15	-4.59	[-6.25, -2.89]	-1.62	[-4.18, 0.92]
Number of children	-1.46	[-2.43, -0.35]	-1.01	[-2.4, 0.55]
Age	-0.15	[-0.22, -0.07]	-0.02	[-0.13, 0.09]
Self assessed health	-2.31	[-3.43, -1.15]	-0.88	[-2.37, 0.74]
Partnership status (ref. group: single)				
Full-time work	-1.89	[-3.57, -0.22]	-3.14	[-5.22, -0.98]
Part-time work	0.32	[-2.05, 2.75]	-1.14	[-3.6, 1.38]
Not employed	1.72	[-0.85, 4.24]	4.03	[1.13, 6.68]
Self-employed	7.58	[5.96, 9.11]	5.30	[3.08, 7.13]
Location (ref. group: urban)				
Inner regional	2.53	[1.08, 3.91]	1.76	[-0.62, 4.23]
Remote	7.15	[5.4, 8.8]	1.03	[-3.06, 4.93]
Panel B: Men				
	GPs		Specialists	
	Point est.	90% CIs	Point est.	90% CIs
Age of youngest child (ref. group: no dependent children)				
0-4	-4.00	[-6.42, -1.59]	-1.73	[-3.36, -0.13]
5-9	-2.98	[-5.05, -1.06]	-1.48	[-2.9, 0.09]
10-15	-2.45	[-4.21, -0.81]	-0.59	[-1.94, 0.85]
Number of children	2.44	[1.42, 3.41]	1.82	[1.1, 2.61]
Age	-0.16	[-0.24, -0.1]	-0.18	[-0.3, -0.1]
Self assessed health	-1.20	[-2.31, -0.14]	0.01	[-0.88, 0.8]
Partnership status (ref. group: single)				
Full-time work	2.42	[0.11, 4.77]	0.15	[-1.72, 2.22]
Part-time work	0.60	[-1.71, 2.83]	-0.40	[-2.31, 1.54]
Not employed	0.39	[-1.95, 2.65]	-0.53	[-2.44, 1.36]
Self-employed	7.45	[6.39, 8.62]	3.54	[2.6, 4.54]
Location (ref. group: urban)				
Inner regional	1.88	[0.55, 3.07]	-0.50	[-1.68, 0.67]
Remote	4.20	[2.61, 5.7]	-0.18	[-2.2, 1.83]

Table 3: Comparison of simulated wage elasticities

	Women				Men			
	GPs		Specialists		GPs		Specialists	
	Point est.	90% CIs	Point est.	90% CIs	Point est.	90% CIs	Point est.	90% CIs
Panel A: structural model								
Using observed wage								
5 mid-points	-0.081	[-0.123, -0.042]	-0.112	[-0.152, -0.069]	-0.085	[-0.114, -0.058]	-0.112	[-0.131, -0.096]
10 mid-points	-0.094	[-0.136, -0.052]	-0.117	[-0.156, -0.076]	-0.090	[-0.121, -0.063]	-0.126	[-0.145, -0.108]
13 mid-points	-0.104	[-0.147, -0.061]	-0.115	[-0.152, -0.074]	-0.096	[-0.125, -0.069]	-0.133	[-0.152, -0.116]
Using imputed wages								
5 mid-points	-0.037	[-0.215, 0.127]	-0.102	[-0.189, -0.014]	-0.173	[-0.280, -0.076]	-0.076	[-0.113, -0.040]
10 mid-points	-0.119	[-0.282, 0.041]	-0.070	[-0.154, 0.012]	-0.181	[-0.279, -0.093]	-0.092	[-0.131, -0.057]
13 mid-points	-0.103	[-0.277, 0.057]	-0.076	[-0.157, 0.011]	-0.207	[-0.306, -0.109]	-0.097	[-0.135, -0.061]
Panel B: reduced-form model								
	Point est.	95% CIs	Point est.	95% CIs	Point est.	95% CIs	Point est.	95% CIs
Observed wage	-0.105	[-0.171, -0.040]	-0.103	[-0.161, -0.045]	-0.113	[-0.153, -0.074]	-0.134	[-0.164, -0.103]
Imputed wage[a]	-0.052	[-0.311, 0.207]	-0.070	[-0.185, 0.046]	-0.202	[-0.339, -0.065]	-0.087	[-0.146, -0.028]
Observed wage (IV)[b]	-0.064	[-0.329, 0.199]	-0.080	[-0.194, 0.035]	-0.200	[-0.341, -0.054]	-0.108	[-0.165, -0.052]
N	1067		769		1128		1908	

[a]*: We obtain the imputed wages from the wage regressions presented in Table A.1.*

[b] *In the IV regressions we control for the same variables as in Table A.2, and instrument for the wage using the equation presented in Table A.1.*

Table 4: Average estimated wage elasticities by working hours and family status

	GPs			Specialists		
	Hours: 10-30	Hours: 30-50	Hours: 50 plus	Hours: 10-30	Hours: 30-50	Hours: 50 plus
Panel A: Women						
No dependent child	0.068	-0.027	0.104	-0.186	-0.098	-0.182
Youngest child 0-4	-0.377	-0.372	-0.556	-0.006	-0.01	-0.183
Youngest child 5-9	0.111	0.218	0.159	0.098	0.068	0.024
Youngest child 10-15	-0.26	-0.043	0.116	-0.112	-0.152	-0.233
Panel B: Men						
No dependent child	-0.086	-0.202	-0.185	-0.203	-0.112	-0.091
Youngest child 0-4	-0.239	-0.274	-0.285	-0.002	-0.023	-0.012
Youngest child 5-9	-0.17	-0.262	-0.301	-0.078	-0.059	-0.053
Youngest child 10-15	-0.001	-0.055	-0.093	-0.139	-0.126	-0.108

Note: Based on model using imputed wages and 10 mid-points.

Table 5: Policy simulation: changes in working hours due to different wage increases (imputed wages)

	Women				Men			
	GPs		Specialists		GPs		Specialists	
	Point est.	90% CIs	Point est.	90% CIs	Point est.	90% CIs	Point est.	90% CIs
Panel A: Predicted relative changes (%) in hours worked in response to simulated wage increases								
1% wage increase								
Current population	-0.119	[-0.283, 0.041]	-0.070	[-0.154, 0.012]	-0.181	[-0.279, -0.093]	-0.092	[-0.131, -0.057]
Projected population	-0.079	[-0.26, 0.084]	-0.130	[-0.231, -0.03]	-0.203	[-0.303, -0.114]	-0.077	[-0.116, -0.043]
5% wage increase								
Current population	-0.343	[-1.151, 0.464]	-0.261	[-0.694, 0.149]	-0.810	[-1.322, -0.33]	-0.467	[-0.663, -0.291]
Projected population	-0.138	[-1.03, 0.7]	-0.557	[-1.046, -0.067]	-0.920	[-1.45, -0.454]	-0.393	[-0.586, -0.225]
10% wage increase								
Current population	-0.109	[-1.734, 1.692]	-0.294	[-1.193, 0.545]	-1.386	[-2.53, -0.295]	-0.950	[-1.359, -0.594]
Projected population	0.303	[-1.57, 2.199]	-0.882	[-1.872, 0.143]	-1.611	[-2.787, -0.542]	-0.802	[-1.2, -0.46]
Panel B: Predicted absolute changes in hours worked (per week) in response to simulated wage increases								
1% wage increase								
Current population	-0.035	[-0.089, 0.018]	-0.030	[-0.059, 0.001]	-0.084	[-0.127, -0.046]	-0.041	[-0.058, -0.025]
Projected population	-0.023	[-0.085, 0.037]	-0.053	[-0.09, -0.016]	-0.094	[-0.138, -0.055]	-0.035	[-0.053, -0.019]
Current population FTE	-8.0		-4.6		-31.1		-16.8	
5% wage increase								
Current population	-0.091	[-0.367, 0.169]	-0.118	[-0.267, 0.037]	-0.379	[-0.602, -0.169]	-0.208	[-0.297, -0.13]
Projected population	-0.027	[-0.349, 0.259]	-0.231	[-0.413, -0.046]	-0.426	[-0.657, -0.219]	-0.179	[-0.269, -0.1]
Current population FTE	-21.0		-17.8		-140.0		-85.4	
10% wage increase								
Current population	0.007	[-0.558, 0.599]	-0.152	[-0.466, 0.164]	-0.653	[-1.152, -0.186]	-0.424	[-0.612, -0.262]
Projected population	0.141	[-0.543, 0.772]	-0.374	[-0.742, 0.004]	-0.749	[-1.263, -0.275]	-0.366	[-0.552, -0.2]
Current population FTE	1.6		-22.8		-241.5		-174.0	

Note: the estimates for the current population predict changes in working hours for the estimation sample, using no weights.
We calculate the estimates for the projected population as a weighted average of the estimates for the current population. We weight the older cohorts of female GPs and specialists so that they represent a similar proportion of female doctors as is currently observed in the younger doctor cohorts (i.e. those aged younger than 39).

Figure 1: Kernel density estimation of hours worked

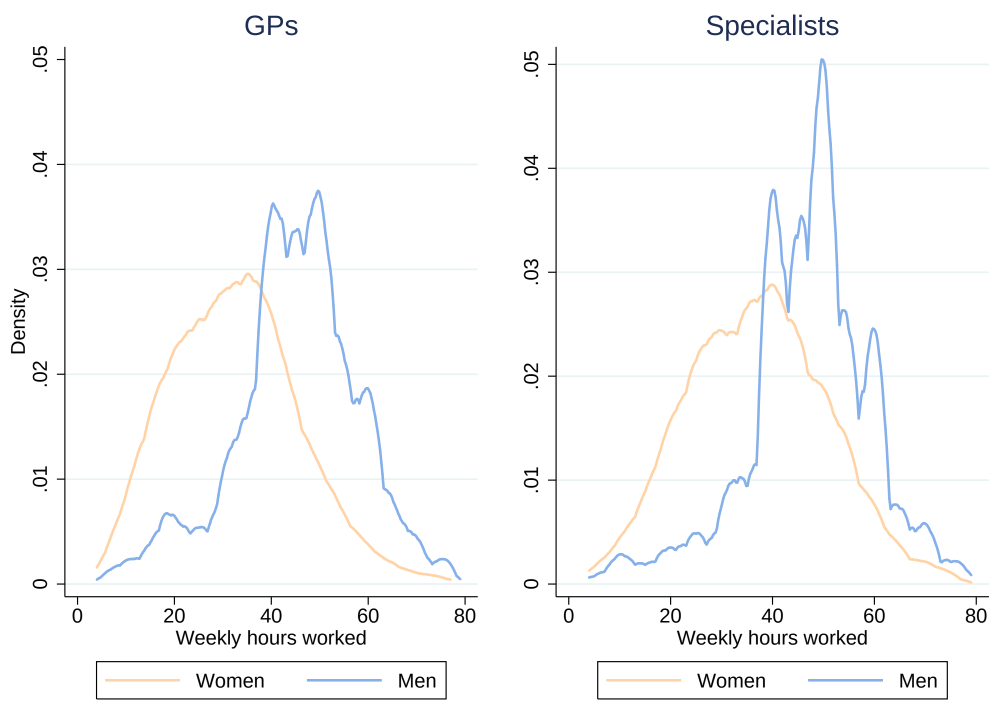


Figure 2: Distribution of hours worked by age group and doctor type

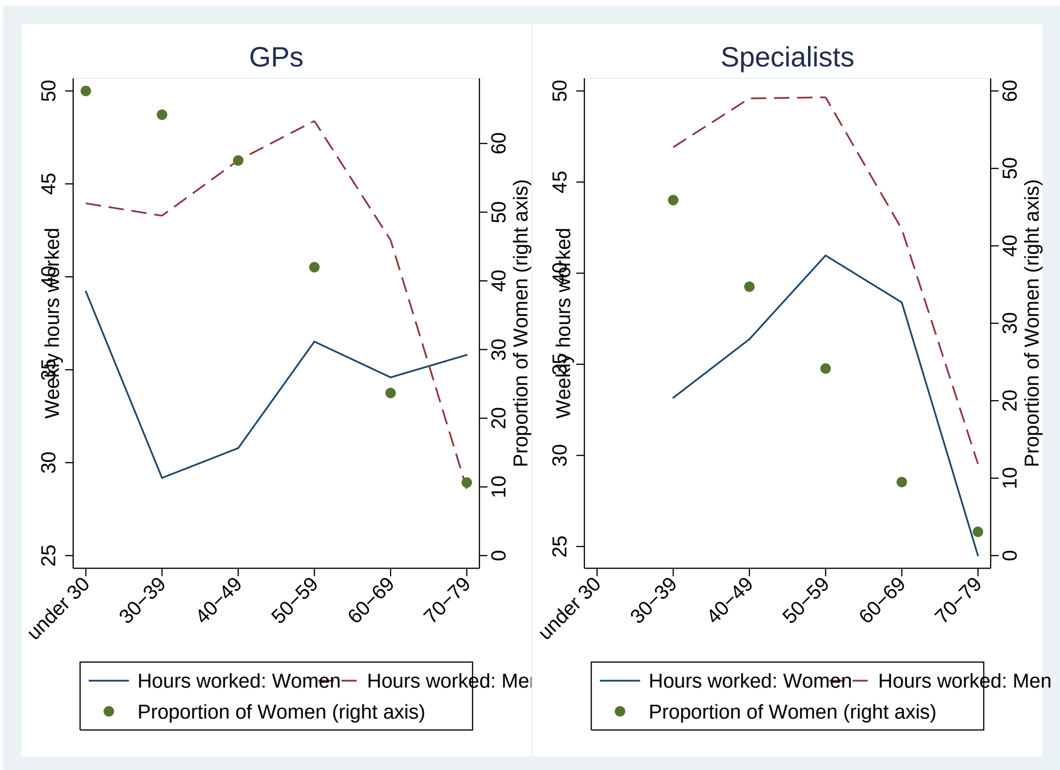


Figure 3: Distribution of wage elasticities across individual doctors (imputed wages, 10 mid-points)

Figure 4: Estimated wage elasticities for subgroups, by doctor type and gender (imputed wages, 10 mid-points)

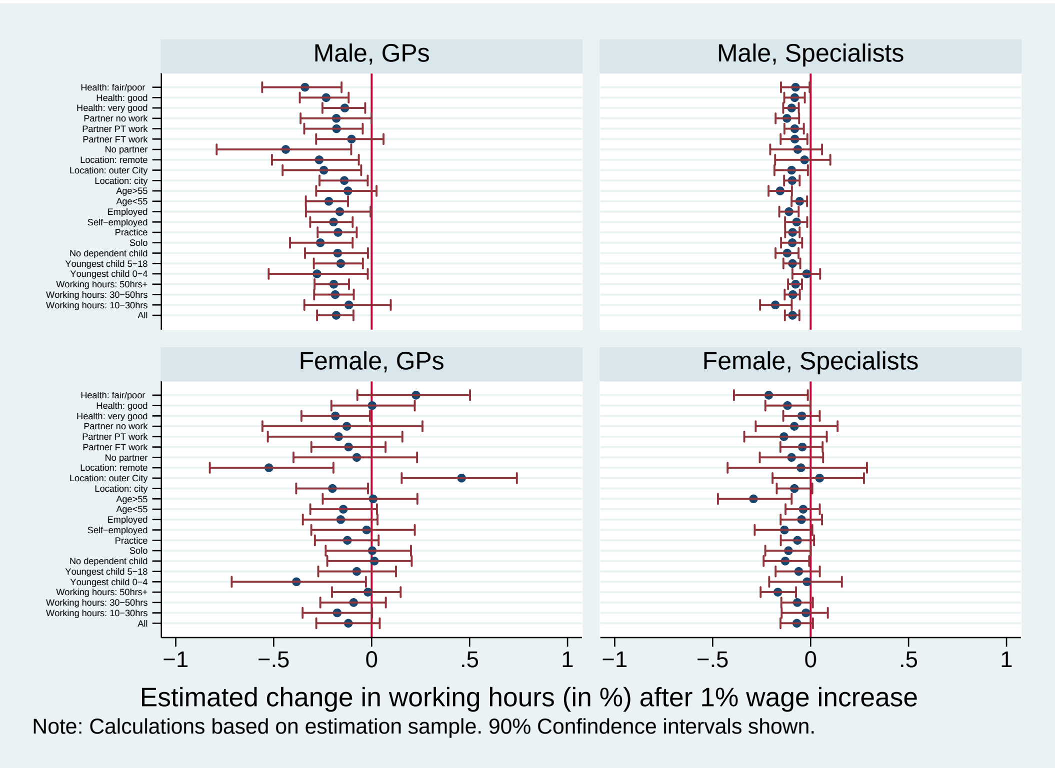
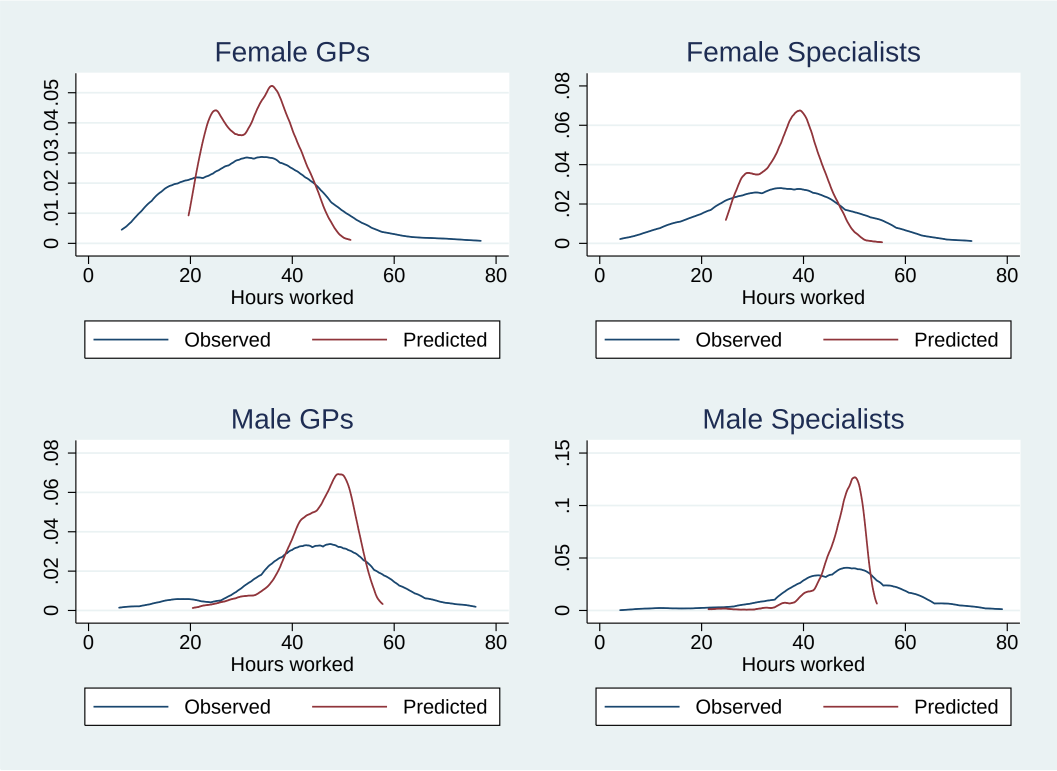


Figure 5: Distribution of observed and predicted hours



APPENDIX

Table A.1: OLS of ln(wage)

	Women		Men	
	GPs	Specialists	GPs	Specialists
Australian medical school	-0.096***	-0.111**	0.010	0.005
	(0.036)	(0.047)	(0.037)	(0.028)
Number of postgraduate qualifications	-0.026	-0.030	0.071	-0.017
	(0.042)	(0.098)	(0.047)	(0.066)
Temporary visa holder	0.037	-0.057	-0.084	-0.122
	(0.107)	(0.213)	(0.091)	(0.131)
Actual work experience				
15-19 years	-0.025	0.073	0.173***	0.091**
	(0.039)	(0.047)	(0.058)	(0.040)
20-24 years	0.005	0.046	0.062	0.125***
	(0.036)	(0.049)	(0.050)	(0.039)
25-29 years	-0.032	-0.046	0.143***	0.093**
	(0.039)	(0.052)	(0.048)	(0.039)
30-34 years	-0.055	-0.006	0.087*	0.083**
	(0.049)	(0.063)	(0.049)	(0.041)
35-39 years	-0.030	0.043	0.043	0.052
	(0.071)	(0.106)	(0.057)	(0.043)
40-45 years	0.164	0.004	0.103	0.051
	(0.111)	(0.158)	(0.069)	(0.049)
45 or more years	-0.108	-0.147	0.097	-0.178***
	(0.286)	(0.263)	(0.078)	(0.059)
State dummies				
VIC	-0.041	0.028	0.068*	-0.032
	(0.034)	(0.043)	(0.038)	(0.026)
QLD	0.044	0.177***	0.090**	0.146***
	(0.038)	(0.054)	(0.043)	(0.032)
SA	-0.012	0.065	0.038	-0.012
	(0.054)	(0.060)	(0.053)	(0.041)
WA	0.022	0.063	0.146***	0.057
	(0.047)	(0.071)	(0.052)	(0.041)
NT	0.017	0.382	0.007	-0.081
	(0.160)	(0.239)	(0.143)	(0.140)
TAS	-0.033	0.004	-0.020	-0.155**
	(0.069)	(0.118)	(0.081)	(0.070)
ACT	0.042	0.071	0.043	-0.031
	(0.080)	(0.147)	(0.123)	(0.081)
Inner regional area	-0.016	-0.051	0.070*	0.067*
	(0.038)	(0.072)	(0.040)	(0.035)
Remote area	0.051	-0.223*	0.104**	0.044
	(0.045)	(0.118)	(0.049)	(0.064)
Self-employed	0.163***	0.139***	0.067**	0.190***
	(0.029)	(0.041)	(0.031)	(0.024)
Practice size				
2-3 doctors	-0.024		0.147***	
	(0.069)		(0.053)	
4-5 doctors	0.020		0.180***	
	(0.068)		(0.053)	

...table A.1 continued

	Women		Men	
	GPs	Specialists	GPs	Specialists
6-9 doctors	-0.006		0.237***	
	(0.068)		(0.050)	
10 or more doctors	0.069		0.340***	
	(0.072)		(0.058)	
PG Certificate or Diploma	0.040	0.004	-0.098	0.002
	(0.058)	(0.125)	(0.065)	(0.083)
Masters or PhD	-0.029	-0.001	-0.128	-0.003
	(0.069)	(0.116)	(0.084)	(0.083)
Fellowship of Colleges	0.076***	0.047	0.023	0.051
	(0.028)	(0.101)	(0.030)	(0.056)
Other qualifications	0.111	-0.025	-0.105	0.039
	(0.086)	(0.135)	(0.088)	(0.091)
% of time in clinical work	0.003***	0.003***	0.001	0.004***
	(0.001)	(0.001)	(0.001)	(0.000)
Local median house price	0.000**	0.000	0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Main speciality				
Cardiology		0.342		-0.095
		(0.470)		(0.107)
Gastroenterology		0.577		-0.079
		(0.462)		(0.097)
General medicine		0.464		-0.286***
		(0.458)		(0.096)
Intensive care - internal medicine		0.789		
		(0.502)		
Paediatric medicine		0.259		-0.372***
		(0.451)		(0.087)
Thoracic medicine		0.013		-0.233**
		(0.467)		(0.101)
Other internal medicine		0.410		-0.244***
		(0.450)		(0.079)
Pathology		0.687		-0.004
		(0.453)		(0.090)
General surgery		0.402		-0.000
		(0.464)		(0.087)
Orthopaedic surgery		0.952*		0.236***
		(0.517)		(0.091)
Other surgery		0.427		0.156*
		(0.456)		(0.087)
Anaesthesia		0.740*		0.084
		(0.449)		(0.078)
Diagnostic radiology		0.761*		0.273***
		(0.455)		(0.087)
Obstetrics and gynaecology		0.757*		0.079
		(0.452)		(0.087)
Psychiatry		0.411		-0.239***
		(0.450)		(0.080)
N	1067	769	1128	1908

Table A.2: Reduced form results: OLS of ln(hours)

	Women		Men	
	GPs	Specialists	GPs	Specialists
Ln(hourly wage)	-0.052	-0.070	-0.202***	-0.087***
	(0.132)	(0.059)	(0.070)	(0.030)
Age of youngest child (ref. group: no child or child over 15)				
0-4	-0.443***	-0.337***	-0.119***	-0.028
	(0.043)	(0.052)	(0.035)	(0.020)
5-9	-0.322***	-0.195***	-0.085***	-0.034*
	(0.041)	(0.056)	(0.028)	(0.018)
10-15	-0.154***	-0.021	-0.070***	-0.023
	(0.038)	(0.047)	(0.024)	(0.018)
Number of children	-0.023*	-0.027	0.024***	0.019***
	(0.012)	(0.017)	(0.009)	(0.006)
Age	0.161	0.616***	0.568***	0.825***
	(0.119)	(0.169)	(0.098)	(0.110)
Age squared	-0.023*	-0.067***	-0.063***	-0.087***
	(0.013)	(0.017)	(0.010)	(0.011)
Health status	-0.039***	-0.000	-0.010	0.007
	(0.013)	(0.018)	(0.010)	(0.008)
Partner’s employment (reference group: single)				
not employed	0.126***	0.119**	0.094*	-0.014
	(0.048)	(0.047)	(0.053)	(0.029)
works full-time	-0.017	-0.089*	0.175***	0.054*
	(0.041)	(0.049)	(0.052)	(0.031)
works part-time	0.063	-0.028	0.135**	0.030
	(0.051)	(0.059)	(0.052)	(0.031)
Self-employed	0.251***	0.132***	0.201***	0.081***
	(0.035)	(0.033)	(0.021)	(0.018)
Outer city	0.053	0.054	0.030	-0.008
	(0.034)	(0.049)	(0.022)	(0.020)
Remote	0.217***	0.051	0.097***	-0.021
	(0.036)	(0.060)	(0.026)	(0.041)
Other income	-0.008***	-0.001	-0.008***	-0.007***
	(0.003)	(0.003)	(0.002)	(0.002)
N	1067	769	1128	1908
Adj. R-squared	0.2876	0.1802	0.2866	0.2373

Table A.3: Coefficients from multinomial logit model with 10 points, imputed wages

	Women				Men			
	GPs		Specialists		GPs		Specialists	
	coef	S.E.	coef	S.E.	coef	S.E.	coef	S.E.
Weekly net income	-16.418	(14.807)	5.621	(7.628)	-17.073	(10.561)	1.780	(3.119)
Weekly net income^2	2.797**	(1.300)	0.372**	(0.163)	0.964	(0.619)	-0.025	(0.050)
Weekly net income interacted with								
Weekly hours	-2.236**	(1.119)	-0.839***	(0.240)	-1.164*	(0.602)	-0.002	(0.082)
Age of youngest child (reference group: no child)								
0-4	0.885	(2.469)	-0.984	(0.736)	1.314	(1.911)	0.155	(0.412)
5-9	4.953**	(2.181)	-0.264	(0.752)	0.057	(1.811)	0.113	(0.373)
10-15	2.260	(1.787)	-0.358	(0.729)	1.629	(1.547)	-0.132	(0.340)
Age	5.874	(6.454)	-1.041	(3.293)	4.935	(4.190)	-0.308	(1.193)
Age squared	-0.526	(0.669)	0.038	(0.345)	-0.399	(0.399)	-0.003	(0.112)
Number of children	-1.721***	(0.570)	0.266	(0.228)	-0.309	(0.493)	-0.093	(0.096)
Health status	-1.288*	(0.660)	0.177	(0.232)	0.652	(0.505)	-0.076	(0.114)
Partner's employment (reference group: single)								
not employed	-1.028	(2.668)	0.049	(0.838)	1.525	(1.916)	-0.274	(0.491)
works part-time	-0.747	(2.222)	-0.342	(0.767)	1.716	(1.882)	-0.130	(0.482)
works full-time	0.515	(1.768)	-0.014	(0.615)	2.881	(1.937)	-0.191	(0.507)
Self-employed	-1.863	(1.807)	-1.202**	(0.609)	-1.438	(1.085)	0.551*	(0.304)
Outer city	7.072***	(1.792)	0.838	(0.782)	-0.921	(1.274)	-0.032	(0.300)
Remote	-3.154*	(1.841)	0.511	(1.147)	-1.461	(1.347)	0.426	(0.475)
Weekly hours	9.850	(6.472)	-3.528	(4.941)	8.324	(5.136)	-2.710	(2.279)
Weekly hours^2	-0.024	(0.246)	0.016	(0.099)	-0.059	(0.151)	-0.371***	(0.041)
Weekly working hours interacted with								
Age of youngest child (reference group: no child)								
0-4	-1.510	(1.094)	-0.172	(0.488)	-1.022	(0.950)	-0.284	(0.324)
5-9	-3.027***	(0.985)	-0.302	(0.507)	-0.302	(0.931)	-0.229	(0.305)
10-15	-1.382*	(0.795)	0.112	(0.480)	-1.041	(0.786)	0.047	(0.284)
Age	-2.123	(2.839)	2.022	(2.129)	-1.004	(2.060)	2.319***	(0.873)
Age squared	0.168	(0.297)	-0.171	(0.222)	0.044	(0.198)	-0.217***	(0.081)
Number of children	0.688***	(0.252)	-0.214	(0.148)	0.269	(0.250)	0.161**	(0.081)
Health status	0.457	(0.290)	-0.150	(0.156)	-0.380	(0.253)	0.060	(0.092)
Partner's employment (reference group: single)								
not employed	0.604	(1.127)	0.281	(0.559)	-0.729	(0.947)	0.164	(0.401)
works part-time	0.356	(0.969)	0.138	(0.513)	-0.805	(0.934)	0.064	(0.394)
works full-time	-0.400	(0.763)	-0.228	(0.407)	-1.215	(0.952)	0.163	(0.413)
Self-employed	1.494*	(0.825)	1.194***	(0.441)	1.394**	(0.546)	-0.100	(0.249)
Outer city	-2.856***	(0.763)	-0.415	(0.513)	0.631	(0.642)	-0.022	(0.249)
Remote	2.019**	(0.834)	-0.257	(0.743)	1.122	(0.692)	-0.350	(0.394)
N	1067		769		1128		1908	

Note: for ease of interpretation, weekly net income has been divided by 1000, and weekly hours and age have been divided by 10.

Table A.4: Marginal effects on hours worked for the model with 10 discrete points, observed wages

Panel A: Women	GPs		Specialists	
	Point est.	90% CIs	Point est.	90% CIs
Age of youngest child (ref. group: no child or child over 15)				
0-4	-11.28	[-12.91, -9.47]	-9.57	[-11.71, -7.2]
5-9	-8.76	[-10.6, -6.77]	-5.56	[-8.15, -3.12]
10-15	-4.39	[-6.07, -2.68]	-0.95	[-3.42, 1.5]
Age	-0.12	[-0.19, -0.05]	0.03	[-0.07, 0.14]
Number of children	-1.22	[-2.26, -0.15]	-1.95	[-3.22, -0.44]
Self assessed health	-1.84	[-2.88, -0.76]	-0.41	[-1.9, 1.23]
Partnership status (ref. group: single)				
Full-time work	-2.03	[-3.62, -0.41]	-2.80	[-4.83, -0.72]
Part-time work	0.85	[-1.45, 2.98]	-0.46	[-2.88, 2.01]
Not employed	2.76	[0.33, 4.92]	3.80	[0.94, 6.44]
Self-employed	7.70	[6.39, 8.9]	4.01	[2.11, 5.64]
Location (ref. group: urban)				
Inner regional	1.37	[0.02, 2.89]	1.46	[-0.94, 3.83]
Remote	6.59	[4.83, 8.3]	0.97	[-3.07, 4.82]

Panel B: Men	GPs		Specialists	
	Point est.	90% CIs	Point est.	90% CIs
Age of youngest child (ref. group: no child or child over 15)				
0-4	-4.02	[-6.33, -1.76]	-1.52	[-3.06, 0.03]
5-9	-3.03	[-5.13, -1.11]	-1.37	[-2.76, 0.15]
10-15	-2.13	[-3.82, -0.42]	-0.42	[-1.73, 0.94]
Age	-0.17	[-0.23, -0.11]	-0.22	[-0.28, -0.17]
Number of children	2.53	[1.5, 3.53]	2.11	[1.43, 2.84]
Self assessed health	-0.86	[-1.94, 0.23]	0.30	[-0.6, 1.05]
Partnership status (ref. group: single)				
Full-time work	2.61	[0.33, 5.22]	-0.21	[-2.03, 1.75]
Part-time work	0.60	[-1.69, 2.88]	-0.70	[-2.49, 1.13]
Not employed	0.56	[-1.64, 2.91]	-0.89	[-2.75, 0.94]
Location (ref. group: urban)				
Self-employed	7.30	[6.2, 8.41]	4.42	[3.6, 5.25]
Inner regional	1.63	[0.32, 2.89]	-0.20	[-1.32, 0.89]
Remote	3.86	[2.4, 5.31]	-0.10	[-1.98, 1.83]

Note: 90% confidence intervals based on 1000 draws.

Table A.5: Marginal effects on hours worked for reduced form model, imputed wages

Panel A: Women

	GPs		Specialists	
	Point est.	95% CIs	Point est.	95% CIs
Age of youngest child (ref. group: no dependent children)				
0-4	-11.96	[-14.19, -9.73]	-10.74	[-13.61, -7.87]
5-9	-9.07	[-11.43, -6.71]	-5.82	[-9.14, -2.51]
	-4.69	[-6.82, -2.56]	-0.50	[-3.64, 2.64]
Number of children	-0.72	[-1.4, -0.04]	-1.06	[-2.03, -0.08]
Age	-0.14	[-0.23, -0.05]	0.02	[-0.12, 0.17]
Self assessed health	-1.13	[-1.9, -0.35]	-0.31	[-1.39, 0.78]
Partnership status (ref. group: single)				
Not employed	4.12	[1.08, 7.15]	4.08	[0.69, 7.47]
Full-time work	-0.12	[-2.72, 2.48]	-2.38	[-5.53, 0.78]
Part-time work	2.31	[-0.87, 5.5]	-0.49	[-4.04, 3.06]
Self-employed	7.89	[5.87, 9.91]	4.62	[2.43, 6.81]
Location (ref. group: urban)				
Inner regional	1.85	[-0.07, 3.77]	1.59	[-1.43, 4.61]
Remote	6.86	[4.61, 9.11]	1.13	[-3.33, 5.59]

Panel B: Men

	GPs		Specialists	
	Point est.	95% CIs	Point est.	95% CIs
Age of youngest child (ref. group: no dependent children)				
0-4	-4.62	[-7.2, -2.05]	-1.36	[-3.1, 0.37]
5-9	-3.41	[-5.63, -1.18]	-1.25	[-2.81, 0.31]
	-2.46	[-4.37, -0.56]	-0.65	[-2.18, 0.87]
Number of children	1.19	[0.56, 1.82]	0.86	[0.38, 1.34]
Age	-0.23	[-0.31, -0.14]	-0.21	[-0.28, -0.15]
Self assessed health	-0.63	[-1.3, 0.05]	0.07	[-0.48, 0.63]
Partnership status (ref. group: single)				
Not employed	1.98	[-1.22, 5.18]	0.51	[-1.7, 2.71]
Full-time work	5.40	[2.02, 8.77]	2.42	[0.01, 4.84]
Part-time work	3.31	[0.02, 6.6]	1.77	[-0.52, 4.07]
Self-employed	7.78	[6.34, 9.23]	3.57	[2.36, 4.77]
Location (ref. group: urban)				
Inner regional	1.63	[0.06, 3.21]	-0.19	[-1.66, 1.28]
Remote	4.17	[2.23, 6.12]	-0.60	[-3.03, 1.84]

Figure A.1: Estimated relative labour supply (%) change in response to 5% wage increase for subgroups, by doctor type and gender (imputed wages, 10 mid-points)

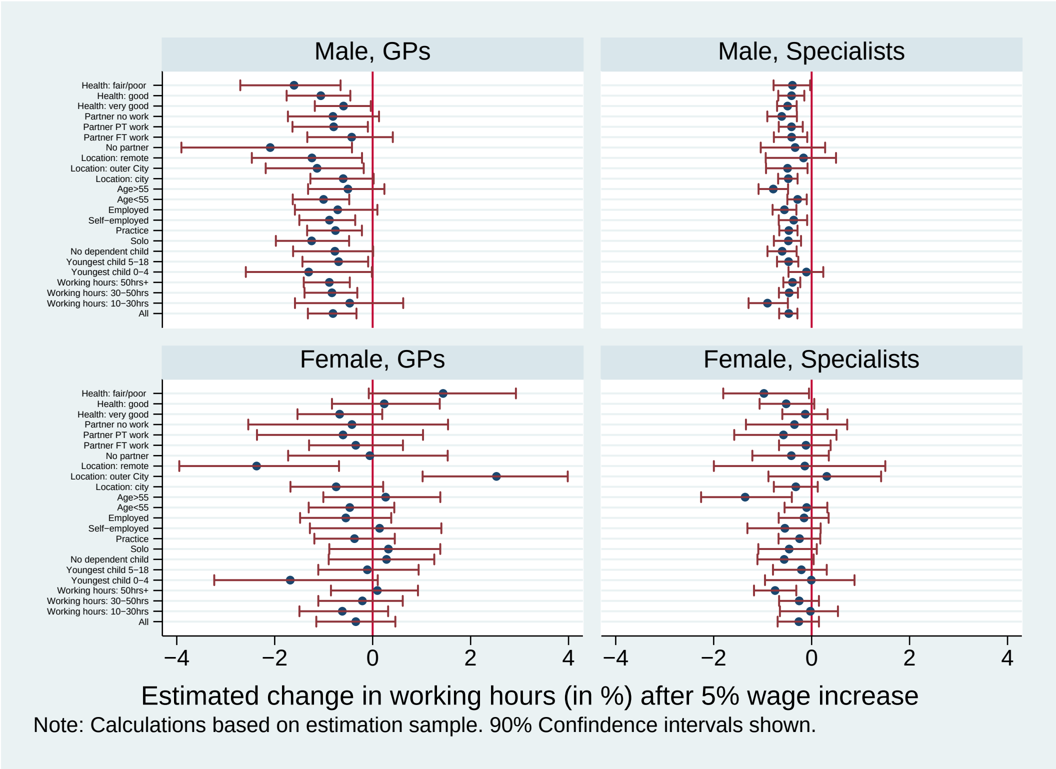


Figure A.2: Estimated relative labour supply (%) change in response to 10% wage increase for subgroups, by doctor type and gender (imputed wages, 10 mid-points)