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Topics

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Nurse Practitioners and Their Effects on Visits to Primary Care Physicians

Abstract: The demand for primary care services is expected to increase at a time of persistent shortages of primary care physicians (PCPs) in the United States. A proposed solution is to expand the role of other allied health professions. This study examines the causal effects of visits to nurse practitioners (NPs) on the demand for services from PCPs. We employ a system of simultaneous equations and dynamic panel estimators to control for endogeneity of visits to NPs. Results indicate that patients who visited an NP are significantly less likely to visit PCPs and to receive prescribed medication, medical check-up, and diagnosis from PCPs. Findings were robust to other specification and passed a falsification test. The results suggest that the use of NPs could serve as a potential option to address shortages in supply of primary care services.

Keywords: nurse practitioners, endogeneity, supply of physicians

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1 Introduction

Shortages of primary care physicians (PCPs) have been a growing public health concern in the United States. Current health workforce projections indicate that the shortage of PCPs is likely to worsen, and by 2025 the country will require 52,000 additional PCPs (Petterson et al. 2012). Some possible explanations for the projected mismatch of PCPs vis-à-vis expected increases in demand for primary health care services are population growth, disproportionate ageing of the population, and the passage of the Patient Protection and Affordable Care

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Act (2010) – which is expected to extend health insurance coverage to an estimated 34 million people in the United States. Given that physicians' time is already highly constrained and may not be efficiently allocated across patients with different health care needs (Tai-Seale and McGuire 2012), a PCP shortage could impede patients' access to care and further strain physicians' workloads.

Several proposals have been put forward to help alleviate the current PCPs shortage. These include increasing the inflow of PCPs from abroad, consolidating physician practices from solo to shared, expanding the use of technology (e.g., electronic records and the internet), and expanding the use of other allied health care professionals such as nurse practitioners (NPs) and physician assistants (PAs).[1] In fact, simulations from Green, Savin, and Lu (2013) show that if some of these proposals are implemented effectively, the problem of PCP shortages could be mitigated or even eliminated.

The proposal to expand the role of NPs in primary care settings merits special attention for several reasons. First, the NP labor force in the United States has grown considerably. In the past decade, the growth of primary care physicians has been declining, but the number of NPs increased from 81,000 in 1999 to 180,000 in 2011 (Pearson 2011) and now constitutes about 19% of the U.S. primary care labor force (Stange 2013). Second, compared to PCPs, the cost of training NPs is relatively lower and the length of training NPs is relatively shorter (Dierick-van Daele et al. 2010). Research also shows that the quality of care and health outcomes achieved by the two professions is comparable.[2]

There are several of studies that pertain to our paper. Studies by Stange (2013) and Traczynski and Udalova (2013) identified the effects of NPs' supply and regulations on various measures of utilization. Stange (2013) applies fixed effects and IV estimators to identify the county level supply of NPs on individual health care use and finds insignificant relationships between these variables. Traczynski and Udalova (2013) use variation in state legislature on NPs scope of practice to identify whether NPs independence from physician's oversight affected individual's utilization. The authors found that expansion of NPs'

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1 Patient Protection and Affordable Care Act (2010) authorized funding to promote many of these strategies.

2 Literature provides ample evidence in this regard. Newhouse et al. (2011) finds that between 1990 and 2008, NPs and PCPs consistently delivered similar quality of care. In a study that followed randomly assigned patients to NPs or PCPs over a two year period, Lenz et al. (2004) did not find significant differences in health status, disease-specific measures, satisfaction with care, and the use of specialists, emergency room services or inpatient services between patients assigned to NPs and PCPs. Two other studies also did not find differences in the quality of care provided by NPs and PCPs for patients with eczema (Schuttelaar et al. 2010) and asthma (Kuethe et al. 2013).

independence increased patients' utilization measures and reduced visits to emergency rooms.

A number of studies have examined the effects of states' NP regulations on physicians' incomes (Perry 2009) and enrollment in NP programs (Kalist and Spurr 2004). Other studies have examined the substitution patterns between private and public providers (Atella and Deb 2008), hygienists and dentists (Kleiner and Park 2010), PAs and overall office-based visits (Morgan et al. 2008), and primary and specialty care (Fortney et al. 2005). These studies find significant evidence of substitution between these related health professions. However, substitution patterns between patients' NP visits and patients' PCP visits have not been examined in the current literature.

This paper contributes to the literature by examining whether patients' visits to NPs affect the demand for care from PCPs using nationally representative data from Medical Expenditures Panel Survey (MEPS) on 25–64 years old adults. Specifically, we examine the effects of patients' NP visits on the probability and number of visits to PCPs. We also examine the effects of patients' NP visits on the probabilities of receiving the following specific services from PCPs: prescriptions, laboratory tests, medical check-ups, diagnoses, and vaccinations. A key challenge in identifying these effects stems from the endogeneity associated with the non-random selection of patients' visits to NPs. Patients with visits to NPs are often healthier than those with visits to PCPs. Also, patients with visits to NPs may be disproportionately located in medically underserved areas where preferences for health and health care differ considerably. The presence of these omitted factors can bias our estimates downward.

To account for the endogeneity associated with the non-random selection of visits to NPs, we employ a system of simultaneous equations where states' educational requirement for obtaining an NP license is used as an identifying exclusion. We conducted several robustness checks and applied alternative estimation technique using panel data. The results suggest that the care provided by the two professions has significant overlap and NPs could serve as a potential option for filling the shortage in the supply of primary care services.

2 Conceptual model

To frame the analysis, we consider a simplified version of Grossman's (1972) model of the demand for health where patient's health is determined by a health production function with two types of inputs. Specifically, the utility function $U(C, H)$ is defined over health, H and consumption C. The health production function H is determined by two types of health care inputs which consists of care received from a PCP, m_{PCP}, and an NP, m_{NP}

$$U(C, H(m_{\mathrm{PCP}}, m_{\mathrm{NP}})) \qquad [1]$$

We assume that

$$\frac{\partial H}{\partial m_{\mathrm{PCP}}} = H_1 > 0, \frac{\partial H}{\partial m_{\mathrm{NP}}} = H_2 > 0, \text{ and } \frac{\partial^2 H}{\partial m_j^2} = H_{jj} \le 0, j = \mathrm{PCP}, \mathrm{NP}$$

The individual's budget constraint is

$$I = m_{\mathrm{PCP}}\, p_{\mathrm{PCP}} + m_{\mathrm{NP}}\, p_{\mathrm{NP}} + C \qquad [2]$$

where I is income, p_{PCP} and p_{NP} are prices for a unit of care received from a PCP and an NP while the price of consumption C is normalized to one. The individual's problem is to choose m_{PCP}, m_{NP}, and C to maximize the utility function subject to health production function and the budget constraint. Specifically, the individual maximizes

$$\frac{\max}{m_j} U(1 - m_{PCP}\, p_{PCP} - m_{NP}\, p_{PCP}, H[m_{PCP}, m_{NP}]) \qquad [3]$$

The first-order conditions are

$$\frac{U_H}{U_c} = \frac{p_j}{H_j}, \qquad [4]$$

where p_j/H_j represents the cost to a patient of producing an extra unit of health from a provider j. At the optimum, patient's marginal rate of substitution between health and a consumer good equals their price ratio. The comparative statics analysis that identifies the effect of visiting one provide type on the demand from another yields the following expression

$$\frac{\partial m_j}{\partial m_k} = \frac{p_j(p_k U_{CC} - U_{CH} H_k) + H_j(-p_k U_{HC} + U_{HH} H_k) + U_H H_{jk}}{-\partial\Omega/\partial m_j}\; j \ne k \qquad [5]$$

where $\partial m_j/\partial m_k$ is the change in demand from provider j in response to a change in the demand for care from provider k, and $\partial\Omega/\partial m_j$ is the second-order conditions of the optimization problem and it is assumed to be satisfied, i.e. $\partial\Omega/\partial m_j < 0$. In this framework, NPs and PCPs are considered substitutes (complements) if $\frac{\partial m_j}{\partial m_k} < 0 (> 0)$. The sign in eq. [5] will depend on the sign of H_{jk} and the relative magnitude of $U_H H_{jk}$ and $p_j(p_k U_{CC} - U_{CH} H_k) + H_j(-p_k U_{HC} + U_{HH} H_k) = A$. If $H_{jk} > 0$ and $U_H H_{jk} > A$, then NPs and PCPs are complements, otherwise, the two provider types are substitutes.

If $H_{jk} = \frac{\partial[\partial H/\partial m_j]}{\partial m_k} > 0$, an increase in health care input m_k not only shifts health production function upward but also causes each unit of m_j to have a greater effect on health. This can occur if provider k supplements a work of a provider j, for instance, if an NP measures a patient's blood pressure while a PCP diagnoses a patient, in which case the two provider types are considered as technical complements. On the other hand, if $H_{jk} < 0$, the two provider types are considered technical substitutes. The exact nature of the relationship between NPs and PCPs will depend on the severity of patient's illness. A review by Bauer (2010) suggests that the portion of health services that can be provided by NPs range from 25% in some specialty health services to 90% in primary care. Treatment of patients with severe health problems that are beyond the range of NP's practice would allocate NP's services to complement those provided by PCPs. Therefore, the sign of expression [5] can only be identified empirically which is an objective of our analysis. Given that our focus is on primary care setting where an NP can perform about 90% of the services of a PCP, we expect substitution between these two types of providers.

3 Econometric methods

Our primary objective is to examine the effects of patients' NP visits on the probability of PCP visits and the number of PCP visits. As mentioned above, patients who visit NPs are likely to have unobserved characteristics that affect the demand for care provided from PCPs. For our dichotomous dependent variables, we estimate bivariate probit models of the following form:

$$\text{PCP}_i = F(b_1 NP_i + X_i{'}B_1 + e_{i1}) \qquad [6]$$

$$\text{NP}_i = G(Z_i{'}B_2 + e_{i2}) \qquad [7]$$

where the dichotomous variables PCP and NP equal one if person i had a PCP visit and an NP visit any time during the year, respectively; X and Z are vectors of observed characteristics hypothesized to influence health care use; b_1, B_1 B_2 are coefficients, and F and G are the cumulative normal distributions. The error terms e_1 and e_2 have bivariate normal distributions with zero mean, unit variance, and correlation coefficient ρ that captures unobservables common to both equations. Equations [6] and [7] are also used to identify the effects of patients' NP visits on the probabilities of receiving a prescription, a laboratory test, a vaccination, a diagnosis, and a medical check-up during a visit to a PCP.

The estimate of interest b_1 measures the extent to which patients' visits to NPs affect their likelihood of visiting PCPs. A negative sign on b_1 suggests that services provided by NPs offset the demand for care provided by PCPs, implying that the two professions provide substitutable services. We are also interested in whether visits to NPs affect the number of visits to PCPs. To accommodate this outcome variable, we estimate systems of equations similar to eqs [6] and [7] but instead of a probit in eq. [6] we estimate a negative binomial using the following specification:

$$\mu_i = \exp\left(b_3 NP_i + X_i{}' B_3 + e_3\right) \quad [8]$$

$$\mathrm{NP}_i = G\left(Z_i{}' B_4 + e_4\right) \quad [9]$$

where μ_i represents the conditional mean of PCP visits y_i. The density for y_i follows conventional negative binomial distribution:

$$f_i(y_i|\mathrm{NP}_i, X; e_3) = \frac{\Gamma(y_i + \psi)}{\Gamma(y_i + 1)\Gamma(\psi)} \theta^{\psi}(1 - \theta)^{y_i}$$

where $\psi = \frac{1}{\alpha}$, and $\theta = \frac{1}{1+\alpha\mu_i}$ and α is the dispersion parameter identified by the model. Equations [8]–[9] are correlated through the residuals e_3 and e_4 which are decomposed into:

$$e_{i3} = \rho_1\delta_i + \varepsilon_{i3} \text{ and } e_{i4} = \rho_2\delta_i + \varepsilon_{i4} \text{ and } e_{i4} = \rho_2\delta_i + \varepsilon_{i4} \quad [10]$$

In eq. [10] δ_i is normally distributed and represents the unobserved component common to both equations; and ρ_1 and ρ_2 are factor loadings that measure the extent of unobserved component in each of the equations. The system of equations in eqs [8] and [9] is estimated jointly as a single likelihood function by integrating over the unobserved component δ_i for each individual. The identification of the system of equations in [6, 7] and [8, 9] is achieved through nonlinearity and the exclusion restriction described below. The system of equations in [8] and [9] is estimated using aML (Lillard and Panis 2003).

3.1 Identification

Although identification of the system of equations in [6]–[10] can be secured without exclusion restrictions, it is recommended that at least one variable in Z should be omitted from X (Wilde 2000; Atella and Deb 2008). A valid exclusion restriction has two requirements. First, it should have a significant effect on the endogenous variable. Second, theoretically and statistically, it should not be related to unobservables that affect visits to PCPs. We suspect that patients with severe health problems, stronger preferences for health care, and residence in urban areas are more likely to visit PCPs than NPs. Our choice of an exclusion restriction is an indicator for states' Master's Degree requirements for practicing as a licensed NP.

The education requirement can impact demand for NPs' services in a number of ways. First, the educational requirement has been a significant barrier to entry into the medical profession and is likely to account for differences in earnings across medical occupations (Bhattacharya 2005). In 2008–2009, 24 states required nurses to have a Master of Arts (MA) degree to practice as a licensed NP (Buppert 2012; Pearson 2009). Additionally, about 88% of the currently licensed NPs have an MA degree which indicates that the educational requirement is binding (U.S. Department of Health and Human Services 2010). It is also possible that nurses can first obtain their NP licenses, and then acquire an MA degree to expand their job opportunities.[3] In this case, states that do not require NPs to obtain an MA degree have lower barriers to entry for nurses into the NP profession and, consequently, will affect the supply of NPs. Using data from Area Resource File (ARF) we find that states with MA requirement have significantly less NPs per capita than states with this requirement.

Second, occupational licensing may be a mechanism to improve quality and move under- or over supply of products to optimal levels. As shown in Akerlof (1970) and Leland (1979), markets with asymmetric information between buyer and seller reach suboptimal quality levels. If education requirements improve quality of services, this would clearly increase demand for NPs services. On the other hand, higher quality of care may be reflected in higher prices which would reduce demand from educated NPs. The literature finds overwhelming evidence that NP's quality of care is consistent in different settings (Newhouse et al. 2011) and mostly comparable to PCPs. In our data, we find that in states with MA degree requirements, patients are significantly less likely to visit NPs ($p < 0.05$), implying that education either operates as a barrier to entry or it is reflected in NP's wages. This may reduce the demand for care from NPs.

The validity of our exclusion restriction also depends on whether the educational requirement has a direct effect on the demand for services from PCPs. It is unlikely that the mechanisms described above could impact the demand for care

3 Published evidence of the percent of NPs who obtained an MA degree after receiving an NP license is nonexistent. However, through discussions with several NPs, it became clear that such instances are not uncommon. We found evidence suggesting that about 16% of nurses obtained a MA after receiving a Bachelor's Degree (U.S. Department of Health and Human Services 2010).

from PCPs. However, it is possible for this policy law to be endogenous to the demand for PCP services. Although we cannot prove the null hypothesis of no effect, we examined several key state indicators that could shed light on this issue. Specifically, states with less stringent licensing requirements may lack adequate number of physicians, experience high demand for primary care services, and have lower quality of care. To test this possibility, we used states' number of physicians per capita, states' mortality rates, and states' infant mortality rates as potential proxies for these sources of policy endogeneity. We did not find any significant difference in these characteristics between states that require an MA degree for NP licensing and those that do not have such requirements. Our *F*-test rejected the joint significance in a regression of state characteristics on an MA degree. We also identified specified models using state characteristics as controls; however, due to their insignificant effects we present results without controls for state characteristics.[4] It is worth mentioning that these patterns are only suggestive and policy endogeneity remains a concern.

Although the validity of our exclusion restriction cannot be tested definitively, the over-identification test is commonly used in the literature that relies on these types of models and is deemed to be the best diagnostic available for testing the validity of instruments (Davidson and MacKinnon 1993). We estimate our system of equations with and without the exclusion restriction appearing in eqs [2] and [3]. We could not reject the null hypothesis from the likelihood ratio (LR) test that the two specifications are significantly different (Table 3). In this case, the exclusion restriction is valid. For completeness, we tested differences in observables between states that do and do not require MA and this information is presented in Appendix Table 10. Respondents residing in states that require MA are more likely to be Hispanic, Asian and to live in Midwestern and Western parts of the United States. However, we find that along many important dimensions, such as health and education, differences between individuals residing in those states are not significant.

Several additional details are noteworthy. All regression results are presented as marginal effects. Unlike the two stage least squares (2SLS) which is limited to local average treatment effects, the marginal effects from bivariate probit specifications are equivalent to average treatment effects. However, this identification is based entirely on assumptions about normality of the error terms (Angrist and Pischke 2008). The corresponding standard errors are derived using the delta method. All results are weighted using nationally representative weights, and standard errors account for the complex survey design of our data.

4 The estimates of interest remained, mostly, unchanged with and without controls for state characteristics.

4 Data

Our primary data source is the Household Component of Medical Expenditure Panel Survey (MEPS), which is a nationally representative survey of the U.S. non-institutionalized population. In each year, the MEPS consists of two panels drawn from the National Health Interview Survey where a new panel begins and the old one ends participation in the survey. For the cross-sectional analysis, we pooled the three most recent years of available data (2008–2010) and analyze the data as a repeated cross section. We limit our sample to individuals 25 to 64 years of age who were in scope the entire period of our analysis. We use information from the MEPS office visits and outpatient visits files which are person-visit level files to create our dependent variables. For each visit, information is available on the type of provider, the specialty of the provider, and the month of the visit. We created a measure that captures visits to PCPs if a patient had a reported visit to a physician specializing in a family, a general practice, or internal medicine.

To create an indicator for visits to NPs, we use the measure indicating whether a patient visited a nurse or NP. The use of this measure alone can introduce measurement error and bias our results toward complementarities between NPs and PCPs. We address this issue by requiring that in addition to patients' reported visit to a nurse or NP, the patient must also receive a medical check-up, a diagnosis, or physiotherapy/mental counseling services. We use this approach because nurses who do not have an NP license are not authorized to provide any of the above-mentioned services. To check the accuracy of this definition, we resorted to the National Ambulatory Medical Care Survey (NAMCS), which explicitly asks question about visits to NPs. According to the National Health Statistics Report (Hsiao et al. 2010), about 1.9% of office visits constitute visits to NPs. In our sample, about 2.6% of office visits were visits to NPs.

Additional concern arises that MEPS first asks if respondents saw a physician and, if not, the survey asks about seeing other providers. This is likely to result in under-reporting of visits to other types of providers. In a comprehensive review of this issue, Morga et al. (2007) assess representativeness of NPs in MEPS, NAMCS, and Community Tracking Survey (CTS). The study suggests that a collection methodology of CTS seems to be more representative than in MEPS and NAMCS. According to CTS, visits to PA and NP constitute about 8% of total outpatient visits. Since NPs represent about 64% of NP and PA labor force (Stange 2013), we should expect NPs to account for about 4.8% of total physician visits. Based on our definition of NP, we find that NP visits constitute about

3% of total physician visits and 9% of PCP visits. These numbers are clearly lower but do not seem to be exceedingly off the CTS data.

In either case, the existing data issues can introduce several sources of biases which merit attention. First, during a visit, if a patient sees both an NP and a PCP but reports seeing only a PCP, our results will be biased toward substitutes. Although possible, this scenario does not seem to be likely purely because it is unusual for a patient to see both an NP and a PCP in one visit in a primary care setting.[5] Second, if visits to NPs are remembered for their high quality of care (thus removing the need to visit a PCP), our results will be biased toward substitutes. Third, respondents' misreporting may be purely random which is likely to introduce a classical measurement error, biasing results toward zero. Although the econometric approach in our study accounts for the presence of measurement error, we acknowledged these issues need in our analysis.

We linked the MEPS data to the ARF to extract county-level variables that measure the number of physicians and rural residents per capita. We also use the Pearson (2009) report to create an indicator that captures states' educational requirements for practicing as a licensed NP. Given differences in health care needs and health preferences, the concentration of physicians and NPs are likely to be different across rural and urban centers and in areas with predominantly elderly populations. These area-level variables, therefore serve as controls in all models to help capture local demand factors that may be correlated with visits to NPs and PCPs.

In a cross-sectional analyses, we also examine the effects of NP visits on specific services provided by PCPs such as check-ups, diagnoses, prescriptions, and laboratory exams. In our simultaneous equation models, the dependent variables measure patients' utilization during the year. Rates of specific service use are rare in the quarterly data, so we examine the effects of NP visits on specific PCP services only in the simultaneous equation models.

Table 1 provides information on the names, definitions, and descriptive statistics of the remaining variables among those who visited PCPs and NPs. Overall, individuals with NP visits are similar to those with PCP visits along many dimensions, such as education, poverty, and employment. Individuals with NP visits are more likely to be female, live in rural areas, and report to have poor or fair health. In all models, we control for all the covariates presented in Table 1. The analytic sample comprises 48,316 person-year observations in a cross-sectional sample. For the dynamic models, we expand this sample to quarterly periods where the sample is further restricted to individuals with non-missing observation on visits in each quarter. Because we lose the first quarter, the final sample results in 143,795 person-quarters of observations.

5 We make this claim based on internal discussions with primary care providers.

Table 1: Variable definitions and sample statistics

	Definition	Patients with visits to PCPs	Patients with visits to NPs	Entire sample
Demographics				
Black	1 if respondent is black	0.110	0.079	0.116
		(0.006)	(0.007)	(0.006)
Hispanic	1 if respondent is Hispanic	0.115	0.063	0.145
		(0.007)	(0.006)	(0.008)
Asian	1 if respondent is Asian	0.041	0.022	0.049
		(0.003)	(0.003)	(0.003)
Female	1 if respondent is female	0.556	0.723	0.510
		(0.004)	(0.009)	(0.003)
Age	Respondent's age	45.566	44.415	44.154
		(0.157)	(0.385)	(0.138)
Age squared	Respondent's age squared/ 1,000	2.291	2.105	2.076
		(0.014)	(0.034)	(0.012)
High school	1 if respondent graduated from high school	0.458	0.433	0.470
		(0.007)	(0.014)	(0.006)
Some college	1 if respondent has some college education less than Bachelor's degree	0.102	0.115	0.095
		(0.003)	(0.009)	(0.003)
College	1 respondent graduated college with Bachelor's degree	0.225	0.251	0.214
		(0.006)	(0.013)	(0.005)
Graduate	1 if respondent went to graduate school	0.117	0.141	0.107
		(0.005)	(0.010)	(0.004)
Poverty1	1 if respondent's household income is below poverty level	0.101	0.091	0.112
		(0.003)	(0.006)	(0.003)
Poverty2	1 if respondent's household income is 100% to less than 125% of poverty level	0.029	0.031	0.034
		(0.001)	(0.004)	(0.001)
Poverty3	1 if respondent's household income is 125% to less than 200% of poverty level	0.104	0.104	0.120
		(0.003)	(0.008)	(0.003)
Poverty4	1 if respondent's household income is 200% to less than 400% of poverty level	0.295	0.291	0.305
		(0.005)	(0.012)	(0.004)
Private insurance	1 if respondent had private health insurance any time during a year	0.794	0.811	0.735
		(0.005)	(0.010)	(0.006)
Public insurance	1 if respondent had public health insurance any time and no private coverage	0.110	0.104	0.091
		(0.004)	(0.007)	(0.003)

(*continued*)

Table 1: (*Continued*)

	Definition	Patients with visits to PCPs	Patients with visits to NPs	Entire sample
Family and Employment				
Married	1 if respondent was married any time during a year	0.610 (0.007)	0.595 (0.015)	0.583 (0.007)
Divorced	1 if respondent was divorced any time during a year and not married	0.149 (0.004)	0.147 (0.009)	0.139 (0.003)
Family size	Respondent's family Size	2.75 (0.022)	2.661 (0.040)	2.905 (0.022)
Employed	1 if respondent was employed any time during a year	0.729 (0.006)	0.737 (0.010)	0.747 (0.004)
Area characteristics				
Midwest	1 if respondent resides in Midwest	0.228 (0.007)	0.296 (0.016)	0.219 (0.006)
South	1 if respondent resides in South	0.360 (0.008)	0.309 (0.018)	0.363 (0.008)
West	1 if respondent resides in West	0.219 (0.008)	0.222 (0.017)	0.235 (0.008)
MSA	1 if respondent lives in urban area	0.849 (0.012)	0.765 0.026	0.854 (0.012)
Doctors per capita	Number of doctors per capita in respondent's county	0.027 (0.001)	0.028 (0.001)	0.077 (0.002)
Rural residents per capita	Number of rural residents per capita in respondent's county	0.189 (0.006)	0.251 (0.012)	0.287 (0.004)
MA	1 if state requires Masters of Arts in nursing to practice as a licensed nurse practitioner	0.499 (0.020)	0.461 (0.028)	0.513 (0.020)
Health Characteristics				
Diabetes	1 if respondent has diabetes	0.118 (0.003)	0.101 (0.008)	0.076 (0.002)
High blood pressure	1 if respondent has high blood pressure	0.390 (0.006)	0.331 (0.011)	0.287 (0.001)
Asthma	1 if respondent has asthma	0.118 (0.003)	0.127 (0.008)	0.091 (0.004)
Emphysema	1 if respondent has emphysema	0.023 (0.001)	0.022 (0.003)	0.015 (0.002)
Heart disease	1 if respondent has heart disease	0.153 (0.004)	0.166 (0.009)	0.114 (0.001)

(*continued*)

Table 1: (*Continued*)

	Definition	Patients with visits to PCPs	Patients with visits to NPs	Entire sample
Joint pain	1 if respondent has joint pain	0.527 (0.007)	0.539 (0.015)	0.438 (0.006)
Limitation	1 if respondent has limitation (ADL or IADL)	0.056 (0.002)	0.049 (0.005)	0.036 (0.001)
Very good health	1 if respondent reported very good health	0.318 (0.005)	0.329 (0.011)	0.328 (0.003)
Good health	1 if respondent reported good health	0.288 (0.004)	0.259 (0.010)	0.267 (0.002)
Fair or poor health	1 if respondent reported poor or fair health	0.182 (0.004)	0.171 (0.009)	0.136 (0.002)
Year Fixed Effects				
Year 2	1 if year is 2009	0.332 (0.003)	0.332 (0.009)	0.359 (0.001)
Year 3	1 if year is 2010	0.335 (0.004)	0.335 (0.012)	0.322 (0.006)
N	Number of observations	23,036	2,625	48,316

5 Results

5.1 Descriptive statistics and simultaneous equations

Table 2 presents information on the distribution of visits to PCPs and NPs. As expected, visits to PCPs dominate visits to NPs. In particular, 51% of nonelderly

Table 2: Distribution of PCP and NP visits (in percent)

Visits	PCP	NP	PCP | NP > 0	NP | PCP > 0
0	49.34	92.83	44.87	91.96
	(0.00)	(0.00)	(0.01)	(0.01)
1	21.93	4.84	20.74	5.26
	(0.00)	(0.00)	(0.00)	(0.01)
2	12.15	1.05	12.46	2.13
	(0.01)	(0.00)	(0.00)	(0.01)
3	6.54	0.46	7. 93	0.51
	(0.01)	(0.00)	(0.00)	(0.00)
4 +	10.01	0.08	14.36	0.12
	(0.01)	(0.00)	(0.00)	(0.01)

Note: Standard errors in parenthesis.

adults (age 25–64) had at least one visit to a PCP during the year compared with only about 7% with at least one visit to an NP. Table 2 also presents information on the frequency of visits to one provider type, conditional on visit to the other providers. The conditional frequency of zero visits to a PCP is smaller than the unconditional frequency of zero visits to a PCP. Conversely, the conditional frequencies of positive visits to a PCP are larger than the unconditional frequency of positive visits to a PCP. These results imply that the services of NPs are likely to be complements to the services of PCPs. However, the results do not account for a number of factors that are correlated with visits to both provider types.

Table 3 presents results from the bivariate probit and count models as well as the baseline probit and negative binomial models. Results from the baseline specifications indicate that there are no significant relationships between visits to NPs and PCPs. After accounting for the endogeneity of patients' NP visits, the results show that visits to NPs reduce the likelihood of visits to PCPs by 22.2 percentage points. The results also show that visits to NPs reduce the number of visits to PCPs by 27.0 percentage points. These are relatively large marginal effects suggesting strong responsiveness of patients to visits between the two professions.

Table 3: Marginal effects of NP visits on the likelihood and number of visits to PCP

	PCP		PCP Visits	
	Bivariate probit	**Baseline probit**	**Negative binomial with correction for endogeneity**	**Baseline negative binomial**
NP visit	−0.222***	−0.008	−0.270***	−0.051
	(0.064)	(0.012)	(0.053)	(0.042)
Rho	0.236***	–	–	–
	(0.073)			
Loading factor	–	–	1.48***	–
			(0.468)	
F test	6.993	–	6.990	–
Over-identification test (lambda)	1.991	–	0.135	–
	[0.158]			

Note: Standard errors in parenthesis and *p*-value in brackets. Complete estimates are provided in Appendix Table 9.
* Statistically different from zero at the 0.10 level, two-tailed test.
** Statistically different from zero at the 0.05 level, two-tailed test.
*** Statistically different from zero at the 0.01 level, two-tailed test.

In both models, we find evidence of significant unobserved heterogeneity that jointly affects visits to PCPs and NPs. In the bivariate probit specification, this is captured by the correlation coefficient ($\rho = 0.236$) and in the negative binomial this is captured by the factor loading indicator (1.48).

In Appendix Table 9, we present information on the complete set of estimated coefficients. As expected, patients with complex health conditions are more likely to visit a PCP than an NP. For instance, compared to visits to NPs the likelihood of visits to PCPs are greater for patients with diabetes, high blood pressure, asthma, joint pain, and disability limitations, and for patients in poor overall health. Respondents living in predominantly rural counties are much more likely to visit an NP but the differences across regions or Metropolitan Statistical areas (MSAs) are, generally, not significant.

Table 4: Selected services received during PCP and NP visits. Sample Statistics

	Prescribed medication	Shot	Lab test	Diagnoses	Check-up
PCP	0.621	0.021	0.575	0.717	0.659
	(0.006)	(0.001)	(0.007)	(0.005)	(0.006)
NP	0.419	0.072	0.452	0.625	0.407
	(0.015)	(0.006)	(0.015)	(0.012)	(0.012)

Note: Standard errors in parenthesis.

Next, we explore the types of physician services that are affected by visits to NPs. Table 4 presents information on the rates of selected services delivered by PCPs and NPs and help gauge the distribution of these selected health services across provider types. In most cases, patients who visit PCPs are more likely to receive prescriptions, laboratory tests, diagnoses, and medical check-ups than patients who visit NPs. However, patients who visit NPs are more likely to receive vaccinations (7.2%) compared with patients who visit PCPs (2.1%). This suggests that PCP and NP provide different services and patients visit these providers for different reasons.

Table 5 presents information from our bivariate probit models that examine the effects of visits to NPs for any service on patients' likelihood of receiving prescriptions, vaccination, laboratory tests, diagnoses, and medical check-ups during visits to PCPs. The results reinforce our findings from Table 3, that is, visits to NPs reduce patients' likelihood of receiving all of the selected health services from PCPs.

The marginal effect of 27% in Table 3 implies that 185,186 NPs will be needed to do the work of 50,000 PCPs. If currently 56,000 NPs are practicing in primary care (AHRQ 2011), more than a tripling this amount would be required to mitigate the impending PCPs shortage. Meeting this goal may appear unrealistic, given that the number of NPs more than doubled in the last 10 years (Pearson 2011), doubling the current number of NP in the following 10 years

Table 5: Marginal effects of NP visits on selected services received during a visit to PCP

	Prescribed medication	Shot	Lab test	Diagnoses	Check-up
					Baseline Probit
NP	0.001	0.001	−0.010	0.008	−0.016*
	(0.011)	(0.002)	(0.010)	(0.010)	(0.010)
					Bivariate Probit
NP	−0.158***	−0.050**	−0.121**	−0.230*	−0.106*
	(0.060)	(0.025)	(0.059)	(0.080)	(0.056)
Rho	0.250***	0.723***	0.177*	0.345***	0.130
	(0.089)	(0.120)	(0.100)	(0.133)	(0.089)
Over-identification	2.01	1.23	1.13	2.11	2.40

Note. Standard errors in parenthesis. Complete list of controls is provided in Table 1.
*Statistically different from zero at the 0.10 level, two-tailed test.
**Statistically different from zero at the 0.05 level, two-tailed test.
***Statistically different from zero at the 0.01 level, two-tailed test.

would certainly help forestall the shortage of PCPs. Additionally, our estimates are based on the current regulatory environment and NP's scope of practices. We anticipate that an expansion of NP's independence from PCPs and NP's scope of practice would further increase substitutability of services between the two professions. Indeed, as suggested by Green, Savin, and Lu (2013), expansion of NPs in conjunction with implementation of other policies (such as the use of technology and consolidation of physician practices from solo to shared) can solve much of the forthcoming PCP shortages.

6 Sensitivity analysis

6.1 Falsification test

Although we did not find significant association between specific state characteristics and MA requirements, these patterns are suggestive, meaning further tests are needed to evaluate the performance of our models. Specifically, we conduct a falsification test with the objective of finding outcomes that are closely related to PCP visits but are not affected by visits to NPs. Given the complexities of health care demand, visits to different provider types may be interdependent. The challenge is to find health services outcome variables that satisfy this requirement. Health services provided by optometrists, dentists, and psychologists are, potentially, much more independent from health services provided by NPs and do not require referrals from PCPs. If our models are correctly specified, the effects of NP visits on the demand for health services from these provider types should be much smaller.

Table 6 presents the marginal effects from our probit and bivariate probit specifications. In the baseline models, effects of patients' NP visits are significant and positive. However, after accounting for the endogeneity of patients' NP visits, we do not observe any significant effects of patients' NP visits on the likelihood of visiting any of the three provider types – optometrists, dentists, and psychologists. These results do not guarantee validity of the exclusion restriction, because failure to reject the null does not, necessarily, prove the null. Nevertheless, the falsification test yields further evidence of validity of our models and consistency with theoretical expectations.

Table 6: Marginal effects of NP visits on the probabilities of visits to dentists, psychologists, and optometrists

	Dentist	Psychologist	Optometrist
Probit	0.067***	0.009***	0.020***
	(0.011)	(0.002)	(0.005)
Bivariate Probit	0.026	−0.006	−0.037
	(0.208)	(0.018)	(0.064)

Note: Standard errors in parenthesis. Complete list of controls is provided in Table 1.
***Statistically different from zero at the 0.01 level, two-tailed test.

6.2 Effects by NPs' independence of practice

Traczynski and Udalova (2013) show that in states that allow NP's greater independence from doctors, frequency of utilization increases. We build on this finding to examine whether states that allow NPs' independence from PCPs have greater patterns of substitution between the two professions than states that do not such independence. Intuitively, we would expect greater magnitude of substitution between NPs and PCPs in states that allow NPs independence from PCPs. To investigate this possibility, we identify the effects of NP visits on demand for PCP services separately by states that allow NPs to practice independently form PCPs and states that impose some degree of oversight.[6] In Table 7 we identify these effects using bivariate probit and negative

6 The information on the degree of NP independence from physicians was obtained from Pearson Report (2011). States that require any physician involvement in NP diagnosis, treatment, and prescribing medication were flagged as those that require physician oversight.

binomial models as specified in eqs [1]–[2] and [3]–[4]. A visit to NPs reduces the probability of visiting a PCP by 30 percentage points in states that allow NPs independence from PCPs; this is nearly twice higher than for patient who live in states that impose any restrictions on NPs' practices. Similar evidence is found in identifying the effects of NPs on the number of visits to PCPs. These results present further evidence that NPs and PCPs provide similar services and the expansion of NP independence reduces patient visits to PCPs.

Table 7: Marginal effects of NP visits on the probability and number of visits to PCPs by states that do and do not allow NPs independence

Sample	Probability of PCP visit	Number of visits
States that allow independence from PCP	−0.299**	−0.407***
	(0.152)	(0.033)
States that require some degree of oversight	−0.163**	−0.299***
	(0.076)	(0.104)

Note: Results are obtained from estimating bivariate probit and negative binomial models with correction of endogeneity of NP. Standard errors in parenthesis.
**Statistically different from zero at the 0.05 level, two-tailed test.
***Statistically different from zero at the 0.01 level, two-tailed test.

6.3 Dynamic specification

To further shed light on the interactions between services provided by NPs and PCPs, we examine the effects of patients' NP visits on PCP visits using a dynamic framework. The reasoning behind this approach is that if NPs provide adequate primary care services, patients who visit NPs should be less likely to visit PCPs the next period. Although the dynamic model is not as telling about the net effects of patients' NP visits on visits to PCPs, it identifies the possibility of patients switching between different providers and, subsequently, the extent to which the services received from NPs are sufficient to prevent patients from visiting PCPs during the specified period. In applying this estimation technique, we use the expanded, person-quarter level data.[7]

7 In a two year panel, information on patients' visits is available on a monthly basis. Although there is no clear guideline on appropriate definition of the length of a time period, we assume that physician referral or patients switching providers is likely to occur within a month or a quarter from the previous visit. With longer time intervals patients may choose providers based on new information, which is likely to worsen the issue of endogeneity. As a sensitivity test, we re-estimated models [11] and [12] with the following lengths of time interval: one, three, four, and six months. The results were very similar.

To examine the dynamic interactions between a patient i visiting two types of providers between present t and past t–1 periods, we estimate the following specifications:

$$\mathrm{NP}_{it} = b_1\mathrm{NP}_{it-1} + \gamma_1\mathrm{PCP}_{it-1} + X_i^{'}B_1 + e_{it1} \quad [11]$$

$$\mathrm{PCP}_{it} = b_2\mathrm{NP}_{it-1} + \gamma_2\mathrm{PCP}_{it-1} + X_i^{'}B_2 + e_{it2} \quad [12]$$

where NP and PCP are binary indicators of any service use, $b_k, \gamma_k, B_k,$ for $k = 1, 2$ are estimated coefficients, X is a vector of observed characteristics, and e_{itk} is an error term. The primary focus in eqs [11] and [12] are the parameters b_2 and γ_1. A negative estimate of b_2 indicates a patient who visited an NP in the past is less likely to visit a PCP in the current period, suggesting the presence of substitution between services from these two types of providers. The effects of the lagged dependent variables (b_1 and γ_2) are themselves important measures because they indicate how past behaviors influences the same behavior in the current period – or the extent of state dependence. The identifications of specifications [11] and [12], however, are problematic due to potential omitted variables that may be correlated with the error term and the lagged values of NP and PCP visits.

To address this issue, we relax the assumption that e_{itk} is independent of NP_{it-1} and PCP_{it-1} by parameterizing the error term with controls for provider visits in the first period. This approach is similar, in spirit, to the inclusion of the within individual means of time-varying regressors (Mundlak 1978; Chamberlain 1980). Specifically, we decompose the error terms in eqs [11] and [12] into:

$$e_{itk} = \alpha_{k1}\mathrm{NP}_{i1} + \alpha_{k2}\mathrm{PCP}_{i1} + \mu_{ki} + \varepsilon_{kit} \quad [13]$$

where NP_{i1} and PCP_{i1} are binary indicators for whether a respondent had a visit to a type of provider in the first period of the survey, μ_{ki} is a random effect distributed as $N(0, \delta_k^2)$ and ε_{kit} is a time-varying error term distributed as $N(0, 1)$ which implies that specifications in eqs [11] and [12] are estimated as random effects probits. Wooldridge (2005) shows that this is an effective approach of removing correlation between regressors and the error term μ_i and also serves as controls for the initial conditions of NP and PCP visits. The problem of initial conditions occurs when the start of the survey does not coincide with the start of the data generating process of individuals' choices of provider type. In our application, the choices of provider type by respondents who enter the survey are unlikely to be random and thus require correction to mitigate the problem of initial conditions.

Table 8 presents the results from specifications [11] and [12]. Columns two and three present the marginal effects from the pooled probit models and the last two columns present results from the random effects probit models. Both specifications show that patients' visits to NPs in the previous period significantly reduce the likelihood of visits to PCPs in the current period. The magnitude of the marginal effects from the pooled and random effects models ranges between 2.0 and 2.5 percentage points, respectively. Similarly, visit to PCPs in the past significantly reduces the likelihood of visits to NPs in the current period but the marginal effects are relatively smaller (0.1 and 0.2 percentage points). As expected, visiting a provider in the past increases the likelihood of visiting the same provider in the future, indicating the presence of state dependence.

Table 8: Marginal effects from dynamic models

	PCP *t*	NP *t*	PCP *t*	NP *t*
		Pooled		**Random effects**
PCP *t*–1	0.110***	−0.002*	0.023***	−0.001**
	(0.003)	(0.001)	(0.002)	(0.001)
NP *t*–1	−0.020***	0.050***	−0.025***	0.017***
	(0.008)	(0.002)	(0.007)	(0.002)
Within correlation	–	–	0.262***	0.252***
			(0.006)	(0.015)

Note: Standard errors in parenthesis. Complete list of controls is provided in Table 1.
*Statistically different from zero at the 0.10 level, two-tailed test.
**Statistically different from zero at the 0.05 level, two-tailed test.
***Statistically different from zero at the 0.01 level, two-tailed test.

7 Conclusion

In the next decade, the United States will need an additional 50,000 physicians to match the rising demand for primary care services (Petterson et al. 2012). An expanded use of NPs in primary care is one of many proposed solutions to the shortfall in PCPs. However, the previous literature provides limited evidence about the role of NPs in the current market place, particularly, the extent to which the two professions provide similar services. This is the first study that fills this void.

Our findings indicate that the primary care services provided by the two professions are similar. In particular, visits to NPs significantly reduce the likelihood of visits to PCPs by 22.2 percentage points, decreases the number of PCP visits by 27.0 percentage points, and reduces the probability of patients receiving prescriptions, check-ups, diagnoses, and laboratory tests from PCPs. Although the marginal effects are relatively large, the elasticity of NP visit is only 0.07% due to the smaller share of the population with visits to NPs. This result also indicates that a 10% increase in patients' NPs visits reduce visits to PCPs by only 0.7%.

To check for robustness of our results, we conducted a falsification test and found that the reduced form associations between a visit to NPs and dentists, psychologists, and optometrist are significantly positive, but in the simultaneous systems these effects were not significant. As an alternative estimation technique, we estimate dynamic models, testing whether visits to NPs in the past period affects the demand for PCP services in the current period. The results from these models produced negative and significant estimates, suggesting that NPs provide sufficient care to patients – reducing the need for visits to PCPs during the specified period.

There are several limitations in this study that could be addressed in a future research. First, the choice of the exclusion restriction and the presence of measurement errors in the data are important limitation in our empirical methods. Although our findings are robust, future research using other data sources and alternative estimation techniques could shed additional light on the robustness of our results. Second, we did not incorporate patients' interactions with other professions such as PAs and registered nurses into our analysis. The inclusion of these allied health professions in future research may enhance our understanding of other options of meeting the expected increases in demand for primary care services.

Notwithstanding these caveats, the findings in this study provide valuable information about the types of health care services supplied by NPs and how services provided by NPs can help mitigate the current shortfall in PCP services. The findings from this study also highlight the importance of expanding the use of other allied health profession in primary care delivery.

Appendix

Table 9: Complete coefficients estimates from simultaneous equations

	PCP	NP	PCP Visits
		Bivariate probit	Negative binomial
NP	−0.479***	–	−0.370***
	(0.155)		(0.054)
Demographics			
White and other (reference)			
Black	−0.138***	−0.197***	−0.232***
	(0.023)	(0.039)	(0.025)
Hispanic	−0.007	−0.255***	−0.107***
	(0.026)	(0.045)	(0.025)
Asian	−0.208***	−0.401***	−0.364***
	(0.033)	(0.062)	(0.039)
Female	0.222***	0.476***	0.337***
	(0.018)	(0.023)	(0.016)
Age	0.011*	−0.009	0.005***
	(0.006)	(0.009)	(0.001)
Age squared	0.082	0.026	0.065
	(0.070)	(0.000)	(0.047)
Less than High school (reference)			
High school	−0.027	0.120***	0.049*
	(0.025)	(0.042)	(0.025)
Some college	−0.005	0.199***	0.078**
	(0.037)	(0.059)	(0.033)
College	0.043	0.267***	0.096***
	(0.032)	(0.053)	(0.030)
Graduate school	−0.031	0.318***	0.059*
	(0.039)	(0.063)	(0.035)
Poverty ≥ 400% of poverty (reference)			
Poverty1	−0.046	−0.108**	−0.136***
	(0.032)	(0.052)	(0.029)
Poverty2	−0.109***	−0.035	−0.169***
	(0.041)	(0.064)	(0.043)
Poverty3	−0.070**	−0.054	−0.184***
	(0.027)	(0.048)	(0.026)
Poverty4	−0.015	−0.064*	−0.052***
	(0.023)	(0.032)	(0.018)
Uninsured (reference)			
Private insurance	0.540***	0.245***	0.632***
	(0.026)	(0.041)	(0.016)

(*continued*)

Table 9: (*Continued*)

	PCP	NP	PCP Visits
		Bivariate probit	Negative binomial
Public insurance	0.566***	0.258***	0.676***
	(0.032)	(0.047)	(0.012)
Family and Employment			
Other family formations (reference)			
Married	0.114***	0.032	0.126***
	(0.022)	(0.041)	(0.021)
Divorced	0.038	−0.009	0.052**
	(0.026)	(0.041)	(0.025)
Family size	−0.043***	−0.048***	−0.477***
	(0.007)	(0.012)	(0.006)
Employed	−0.002	−0.010	−0.071***
	(0.019)	(0.029)	(0.019)
Area characteristics			
Northeast (reference)			
Midwest	0.038	0.126*	0.084***
	(0.049)	(0.069)	(0.024)
South	0.013	−0.037	0.024
	(0.044)	(0.065)	(0.022)
West	0.023	0.146**	0.069***
	(0.045)	(0.073)	(0.023)
MSA	0.049	−0.091	0.008
	(0.037)	(0.068)	(0.028)
Doctors per capita	1.947**	1.257	2.575***
	(0.970)	(0.319)	(0.567)
Rural residents per capita	0.226***	0.464***	0.168***
	(0.057)	(0.126)	(0.046)
MA	-	−0.083**	-
		(0.034)	
Health characteristics			
Diabetes	0.367***	0.128***	0.401***
	(0.031)	(0.046)	(0.026)
High blood pressure	0.324***	0.104***	0.411***
	(0.019)	(0.028)	(0.017)
Asthma	0.183***	0.049	0.237***
	(0.029)	(0.038)	(0.024)
Emphysema	0.033	0.002	0.012
	(0.068)	(0.091)	(0.010)
Heart disease	0.053***	0.138***	0.127***
	(0.027)	(0.038)	(0.025)

(*continued*)

Table 9: (*Continued*)

	PCP	NP	PCP Visits
		Bivariate probit	Negative binomial
Joint pain	0.163***	0.135***	0.276***
	(0.018)	(0.029)	(0.016)
Limitation	0.249***	−0.003	0.414***
	(0.049)	(0.058)	(0.036)
Excellent health (reference)			
Very good health	0.146***	0.029	0.263***
	(0.022)	(0.035)	(0.021)
Good health	0.227***	0.031	0.408***
	(0.026)	(0.036)	(0.022)
Fair or poor health	0.361***	0.128***	0.743***
	(0.034)	(0.046)	(0.028)
Year Fixed Effects			
Year 2	0.009	0.006	0.010
	(0.018)	(0.029)	(0.012)
Year 3	0.020	0.006	0.031
	(0.018)	(0.039)	(0.042)

Note: Standard errors in parenthesis. In the case of a model that jointly estimates negative binomial and probit, results from probit are not presented as they are qualitatively similar to the ones obtained from bivariate probit identified in the NP equation.
*Statistically different from zero at the 0.10 level, two-tailed test.
** Statistically different from zero at the 0.05 level, two-tailed test.
*** Statistically different from zero at the 0.01 level, two-tailed test.

Table 10: Complete coefficients estimates from simultaneous equations

	States with Master's degree requirements for NP license	States without Master's degree requirements for NP license
Demographics		
Black	0.116	0.117
	(0.044)	(0.006)
Hispanic	0.183***	0.104
	(0.014)	(0.007)
Asian	0.059***	0.038
	(0.006)	(0.003)
Female	0.508	0.512
	(0.003)	(0.004)
Age	43.973	44.343
	(0.179)	(0.215)

(*continued*)

Table 10: (*Continued*)

	States with Master's degree requirements for NP license	States without Master's degree requirements for NP license
Age squared	2.059	2.095
	(0.015)	(0.018)
High school	0.468	0.471
	(0.008)	(0.008)
Some college	0.086***	0.105
	(0.003)	(0.004)
College	0.214	0.214
	(0.06)	(0.007)
Graduate	0.102	0.112
	(0.006)	(0.006)
Poverty1	0.118**	0.105
	(0.005)	(0.004)
Poverty2	0.036	0.032
	(0.002)	(0.002)
Poverty3	0.124	0.115
	(0.004)	(0.005)
Poverty4	0.303	0.306
	(0.006)	(0.007)
Private insurance	0.722	0.748
	(0.009)	(0.009)
Public insurance	0.089	0.094
	(0.094)	(0.004)
Family and Employment		
Married	0.593	0.573
	(0.009)	(0.009)
Divorced	0.141	0.136
	(0.004)	(0.005)
Family size	2.976	2.830
	(0.031)	(0.031)
Employed	0.747	0.747
	(0.005)	(0.005)
Area characteristics		
Midwest	0.164***	0.276
	(0.016)	(0.018)
South	0.366	0.359
	(0.020)	(0.021)
West	0.379***	0.082
	(0.019)	(0.014)
MSA	0.855	0.845
	(0.018)	(0.020)

(*continued*)

Table 10: (*Continued*)

	States with Master's degree requirements for NP license	States without Master's degree requirements for NP license
Doctors per capita	0.027	0.027
	(0.001)	(0.004)
Rural residents per capita	0.745	0.191
	(0.009)	(0.008)
Health characteristics		
Diabetes	0.077	0.076
	(0.003)	(0.003)
High blood pressure	0.288	0.285
	(0.006)	(0.005)
Asthma	0.084***	0.099
	(0.003)	(0.004)
Emphysema	0.016	0.016
	(0.001)	(0.001)
Heart disease	0.110	0.118
	(0.003)	(0.004)
Joint pain	0.426	0.451
	(0.007)	(0.010)
Limitation	0.036	0.038
	(0.002)	(0.002)
Very good health	0.329	0.326
	(0.005)	(0.006)
Good health	0.272	0.262
	(0.005)	(0.005)
Fair or poor health	0.136	0.135
	(0.004)	(0.004)
Year 2	0.334	0.332
	(0.002)	(0.003)
Year 3	0.334	0.333
	(0.006)	(0.004)

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