
**WHO HAS A CLUE TO PREVENTING THE FLU?
UNRAVELLING SUPPLY AND DEMAND EFFECTS
ON THE TAKE-UP OF INFLUENZA VACCINATIONS**

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Who has a clue to preventing the flu? Unravelling supply and demand effects on the take-up of influenza vaccinations

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Abstract

Influenza is a serious disease, especially for older people, and incomplete vaccination take-up poses a major public health challenge. On both the side of physicians and patients, there could be promising channels for increasing immunization rates, but no attempt has yet been made to empirically unravel their respective influences. Using exclusion restrictions implied by an economic model of physician-patient interactions, our study quantifies the particular effects of supply and demand on influenza immunization. On the supply side, our estimates highlight the importance of physician agency and physician quality, while a patient's education and health behaviors are key demand side factors.

Keywords: Influenza Vaccinations, Supply and Demand, Semiparametric Methods

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1 Introduction

Influenza is an infectious disease that can have severe consequences for those affected. Older people and individuals with specific health conditions, such as heart or respiratory diseases, run a particularly high risk of suffering complications from an infection with one of the influenza viruses. Every year, influenza leads to a large number of excess hospitalizations and deaths worldwide (WHO (2003)).

Even though vaccination can considerably reduce the incidence and severity of influenza, its take-up is often far from complete. Even specifically targeted high-risk groups, such as the older population, often feature substantial gaps in vaccine take-up, with take-up rates below 50 percent at times (Mattke et al. (2006), Pohl (2006)). As a consequence, increasing influenza vaccination is one of the top public health priorities in many countries (WHO (2005)).

Asymmetric information is one of the key features characterizing the market for health care, and patients' perceptions of their own care need are often inaccurate (Arrow (1963), Kenkel (1990)). Influenza is no exception in this regard, and even individuals at high risk of severe complications tend to have considerable misconceptions with respect to the seriousness of influenza and their own resistance (Kroneman et al. (2006)). For this reason, physicians often need to act as agents for their less-informed patients, which leads to an important role for supply-side factors in determining actual patterns of health care use. In this way, physician agency may also offer an important supply-side channel for increasing the take-up rate of influenza vaccinations.

The main objective of this paper is to unravel supply and demand factors in the determination of vaccination take-up and assess their relative importance quantitatively. Disentangling the separate influences of supply and demand is particularly informative for the design of health policies targeting either market side. One important issue in this regard is the role of physician agency for vaccination take-up among high-risk individuals. Do high-risk patients exhibit sufficient health literacy to independently demand influenza vaccination

or do they critically rely on their family physicians to obtain indicated immunizations?

We propose a simple economic model for vaccination take-up that highlights the role of physicians, patients and their interactions in the administration of influenza vaccines to illustrate key subject matters and inform our subsequent empirical analysis. Particularly, our model points out important simultaneity issues implied by physician agency in the physician-patient relationship. At the same time, it offers some guidance on potential exclusion restrictions that we can use to separate the respective influences of supply and demand on vaccination take-up.

To this end, we estimate a semiparametric double index model for influenza vaccine take-up using novel survey data on older individuals in Germany. Specifically, our econometric model features two distinct indices, one for supply and one for demand. Using exclusion restrictions implied by an illustrative theoretical model, we are able to separate structural supply and demand effects as well as quantify the impact of various micro-level factors on vaccination take-up. Importantly, our model also allows us to identify the exact pathway through which key health-related risk characteristics of the patients, such as age or background health, affect the conditional probability of getting vaccinated. We can therefore gauge the extent of physician agency in vaccination decisions based on our estimation results.

The remainder of the paper is organized as follows: Section 2 briefly reviews some non-technical background material on influenza, influenza vaccination and potential barriers to comprehensive immunization coverage. Section 3 presents our illustrative model of patient-physician interactions, which guides our empirical investigation. The corresponding econometric framework is detailed in section 4. This section describes the most important aspects of our semiparametric estimation procedure and gives a detailed discussion of how we define structural effects of supply and demand. Section 5 describes the data underlying our analysis as well as the exact specification of our empirical model. Section 6 presents our estimation results, with section 7 concluding the paper. All tables and figures are collected in the appendix.

2 Background

Influenza is a common seasonal infection with one of the influenza viruses. In the Northern hemisphere, the influenza season typically ranges from November to around May, as virus circulation normally peaks during the winter period. Although influenza may affect people of all ages, it tends to be particularly serious in older individuals for whom it often leads to severe complications such as pneumonia, markedly increased chances of hospitalization or even death. In Germany, influenza-associated excess mortality amounted to an average of around 13,600 deaths per influenza season during 1990-2001 (Zucs et al. (2005)). Reflecting this relatively high death toll, the combined category of "influenza and pneumonia" commonly ranks among the top ten causes of death, and most of these deaths occur in the older population (Statistisches Bundesamt (2006)).¹

Influenza vaccination constitutes the primary policy tool for reducing influenza virus circulation as well as preventing infections and their associated complications (CDC (2007)). The influenza vaccine is mostly administered via so-called flu shots, which are typically injected in the patient's arm. The vaccine thereby consists of three season-specific inactivated influenza viruses. The exact composition of the vaccine changes each year based on projections about which types and strains of viruses are most likely to circulate in the upcoming flu season. As influenza viruses undergo antigenic drift, revaccinations are required each year anew. October is the preferred month for vaccination take-up, since it takes about two weeks for the body to develop sufficient antibodies for effective influenza protection.

Influenza vaccinations are generally deemed efficacious and cost-effective, especially when targeted at persons who are at high risk of complications.² Although the exact degree of protection depends on the age and immunocompetence of the vaccine recipient

¹By and large, influenza epidemiology and associated mortality patterns seem comparable across most industrialized countries. The United States, for example, featured approximately 36,000 deaths per influenza season during 1990-1999, with more than 90 percent of these deaths concentrated among persons aged 65 and older (CDC (2007)).

²See for example CDC (2007) or WHO (2005) for an overview and further references regarding the efficacy and cost-effectiveness of influenza vaccinations.

as well as on the match between vaccine and actual virus circulation, flu shots lead to considerably lower incidence rates of influenza as well as to a substantial mitigation of its adverse consequences in case of infection. Specifically, while vaccination prevents influenza among 70-90 percent of healthy adults age <65, its efficacy tends to be somewhat lower (around 50 percent) for older people. Yet, beyond this (still substantial) reduction in the probability of getting the flu, it has been shown that the vaccine may prevent up to 70 percent of hospitalizations due to pneumonia and influenza, in addition to preventing other secondary complications and death among older adults. In fact, influenza vaccination is often regarded as especially cost-effective for the older population, as its reduced efficacy is more than compensated by the large reductions in hospitalizations and mortality for this population group.

Although there appear to be no universally accepted recommendations for influenza vaccination use, most official agencies base their advice on criteria related to age and the prevalence of other major risk factors for disease complications, such as chronic cardiovascular or respiratory diseases or diabetes (CDC (2007), RKI (2007), WHO (2005)).³ In Germany, the "permanent commission on vaccination" (Ständige Impfkommission, STIKO), which gives advice to the German states on issues related to infectious diseases and vaccination, recommends influenza vaccinations for all individuals aged 60+ and other persons suffering from any high-risk condition. However, not all sixteen German states follow the STIKO in their official vaccination recommendations. For example, the relatively large state of Baden-Württemberg recommends influenza vaccinations for all inhabitants regardless of age and background health.

While some health insurance companies tie vaccination coverage to the STIKO recommendations, most insurers reimburse all expenditures on influenza vaccinations as "voluntary benefits" (freiwillige Satzungsleistungen). As health insurance is obligatory in

³In addition to pure medical criteria, recommendations often also indicate vaccination take-up for persons dealing with high-risk individuals, such as care-givers or healthcare workers. Yet, our study will exclusively focus on medical considerations, as these appear most relevant for individual (utility maximizing) take-up decisions of older people.

Germany, this essentially means that in the vast majority of cases, none of the financial costs of influenza vaccinations are to be borne by the patients. Moreover, patients are also exempt from any practice user fees, as these do not apply to purely preventive doctor visits. In most cases, influenza vaccinations are therefore free of any charge to the patient (Szecsenyi (2005)).⁴

The main providers of influenza vaccinations in Germany are family physicians, who get reimbursed for administering influenza vaccinations. More than 80 percent of the German people report to have a regular family physician (Szecsenyi (2005)), with an even larger fraction among the older population.⁵ Patients usually have more or less regular contacts with their respective physicians, who also play an important role in chronic disease monitoring and management as well as as initial contact points for entering the health care system (even if generally not acting as formal gatekeepers).⁶

Despite the broad indication of influenza immunizations and their general availability at no (financial) cost to the patient, vaccination take-up in Germany is far from complete. Figure 1 plots a nonparametric age profile of influenza vaccination take-up rates in Germany along with a fitted third order age polynomial. The data come from the German subsample of respondents to the first wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) of 2004, the same data set that we will be using throughout this study.^{7,8}

⁴For the small minority of patients that do not have any influenza vaccination coverage, associated financial costs of vaccination would be around EUR 20-30.

⁵For example, among German respondents aged 50+ of the first wave of the Survey of Health, Ageing and Retirement in Europe (SHARE), 95 percent of individuals state that they have a regular family physician.

⁶In the German SHARE sample, more than 85 percent of all respondents report at least one visit to a family physician within the last twelve months.

⁷This paper uses data from the early release 1 of SHARE 2004. This release is preliminary and may contain errors that will be corrected in later releases. The SHARE data collection has been primarily funded by the European Commission through the 5th framework programme (project QLK6-CT-2001-00360 in the thematic programme Quality of Life). Additional funding came from the US National Institute on Ageing (U01 AG09740-13S2, P01 AG005842, P01 AG08291, P30 AG12815, Y1-AG-4553-01 and OGHA 04-064). Data collection in Austria (through the Austrian Science Foundation, FWF), Belgium (through the Belgian Science Policy Office) and Switzerland (through BBW/OFES/UFES) was nationally funded. The SHARE data set is introduced in Börsch-Supan et al. (2005); methodological details are contained in Börsch-Supan and Jürges (2005).

⁸Pohl (2006) compares the SHARE data with national data sources as compiled by Mattke et al. (2006) and finds that the data are by and large comparable, but especially so for Germany.

As can be seen from the figure, vaccination take-up rates gradually increase with age, from around 20 percent among individuals aged 50 to almost 50 percent for persons aged 80. Interestingly, the plotted probabilities do not show any evidence for important discontinuities at age 60, the cutoff age of the STIKO recommendations. Most importantly, however, the figure clearly highlights the rather sizable gap in vaccination take-up, as - irrespective of age - more than half of the population at risk did not get immunized in the previous year.

A better understanding of the micro-barriers impeding more comprehensive vaccination coverage represents an important first step for the design of effective public health interventions aimed at increasing take-up. Specifically, unravelling the role of supply and demand factors is instrumental in identifying potential policy leverages for promoting vaccination and targeting intervention at either market side. To date, most of the health economics research on vaccination take-up has exclusively focussed on demand-side factors (see, for example, Ayyagari (2007a,b), Mullahy (1999) or Parente et al. (2004)), with no formal attempt to separate the simultaneous influences of supply and demand. Yet, the abundance of asymmetric information in health care markets makes it all the more important to bring the supply side in from the cold.

Many patients rely on their family physician as their main advisor on health and health care, since their own health literacy is often limited.⁹ There is pervasive evidence that such instances of physician agency are indeed hugely important for the allocation of health care resources, not least with regard to immunizations. In Germany, around 85 percent of patients report that they would follow the vaccination recommendations of their family physician (RKI (2004)). Moreover, previous public health research indicates that some supply factors feature very high partial correlations with actual vaccination take-up. Kroneman et al. (2006), for instance, highlight that among high-risk individuals in Germany, 62 percent of those who received a personal invitation for vaccination by their family physician also got immunized, whereas the corresponding vaccination rate for those

⁹See for example McGuire (2000) a general overview and further references on physician agency.

who did not get an invitation was only 14 percent. Similarly, Wiese-Posselt et al. (2006) show that having contact with a physician who offers vaccination during the consultation is associated with an almost twentyfold increase in take-up rates.

Apart from any independent impact of supply on vaccination take-up, pervasive physician agency also tends to blur a pure demand interpretation of the effects of patient characteristics on vaccine use, especially when a patient's risk characteristics are concerned. In most models of physician agency, doctors act at least partially in the interest of their patients (McGuire (2000)). Higher immunization rates of say patients with diabetes may therefore be due to higher vaccine demand among diabetics and/or supply responses of caring physicians, who recognize diabetes as an important risk factor on their patients' behalf. In light of these arguments, it seems only appropriate to consider both supply and demand simultaneously and provide some quantitative evidence on the respective importance of each market side for vaccination take-up.

3 A Simple Model of Vaccination Take-up

We model vaccination take-up as the outcome of an interaction between a patient and her family physician.¹⁰ Specifically, we assume that the patient maximizes her expected utility subject to her subjective information set and potential supply of her family physician. The physician, in turn, acts as a pure agent of the patient regarding her health. The doctor therefore maximizes the patient's health utility, albeit subject to her own information set and potential demand of the patient. Finally, vaccination only occurs in the case of mutual consent, i.e. when both demand and supply coincide.

The following paragraphs present the basic ingredients of the model in some more detail and give simple conditions under which vaccination can be supported as a pure strategies Nash-equilibrium. Although we will not aim at identifying each model parameter individually, our theoretical illustration will nonetheless be extremely helpful in guiding

¹⁰The notion of interaction does in this context not only refer to an actual consultation, but would for example also include a personal invitation for vaccination by the physician.

our empirical investigation. Most notably, these theoretical preliminaries will not only inform our model specification, but also suggest exclusion restrictions that allow for separate identification of supply and demand in the subsequent empirical analysis.

3.1 Patient Behavior - Demand

Our model of patient behavior is sufficiently standard in that we assume that each patient maximizes her own expected utility subject to her (possibly limited) information set. In addition, potential supply of the physician may also affect the way in which the patient forms her expectations, allowing for information spillover between the physician and the patient.

Formally, we assume that latent demand D^* can be represented as

$$D^* = \arg \max_{D^* \in \{0,1\}} E^P [U^P (Vac (D^*), H^P) - C^P (D^*, Z_1^P) | \mathfrak{S}^P (Z_2^P), S^*] \quad (1)$$

where $U^P (\cdot, \cdot)$ denotes the patient's health utility of vaccination $Vac (\cdot)$. The probability of vaccination $Vac (\cdot)$ can thereby be influenced by demanding the vaccine or not, corresponding to $D^* = 1$ and $D^* = 0$, respectively. In addition, the patient's health utility also depends on her background health H^P , which summarizes her risk of suffering from influenza-related complications in case of infection. $C^P (\cdot, \cdot)$, in turn, denotes the patient's utility cost of demanding vaccination D^* . These include, for example, the opportunity cost of a doctor visit during the vaccination period and are assumed to depend on some of the patient's background characteristics Z_1^P , such as whether she works or not. The patient makes her decision based on her own information set $\mathfrak{S}^P (\cdot)$, which may also depend on a set of socio-demographic characteristics Z_2^P . For example, the patient's information set $\mathfrak{S}^P (\cdot)$ may depend her educational attainment, capturing potential differences in health literacy across education strata. Also, the patient may respond to any physician advice on vaccination take-up, as summarized by the latent supply variable S^* , included in the conditioning set. Finally, the notation $E^P [\cdot|\cdot]$ further highlights the subjective nature of

the expectations operator used in the optimization.

3.2 Physician Behavior - Supply

"I will use my power to help the sick to the best of my ability and judgement"

From "The Hippocratic Oath" (Chadwick and Mann (1950)).

How to appropriately model physician behavior is a controversial topic in health economics in general, and even more so in the economics of preventive care. Particularly, physicians seem to generally feature a dual objective, on the one hand acting in their own interest, but then also as their patients' advocate. Typical models of physician agency therefore assume that physicians maximize a combination of their income and their patients' utility. This setup typically leads to supplier-induced demand, mostly in form of overconsumption of health care resources relative to the level a well-informed patient would want to use (McGuire (2000)). A similar approach has also been suggested for modelling physician agency in preventive care. In such models, physicians would typically undersupply preventive care in order to reap possible profits from providing more curative care at a later stage (Kenkel (2000)).

From our point of view, it seems doubtful whether standard agency models with dual physician objectives provide an appropriate modelling framework for vaccination take-up in Germany. On the one hand, it is widely believed that medical ethics constitute a natural brake on supply inducement and underprovision, a general argument that appears particularly relevant for preventive health care (McGuire (2004)). Whereas overconsumption of curative care is often merely futile, underprovision of influenza vaccination would actually be harmful, representing an especially severe violation of the key principles of medical ethics.

What's more, it is not even clear whether there are any economic incentives for underprovision in the case of influenza vaccinations in Germany. Family physicians get reimbursed for administering influenza vaccination and it is not obvious whether a physician

can actually increase her profit by undersupplying vaccination in order to profit from increased influenza incidence among her patients. Specifically, the sure income from comprehensive vaccination supply may be higher than the profit from providing curative care to the subset of people that actually get infected. This argument is further reinforced by the fact that more severe cases require inpatient care and these patients may therefore not at all consult their family physician.¹¹

Given the likely role of medical ethics as well as financial incentives that are unclear at best, it seems difficult to reconcile the observed gap in influenza vaccination with models of physician behavior that feature profit maximization. We therefore take a somewhat more optimistic view of physician agency and model physician behavior as being solely guided by the Hippocratic oath. We thus assume that physicians are altruistic and act in the best interest of their patients, subject to their ability and judgement. Abstracting from the complex and hard-to-grasp financial incentives that may underlie the supply of influenza vaccinations, we focus on patient health characteristics as well as physician quality as key determinants of supply.

Formally, we assume that latent supply S^* of the physician is determined according the criterion

$$S^* = \arg \max_{S^* \in \{0;1\}} E^D [U^P (Vac(S^*), H^P) | \mathfrak{S}^D(Q^D), D^*] \quad (2)$$

The physician thus maximizes her patient's health utility $U^P(\cdot, \cdot)$ of vaccination $Vac(\cdot)$ subject to her own information set $\mathfrak{S}^D(\cdot)$ and potential demand D^* . The probability of vaccination take-up $Vac(\cdot) = 1$ can again be influenced by offering it to the patient ($S^* = 1$). As in the patient's maximization problem, her health utility $U^P(\cdot, \cdot)$ depends on her background health H^P , as higher age or specific high-risk health conditions tend to increase the value of vaccination. The physician's information set $\mathfrak{S}^D(\cdot)$ is assumed to depend on her medical quality Q^D , capturing difference in "ability and judgement", as highlighted in

¹¹Note also, that most benefits rendering influenza vaccinations cost-effective stem from its implied reductions in absenteeism and influenza-related disease and mortality burden, rather than the reduced use of health care resources.

the Hippocratic Oath. Finally, the model also allows for physician-patient interactions by incorporating potential vaccination demand of the patient D^* in the conditioning set.

3.3 Vaccination Take-up

As the last building block of our model, we assume that vaccination requires mutual consent between patient and physician. Thus, we only observe take-up if both parties favor immunization, i.e.

$$I\{Vac = 1\} = I\{D^* = 1\} \cdot I\{S^* = 1\} \quad (3)$$

This condition ensures the physician cannot vaccinate against her patient's will, and that the patient cannot insist on vaccination if her physician is unwilling to provide it.

Given the above model elements and its implied optimal response functions, it is easy to see that influenza vaccination take-up ($Vac = 1$) can be supported as a pure strategies Nash-equilibrium if and only if demand and supply satisfy

$$\begin{aligned} & E^P [U^P (Vac(D^* = 1), H^P) - C^P (D^* = 1, Z_1^P) | \mathfrak{S}^P (Z_2^P), S^* = 1] \\ & \geq E^P [U^P (Vac(D^* = 0), H^P) - C^P (D^* = 0, Z_1^P) | \mathfrak{S}^P (Z_2^P), S^* = 1] \end{aligned} \quad (4)$$

and

$$\begin{aligned} & E^D [U^P (Vac(S^* = 1), H^P) | \mathfrak{S}^D (Q^D), D^* = 1] \\ & \geq E^D [U^P (Vac(S^* = 0), H^P) | \mathfrak{S}^D (Q^D), D^* = 1] \end{aligned} \quad (5)$$

respectively.

3.4 Model Implications

Even if the purpose of our theoretical preliminaries is merely illustrative, the model still delivers a few useful insights for our empirical investigation. Firstly, a patient's background health will generally affect both supply and demand. Specifically, as higher age and the prevalence of specific high-risk conditions increase a patient's utility of influenza vaccination, we would expect both latent demand and latent supply to increase with age and be higher for those at risk for complications. Secondly, apart from highlighting simultaneity, the model also suggests a potential remedy to solve this problem, permitting separate identification of supply and demand.

On the one hand, our theoretical illustration highlights that a patient's non-health characteristics, which presumably affect demand, can safely be excluded from the supply equation. A patient's educational attainment, for example, is likely to be a strong predictor of her health literacy. As a consequence, we would expect better educated individuals to have higher vaccine demands. Supply, on the other hand, should not directly respond to the patient's education level, as education does not affect the health utility from vaccination.

The model also offers a potential exclusion restriction for the demand equation. Specifically, while physician quality plays an important role for care use in general and vaccine take-up in particular, this effect solely operates through the supply side. Given the general indication of influenza vaccination among our study population, we would expect better physicians to feature higher levels of supply than their lower quality counterparts *ceteris paribus*.

4 Empirical Model, Estimation and Structural Effects

4.1 Empirical Model

Our theoretical illustration highlighted the importance of both supply and demand factors in determining vaccination take-up. The resulting challenge is therefore to advance a suitable

empirical model that is able to capture the simultaneous effects of both supply and demand on take-up. This challenge is further exacerbated by the fact that both supply and demand respond in parts to the same health characteristics of the patients. Moreover, we only observe any vaccine use in our data, but not which market side actually initiated take-up. We thus face additional issues related to "partial observability", which also complicate separate identification of supply and demand.

We suggest a semiparametric double index binary choice model as a convenient econometric framework for modelling the interplay of supply and demand with regard to vaccination take-up. Within this modeling framework, we can not only allow for partial observability, but also identify the respective effects of either market side without recourse to strong parametric assumptions, as would for example be the case with a partial observability version of the bivariate probit model.

Formally, we model the conditional probability of vaccination take-up $Vac = 1$ given patient health characteristics H^P , patient non-health characteristics $Z^P = (Z_1^P, Z_2^P)$ and physician quality Q^D as

$$P(Vac = 1 | H^P, Q^D, Z^P) = g(S^*, D^*) \tag{6}$$

$$= h(H^P \alpha + Q^D \beta, H^P \gamma + Z^P \delta) \tag{7}$$

$$= h(S_I, D_I) \tag{8}$$

In the empirical formulation, vaccination supply S^* depends on the patient's health characteristics H^P and physician quality Q^D , whereas latent demand D^* is determined by the patient's health and non-health characteristics H^P and Z^P , respectively. We further assume that we can aggregate all supply and demand characteristics into scalar supply and demand indices, $S_I = H^P \alpha + Q^D \beta$ and $D_I = H^P \gamma + Z^P \delta$, where α, β, γ , and δ denote unknown index parameters that need to be estimated. Ultimately, $h(\cdot, \cdot)$ denotes a bivariate nonparametric link function, which maps the supply and demand indices, S_I and D_I , into

the conditional probability of vaccination take-up $P(Vac = 1|H^P, Q^D, Z^P)$. As already mentioned previously, a key advantage of this approach is that the mapping $h(\cdot, \cdot)$ is entirely determined by the data at hand (subject to regularity, mainly smoothness conditions). Moreover, its bivariate nature allows for fully flexible supply and demand interactions, and can therefore incorporate both information spillover as well as our requirement of mutual consent for actual take-up.

Our empirical model directly incorporates the main insights from our theoretical illustration. Firstly, in that patient health characteristics H^P affect both supply and demand, as would be implied by typical models of physician agency. Moreover, physician quality affects take-up only via the supply channel, while a patient's non-health characteristics operate solely through the demand side. These exclusion restrictions allow us to separately identify supply and demand, estimate their respective determinants and assess their impact on vaccination take-up.

4.2 Estimation

Given the empirical model in (8), we follow Klein and Spady (1993) and Klein and Vella (2006), respectively in applying Bayes' law to obtain

$$P(Vac = 1|H^P, Q^D, Z^P) = \frac{f(Vac = 1, S_I; D_I)}{f(Vac = 0, S_I; D_I) + f(Vac = 1, S_I; D_I)} \quad (9)$$

where $f(Vac = 0, \cdot, \cdot)$ and $f(Vac = 1, \cdot, \cdot)$ denote the joint densities of S_I ; and D_I for $Vac = 0$ and $Vac = 1$ respectively.

Using this formulation for the conditional probability of vaccination, we can construct a semiparametric likelihood function for our sample as

$$L(\alpha, \beta, \gamma, \delta) = \frac{1}{N} \sum_{i=1}^N \tau_i (Vac_i Ln [P_i(\alpha, \beta, \gamma, \delta)] + [1 - Vac_i] Ln [1 - P_i(\alpha, \beta, \gamma, \delta)]) \quad (10)$$

where τ_i denotes a trimming function and $P_i(\alpha, \beta, \gamma, \delta) \equiv P(Vac_i = 1|H_i^P, Q_i^D, Z_i^P)$ the

conditional probability of vaccination take-up for individual i .

Semiparametrically efficient estimates for the index parameters α, β, γ , and δ can then be obtained as

$$\left(\widehat{\alpha}, \widehat{\beta}, \widehat{\gamma}, \widehat{\delta}\right) = \arg \max_{(\alpha, \beta, \gamma, \delta)} \widehat{L}(\alpha, \beta, \gamma, \delta)$$

where $\widehat{L}(\alpha, \beta, \gamma, \delta)$ denotes an estimate for $L(\alpha, \beta, \gamma, \delta)$. The latter obtains by replacing all relevant densities/probabilities in (9) and (10) with corresponding estimates. We use an adaptive approach based on multistage local smoothing kernels for this purpose. Details regarding the exact estimation procedure can be found in Klein and Vella (2006).

4.3 Average Structural Effects

Given the resulting estimates for the supply and demand indices, $\widehat{S}_I = H^P \widehat{\alpha} + Q^D \widehat{\beta}$ and $\widehat{D}_I = H^P \widehat{\gamma} + Z^P \widehat{\delta}$, we can compute average structural effects of either market side on vaccination take-up. Yet, given the nonseparable structure in (8), the effects of supply (demand) will generally depend on the particular level of demand (supply) considered and an important question is how to account for this dependence in the definition of average structural effects. To this end, we borrow recent results from the literature on semi- and nonparametric estimation of nonseparable models using control functions that are useful for summarizing the impacts of supply and demand in the presence of interaction effects.

We first compute the average structural function (ASF) of Chamberlain (1984) and Blundell and Powell (2003,2004) to summarize the structural dependence between influenza immunization and supply and demand, respectively. We then scrutinize further how vaccination take-up responds to changes on each market side based on two possible definitions of structural supply and demand effects, namely the average structural response (ASR) and a localized version of it, the local average response (LAR) of Altonji and Matzkin (2005).

4.3.1 Average Structural Function

The ASF of Chamberlain (1984) and Blundell and Powell (2003, 2004) shows how the average probability of vaccination take-up changes with supply or demand. In each case, the ASF integrates out any simultaneous effects of the other market side based in the marginal distribution of its respective index. For example, for a given value of the supply index, the ASF of supply corresponds to the expected probability of take-up, treating demand as if it were fully randomly assigned, completely breaking any potential dependence between the two market sides.

Formally, the ASF is defined as

$$ASF_S(S_I^0) = \int h(S_I^0; D_I) dF_{D_I} \quad (11)$$

$$ASF_D(D_I^0) = \int h(S_I; D_I^0) dF_{S_I} \quad (12)$$

The ASF thus considers the expected probability of vaccination take-up for individuals facing a randomly assigned level of supply or demand respectively.

4.3.2 Average Structural Response

The ASR is nothing but the derivative of the ASF. The ASRs for supply and demand are hence given by

$$ASR_S(S_I^0) = d_{S_I} ASF_S(S_I^0) \quad (13)$$

$$= \int d_{S_I} h(S_I^0; D_I) dF_{D_I} \quad (14)$$

and

$$ASR_D(D_I^0) = d_{D_I} ASF_D(D_I^0) \quad (15)$$

$$= \int d_{D_I} h(S_I; D_I^0) dF_{S_I} \quad (16)$$

respectively, where d_X denotes partial derivatives with respect to argument X . The ASR highlights how changes in either market side affect average vaccination take-up probabilities for a randomly selected individual. The ASR thus corresponds to the average treatment effect with continuous treatments, a common parameter of interest in the literature on policy evaluation.

4.3.3 Local Average Response

The LAR of Altonji and Matzkin (2005) differs from the ASR in that it accounts for the local dependence between supply and demand. Both the ASF and ASR for either side of the market correspond to partial means based on integration with respect to the marginal distribution of the other market side. The LAR of supply (demand), on the other hand, is based on integration with respect to the conditional distribution of demand (supply) given the particular supply (demand) level under consideration. This definition of average structural effects thus accounts for the prevailing dependence between supply and demand, gauging the average effects of small changes on their market side rather than considering full random assignment. For example, the LAR recognizes that local changes from a prevalent level of say supply, only affect individuals that actually feature this particular supply level at baseline. This specific subset of individuals will usually face demands with a conditional distribution that generally differs from its corresponding marginal distribution. To account for this difference, the LAR performs integration with respect to the conditional distribution of demand given the particular supply level at hand, rather than with respect to its marginal distribution.

Formally, the LAR is defined as

$$LAR(S_I^0) = \int d_{S_I} h(S_I^0; D_I) dF_{D_I|S_I^0} \quad (17)$$

and

$$LAR(D_I^0) = \int d_{S_I} h(S_I; D_I^0) dF_{S_I|D_I^0} \quad (18)$$

The LAR has a logic equivalent in the average effect of treatment on the treated, which is also a frequent object of interest in evaluation research.

4.4 Average Partial Effects

Finally, we estimate average partial effects (APEs) for all micro-determinants of supply and demand, in each case highlighting the particular pathway through which it affects vaccination take-up. We compute these APEs by changing the values of the control variables one at a time, first in the supply (demand) index only, before considering the average effects of a simultaneous change operating through both market sides. All other determinants of supply and demand remain thereby fixed at their observed values.

We formally define the APEs for say a change in health variable H_j from H_j^0 to H_j^1 as

$$APE_S(H_j^1; H_j^0) = \int h(S_I(H_j^1); D_I) dF_{S_I(H_j^1)D_I} \quad (19)$$

$$- \int h(S_I(H_j^0); D_I) dF_{S_I(H_j^0)D_I} \quad (20)$$

$$APE_D(H_j^1; H_j^0) = \int h(S_I; D_I(H_j^1)) dF_{S_I D_I(H_j^1)} \quad (21)$$

$$- \int h(S_I; D_I(H_j^0)) dF_{S_I D_I(H_j^0)} \quad (22)$$

$$APE_T(H_j^1; H_j^0) = \int h(S_I(H_j^1); D_I(H_j^1)) dF_{S_I(H_j^1)D_I(H_j^1)} \quad (23)$$

$$- \int h(S_I(H_j^0); D_I(H_j^0)) dF_{S_I(H_j^0)D_I(H_j^0)} \quad (24)$$

where $S_I(H_j^k)$ and $D_I(H_j^k)$ denote the supply and demand indices with H_j set to H_j^k throughout. In the actual computations, integration is performed with respect to the joint distribution of supply and demand and all unknown parameters are replaced by corresponding estimates.

5 Data and Model Specification

Our empirical analysis uses data from the first wave of SHARE. SHARE is a novel multidisciplinary, cross-national micro data base containing information on health and socioeconomic status of some 22,000 Continental Europeans aged 50+ and their partners. As we focus on vaccination take-up in Germany, we only extract the German subsample from the SHARE data base. Also, we only consider age-eligible respondents, deleting all individuals below age 50 from our sample.

Our outcome of interest is whether or not the respondent had an influenza vaccination in the last year. This information is available in the SHARE data in the form of a binary variable indicating vaccination take-up. We also extract information on age and high-risk health conditions (self-reports of doctor-diagnosed asthma, diabetes, heart attack and lung disease), which allow us to characterize each patient's health utility from influenza immunization. As implied by our model of physician agency, these health-related risk factors will appear in both the supply and demand index.

Beyond any effects of objective risk factors for suffering from influenza-related complications, supply may also be influenced by the family physician's ability. Particularly, our theoretical illustration highlighted that a physician's assessment of her patient's health utility from vaccination may crucially depend on the doctor's information set, which we assume to be a function of her care quality in general. To account for the latter, we construct a physician quality score that measures physician performance on a comparable scale for all respondents. We generate this physician quality score using patients' reports on their experienced care quality. These are, in turn, based on indicators for geriatric assessments in primary care, which any family physician should routinely perform. All of these indicators rely on straightforward aspects of medical consultations that are believed to be easily recognized by the respondents, irrespective of their level of education (Santos-Eggimann et al.(2005)). Specifically, we construct the physician quality score as a weighted sum of six specific geriatric assessment indicators, namely whether the family physician

takes information or gives advice on physical activity and exercise, whether she checks the patient's weight and asks about drug use, as well as whether she checks the patient's sense of balance and queries about possible falls during at least some consultations. Whereas the former four types of primary care assessment pertain to all ages considered here, the latter two evaluations are more relevant for older patients (Santos-Eggimann et al.(2005)). To account for this age dependence in some of the indicators, we simply sum the first four care quality indicators, before adding age-adjusted scores for the latter two assessments. Specifically, we do not at all consider balance checks and queries about falls if the respondent is aged 50-59, score them with a weight of 0.5 for individuals aged 60-69, with a weight of 1 for respondents aged 70-79 and a weight of 1.5 if the patient is aged 80 and over. The use of such an age-dependent weighting scheme leads of course to a normalization issue, as the maximal quality score of a physician treating a respondent aged 50-59 is lower than that of a physician whose patient is aged say 80 and over. To attain full comparability, we finally divide the age-weighted sum of our geriatric assessment indicators by the maximal attainable value implied by the respondents' respective ages, such that the resulting physician quality indicator may only take on values between 0 and 1 for each patient. This final renormalization has also an intuitive interpretation in terms of relative care quality. For example, a family physician with a treatment quality score of 0 performs none of the age-specific geriatric assessments, while physicians with treatment quality scores of say 0.6 or 1, perform 60 or 100 percent of all evaluations indicated for a patient of a particular age.

There are also a number of pure demand side factors, which capture observable heterogeneity in the (perceived) value of influenza vaccinations. Firstly, a patient's expected utility of take-up may depend on her self-rated health in general, with individuals that feel more sick also featuring a higher valuation of influenza immunizations. To capture such differences, we include a patient's self-assessment of her general health in our demand index, measuring subjective health perceptions on a scale from 1 ("excellent") to 1 ("bad"). Secondly, not all individuals value their health the same, and such heterogeneity in the

utility of health in general may also represent an important determinant for the demand of influenza vaccinations in particular. As we cannot directly observe a patient's preferences for health, we need to resort to some proxy measure to capture observable differences in health utilities. For these purposes, we construct a health behavior score for each patient that measures her engagement in preventive activities in general, as these should be strongly correlated with individual valuations of health. Starting with a base value of 0, the health behavior score increases each time by 0.25 if the respondent engages in at least some vigorous or moderate physical activity, if she does not drink more than two glasses of alcoholic drinks at least five times a week, if she does not currently smoke and if she had a preventive visit to a dentist within the last twelve months. We thus obtain a scalar health behavior score for each respondents, taking on values between 0 ("very poor general health behavior") and 1 ("good general health behaviors"). Apart from its correlation with general health preferences, this measure of health behaviors has the additional advantage that it is only based on preventive activities that are not related to access to primary care, which facilitates our interpretation as preference shifter.

Beyond the potential demand effects of health perceptions and preferences, several socio-demographic characteristics are also likely to impact on the decision to immunize or not. Firstly, gender and partnership status may affect vaccination take-up. For example, women are commonly found to be more risk averse than men, which may lead to higher vaccination rates among female patients. Also, partnered individuals are likely to feature higher take-up rates, because of shared health information or positive externalities within the couple. Being employed, on the other hand, should generally result in lower take-up rates, as it raises a patient's opportunity cost of vaccination, which would require a doctor visit just before the start of the influenza season. The last demand factor we consider is educational attainment. Clearly, health literacy should have a major impact on health care choices, which tend to require complex information processing in the absence of perfect physician agency. We therefore include a patient's years of education in the demand index to proxy for their health literacy regarding the usefulness of influenza vaccinations.

In our empirical analysis, we only consider individual records with no missing information on any of the aforementioned survey items. Particularly, we can only use respondents who returned the drop-off component of the SHARE questionnaire, as key variables such as influenza vaccination take-up and family physician quality refer to drop-off items. Also, the latter information is only available for respondents who report to have a family physician, which are about 95 percent of all individuals. After all necessary deletions, our final estimation sample features 1,589 observations.

Table 1 presents basic sample statistics for all variables used in our analysis. As the table indicates, only 34 percent of all respondents report an influenza vaccination during the last year. The average age of our estimation sample is around 64 years, with 53 percent of the sample being female and 75 percent reporting to have a partner. Although we only consider individuals age 50+, 28 percent of our sample are still in employment. The average educational attainment, in turn, is around 13.6 years of schooling. In terms of the respondents' background health, we observe that most risk factors for influenza related complications feature relatively low prevalence rates, ranging from 3 percent for asthma to 12 percent for diabetes and heart attacks. Self-perceived health averages at a value of roughly 3.2 in our sample. Reflecting our comparatively strict cutoffs for poor health behaviors, most respondents seem to lead fairly healthy lives, indicated by an average health behavior score of 0.84. Finally, we find that family physicians perform - on average - 50 percent of all indicated geriatric assessments at least some of the time.

6 Results

Following the logic of the underlying econometric model, the discussion of our estimation results proceeds in several steps. We begin by discussing our estimates for the parameters α, β, γ , and δ , which yield our scalar indices for supply and demand. We then present estimates for the nonparametric link function $h(\cdot, \cdot)$, which summarizes how these supply and demand indices affect actual vaccination take-up. As supply and demand may feature

important interaction effects, we also compute some estimates of structural supply and structural demand, in which the respective effects of the other market side have been integrated out. Finally, we present estimates for the average partial effects of each individual control variable on vaccine use, in each case highlighting the particular pathway through which it affects take-up. These partial effects summarize the average impact of each micro-determinant on the conditional probability of vaccination, transmitted through the supply and demand indices, S_I and D_I , as well as the nonparametric link function $h(\cdot, \cdot)$.

6.1 Supply and Demand Indices: Coefficient Estimates

Table 2 presents coefficient estimates and their standard errors for the supply and demand indices. To attain identification, the coefficients of age have been normalized to 0.1 in both indices. The effects of all control variables on the supply and demand indices are therefore measured in age units. Age seems particularly well-suited as a normalization variable in our context, since vaccination take-up features a steep, yet smooth age gradient as highlighted in Figure 1.

Given the positive relationship between age and vaccination, we would expect all risk factors to feature positive coefficients in both the supply and demand indices. Moreover, we would also expect physician quality to enter the supply index with a positive sign. On the demand side, we would expect better education to lead to higher index values, while currently working for pay should have a negative demand coefficient, reflecting higher opportunity costs of vaccination among the employed population.

Almost all of our parameter estimates are in line with expectations. Reporting any health condition always leads to larger values for the supply index. While the effects of heart attack and lung disease seem relatively moderate (parameter estimates of 0.224 and 0.697, which correspond to the same supply response as increasing age by 2.24 and 6.97 years respectively), our results reveal large effects of reporting asthma or diabetes, even if only the latter is statistically significant. Specifically, asthma and diabetes lead to supply

shifts comparable to age increases of 33.24 and 32.09 years respectively, highlighting the importance of these health conditions in determining vaccination supply. Finally, higher physician quality is also associated with considerable and statistically significant increases in the supply index. Having a family physician who performs all indicated geriatric assessments relative to having a doctor who does not perform any evaluation yields the same supply response as a 26.46 year age increase, which is almost as large as the supply effects of asthma and diabetes.

Turning to the other market side, we also tend to find positive demand coefficients for patients' risk factors. These coefficients seem, however, relatively smaller than the effects of age on the demand index and are statistically insignificant throughout. Specifically, we do find positive demand coefficients for asthma, diabetes and lung disease, but estimate a negative coefficient for reporting a heart attack.

The index coefficients for the pure demand factors, on the other hand, all feature the expected relative signs and are generally estimated with much greater precision. Firstly, female and partnered respondents have significantly larger demand index values, with corresponding point estimates of 1.161 and 0.982 respectively. Individuals who report worse ratings for their general health also have larger demand index values, whereas employed respondents feature lower values, even if both effects are not statistically significant. Respondents with better general health behaviors feature higher demand index values, with a corresponding coefficient estimate of 0.231, which is also highly significant. Finally, education has a large and statistically significant effect on the demand index for vaccination take-up. Specifically, its estimated coefficient of 0.35 implies that an increase of say five years in educational attainment has the same demand effect as increasing age by 17.5 years.

6.2 Nonparametric Link Function

Panel A of Figure 2 presents a bivariate estimate for the joint density of our estimated supply and demand indices. First of all clarifying the relevant support of the data is

particularly important for our analysis, as semi- and nonparametric methods do not allow for any off-support predications. Panels B and C of Figure 2, in turn, present contour and surface plots for our estimate of the nonparametric link function $h(\cdot, \cdot)$, which maps the supply and demand indices into conditional probabilities for vaccination take-up. The function $h(\cdot, \cdot)$ thus reveals how our age-unit measures of supply and demand translate into actual take-up probabilities. In Panels B and C, we restrict our attention to supply and demand index values that are sufficiently well supported by the data at hand.

As already speculated, vaccination take-up is generally increasing in both the supply and demand index. More precisely, take-up rates rise from an overall low of less than 20 percent for minimal index values ($S_I = 5; D_I = 10$) to an overall maximum of around 50 percent for the index combination ($S_I = 9.7; D_I = 12.5$), from where take-up probabilities remain largely flat. Moreover, supply and demand feature important interactions in the determination of vaccination, meaning that their respective effects on take-up generally depend on the particular realization of the other market-side. For example, for low levels for the supply index (say $S_I = 5$), the conditional take-up probability continuously steepens with increasing demand index values. For high levels of the supply index (say $S_I = 10$), however, we observe very strong demand effects initially, which then level and eventually vanish completely. Similarly, the effects of supply generally depend on the prevailing level of demand. For example, the estimated supply gradients of vaccination take-up are considerably more pronounced at medium levels of the demand index (say $D_I = 12$) than in its respective tails ($D_I = 10$ and $D_I = 15$).

6.3 Structural Supply

6.3.1 Average Structural Function

We begin by considering the structural dependence between vaccination take-up rates and the supply index as summarized by the ASF. Panel A of Figure 3 presents an estimate for the ASF of supply along with a density estimate for the marginal distribution of the supply

index. For each value of the supply index, any simultaneous demand effects are integrated out based on their marginal distribution. Starting from an initial take-up probability of around 0.24 at $S_I = 5$, the ASF of supply is initially flat up to $S_I = 6$, where it begins to increase until it reaches its maximal value of roughly 0.44 at $S_I = 9.8$, after which it roughly maintains this level. Considering the marginal density of the supply index at the same time, we find that most observations feature supply levels for which the ASF is strongly increasing.

Yet, the average effects of random changes in the supply index on vaccination rates may be better summarized by the ASR - the derivative of the ASF. Local changes from the status quo, on the other hand, would be best captured by the LAR, which is based on integration with respect to the conditional distribution of demand given supply, rather than random assignment.

Panel B of Figure 3 presents an estimate of the ASR of supply, again in combination with our density estimate for the marginal distribution of the supply index. Reflecting the shape of the ASF, the ASR starts out with small negative values at $S_I = 5$, but is steadily rising until the ASF's inflection point at $S_I = 8.1$, where it reaches its maximum of 0.08. From there, the ASR declines again, taking on small-sized negative values towards the upper tail of the marginal distribution of the supply index. Although considering the status quo rather than random assignment, the LAR closely tracks the ASR. Like the ASR, the LAR is mostly positive, increasing until a supply index value of roughly $S_I = 8$ before decreasing again to more or less its initial level.

In sum, all three concepts of structural supply tell a similar story. Firstly, the ASF shows a strong positive dependence between the conditional probability of influenza immunization and randomly assigned supply levels. Moreover, as further highlighted by the ASR and the LAR, most observations are concentrated in the region where both random and marginal supply changes feature a particularly large impact on vaccination take-up.

6.4 Structural Demand

Panel A of Figure 4 presents an estimate for the ASF of demand, highlighting how a patient's health and demographic characteristics affect vaccination take-up through the demand channel. While the ASF of demand covers the same range of take-up probabilities as its supply counterpart (from roughly 0.18 to 0.43), their respective shapes differ considerably. More precisely, the ASF of demand is at first strongly increasing to a level of around 0.35 at $D_I = 12$, from where it continues more or less flat until $D_I = 14$, where it starts to rise again. Accounting for the marginal density of the demand index, the ASF highlights a strong positive dependence between the demand index and expected vaccination take-up only for the tails of the demand index distribution. Particularly, a considerable proportion of the observations falls into regions where the ASF of demand is relatively flat.

This picture is confirmed when we turn to the average effects of fully random or local changes of the demand index on vaccination rates, as summarized by the ASR and LAR, respectively. Although the ASR lies consistently above the LAR this time, both parameters again feature a fairly similar shape. Reflecting the properties of the ASF, the ASR indicates large demand effects initially, but then drops substantially for medium values of the demand index before rising again in its upper tail. The LAR, in turn, features the same pattern, albeit less pronounced and with somewhat smaller structural effects.

In summary, all our estimates for the average structural dependence between vaccination and demand indicate large positive effects of demand on expected take-up in the tails of the demand index, but only small - if any - structural effects for medium index values, the area where most demand is concentrated.

6.5 Average Partial Effects of Individual Control Variables

Ultimately, we should like to quantify the average effect of each control variable on actual vaccination use as well as the particular pathways through which it operates. To this end, estimated average partial effects summarize the impact of each micro-determinant on the

conditional probability of immunization as transmitted by the interplay of the supply and demand indices, S_I and D_I , and the nonparametric link function $h(\cdot, \cdot)$. Table 3 shows corresponding estimates for each control variable. The first column of the table considers variable changes in the supply index only, while the second column looks at pure demand effects. Finally, the third column presents estimates for the overall effects of each individual variable on the conditional vaccination take-up rate, considering simultaneous changes of the supply and demand indices whenever applicable.

Starting with the health determinants common to both market sides, we find that vaccination rates strongly increase with patient age, with larger supply than demand effects. Although the coefficients of patient age are normalized to 0.1 in both indices, our estimates nonetheless indicate larger age effects for supply than demand, reflecting on average stronger responses of vaccination rates to changes in the supply rather than demand index. Increasing a patient's age by one year solely in the supply index leads to a rise of 0.41 percentage points in the take-up rate, whereas the corresponding demand effect is only 0.27 percentage points. Hence, the age effects of supply are about 50 percent larger than those operating through the demand side. Considering the combined effect of supply and demand implied by a one year age increase leads on average to a 0.67 percentage points higher take-up rate of influenza vaccinations.

The impact of the other health-related risk factors is also positive and seems to mainly work through the supply-side as well. Suffering from asthma increases vaccination take-up by 9.06 percentage points through the supply channel, whereas a corresponding demand effect only leads to a take-up rate that is 6.09 percentage point higher. Simultaneous changes in supply and demand due to asthma amount to an overall average increase of 12.51 percentage points in take-up. It seems worth noting that this combined effect is smaller than the mere sum of the individual impacts of supply and demand, due to the presence of interaction effects between both market sides. Similarly, reporting doctor-diagnosed diabetes leads to a supply effect of 9.5 percentage points, while the demand effect of such a diagnoses is considerably smaller with a point estimate of 1.06 percentage points only.

The total effect of reporting diabetes is 10.08 percentage points, which is again smaller than the sum of the pure supply and demand effects. A reported heart attack, in turn, has only a mild positive supply effect (0.93 percentage points), with our estimate for the pure demand effect being even negative (-2.85 percentage points). The total effect of heart attack add up to -1.96 percentage points. Finally, suffering from a lung disease leads again to an increase in vaccination take-up, with individual supply and demand effects of around 3 percentage points each, and an overall effect of 5.59 percentage points for a simultaneous change in both market sides.

Physician quality also has a strong supply-side effect on influenza vaccination take-up. In particular, the large and significant effect of our physician quality measure on the supply index is further amplified by its interplay with the other supply controls, such that its average partial effect is even larger than the impact of any of the health conditions we consider. Changing from a family physician who does not perform any of the indicated geriatric assessments to one that performs all of them leads to an almost 12 percentage point increase in influenza vaccination take-up rates.

A patient's educational attainment and general health behaviors emerge as key demand factors underlying vaccination take-up. Specifically, each additional year of schooling translates on average into a 0.92 percentage point higher probability of immunization, resulting in a roughly 4.5 percentage point difference in vaccination rates between two otherwise identical individuals with 8 and 13 years of schooling respectively. Only a patient's general health behaviors seem more important quantitatively, as patients with very poor health habits (no preventive activities, health behavior score = 0) have a 15.69 percentage point lower take-up probability than patients with healthy life-styles (full take-up of other forms of preventive activities, health behavior score = 1). It is important to note that this effect is conditional on a patient's health literacy as proxied by her education levels, and therefore likely to capture preference heterogeneity rather than information barriers. Hence, a patient's general health preferences appear to be another key determinant of vaccination demand. conditional on health literacy as proxied by her education level.

Finally, we also find some smaller effects for the other demand controls in our model, which - by and large - confirm the findings of previous studies. For example, being female and partnered increases vaccination take-up by 3.25 and 2.96 percentage points respectively, while employed respondents feature slightly lower take-up rates than their non-working counterparts (-0.64 percentage points). Ultimately, individuals with worse self-rated health (change from 1 to 5) show higher rates of vaccination use (3.03 percentage points).

7 Conclusion

Influenza is a serious illness that can be prevented by annual vaccination. Infection with one of the influenza viruses may have severe consequences for those affected, to the point of hospitalization or even premature death, both of which tend to be concentrated among older people. Vaccination decreases the risk of infection substantially and largely alleviates its adverse consequences in case of influenza contraction. As a result, increasing the take-up of influenza vaccinations is one of the chief public health concerns in many countries.

Asymmetric information is particularly widespread in health care markets. For that reason, expert physicians often need to act on behalf of their less informed patients. We analyze a semiparametric double index model for influenza vaccination use that allows us to disentangle the distinct effects of supply and demand on take-up, resolving important simultaneity issues as implied by widespread physician agency. Particularly, our empirical model delivers important insights on the relative importance of various micro-determinants of vaccination usage as well as regarding the exact pathways through which they affect take-up.

Our analysis establishes that both supply and demand have important effects on influenza vaccination take-up among individuals aged 50+ in Germany. Specifically, our estimates for the structural effects of supply and demand indicate that vaccination rates more than double over the respective supports of either market side. Yet, the exact nature of these structural effects differs substantially between supply and demand. While we find

evidence for relatively strong supply effects for most respondents, any large demand effects seem concentrated in the tails of its distribution. Hence, our results indicate larger average supply than demand responses to marginal changes in their respective micro-determinants.

Analyzing the effects of each micro-determinant individually, we find that key risk factors for complications, such as age or specific health conditions, lead to considerably higher vaccination rates, and mainly do so through their effect on the supply side. We interpret this finding as evidence for the importance of physician agency in vaccination take-up, highlighting the important role of family physicians for the delivery of responsive health care.

Beyond the physician's role as agent for her patients, our estimation results also identify physician quality as a key supply-side factor underlying vaccination take-up. Having a family physician who generally complies with indicated geriatric assessments has a strongly significant positive supply effect. Specifically, our estimates indicate on average 12 percentage points higher vaccination rates among respondents whose family physician performs all geriatric assessments relative to those whose doctor does not undertake any evaluation.

On the demand side, a patient's educational attainment and general preventive health behaviors emerge as the most important determinants for vaccination take-up. While the former suggests a significant role for health literacy in explaining influenza immunization take-up, the additional effect of health behaviors - conditional on education - may point to the importance of preference heterogeneity for health in general. Beyond it, we also estimate significant effects of gender and partnership status on vaccination demand. Interestingly, we do not find any significant or quantitatively important employment effects on vaccination take-up, at least for the older population studies here.

In terms of health policy implications, our analysis suggests that both supply and demand interventions may provide suitable leverage for increasing influenza vaccination rates. On the one hand, our estimates of strong education effects indicates that campaigns to improve the health literacy of older patients may indeed represent an important health

policy tool for increasing their take-up of influenza vaccines. At the same time, our evidence for (imperfect) physician agency and the important role of quality of care indicators for take-up further highlight the potential effectiveness of supply-side interventions aimed at increasing awareness among physicians regarding the benefits of influenza vaccinations as well as better compliance with official treatment recommendations. In particular, enhancing the quality of physician agency seems especially important for protecting individuals at high risk from complications, such as the older population or people with chronic diseases.

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Appendix

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Influenza vaccination take-up	0.34	0.47	0.00	1.00
Patient age	64.31	9.44	50.00	97.00
Patient female	0.53	0.50	0.00	1.00
Patient partnered	0.75	0.43	0.00	1.00
Patient working	0.28	0.45	0.00	1.00
Patient years of education	13.65	2.68	0.00	18.00
Patient-reported asthma	0.03	0.17	0.00	1.00
Patient-reported diabetes	0.12	0.32	0.00	1.00
Patient-reported heart attack	0.12	0.33	0.00	1.00
Patient-reported lung disease	0.05	0.22	0.00	1.00
Patient self-rated health	3.21	0.98	1.00	5.00
Patient health behavior score	0.84	0.19	0.00	1.00
Physician quality score	0.49	0.35	0.00	1.00
Number of observations	1589			

Table 2: Parameter Estimates for the Supply and Demand Indices

	Parameter Estimate	Standard Error	P-Value
Supply Index (Physician)			
Patient age	0.100	-----	-----
Patient-reported asthma	3.324	2.882	0.249
Patient-reported diabetes	3.209	1.547	0.038
Patient-reported heart attack	0.224	0.634	0.724
Patient-reported lung disease	0.697	1.082	0.520
Physician quality score	2.646	0.783	0.001
Demand Index (Patient)			
Patient age	0.100	-----	-----
Patient-reported asthma	2.108	2.041	0.302
Patient-reported diabetes	0.171	0.925	0.854
Patient-reported heart attack	-0.994	0.573	0.083
Patient-reported lung disease	1.114	0.954	0.243
Patient self-rated health	0.256	0.216	0.235
Patient female	1.161	0.544	0.033
Patient partnered	0.982	0.498	0.048
Patient working	-0.234	0.584	0.688
Patient years of education	0.350	0.131	0.008
Patient health behavior score	3.696	1.458	0.011

Table 3: Average Partial Effects: Supply, Demand and Total

Variable	Supply Effect	Demand Effect	Total Effect
Patient age	0.0041	0.0027	0.0067
Patient-reported asthma	0.0906	0.0609	0.1251
Patient-reported diabetes	0.0950	0.0106	0.1008
Patient-reported heart attack	0.0093	-0.0285	-0.0196
Patient-reported lung disease	0.0290	0.0307	0.0559
Physician quality score	0.1196	-----	0.1196
Patient female	-----	0.0325	0.0325
Patient partnered	-----	0.0296	0.0296
Patient years of education	-----	0.0092	0.0092
Patient working	-----	-0.0064	-0.0064
Patient health behavior score	-----	0.1569	0.1569
Patient self-reported health	-----	0.0303	0.0303

Figure 1: Nonparametric Age Profiles of Influenza Vaccination Take-up

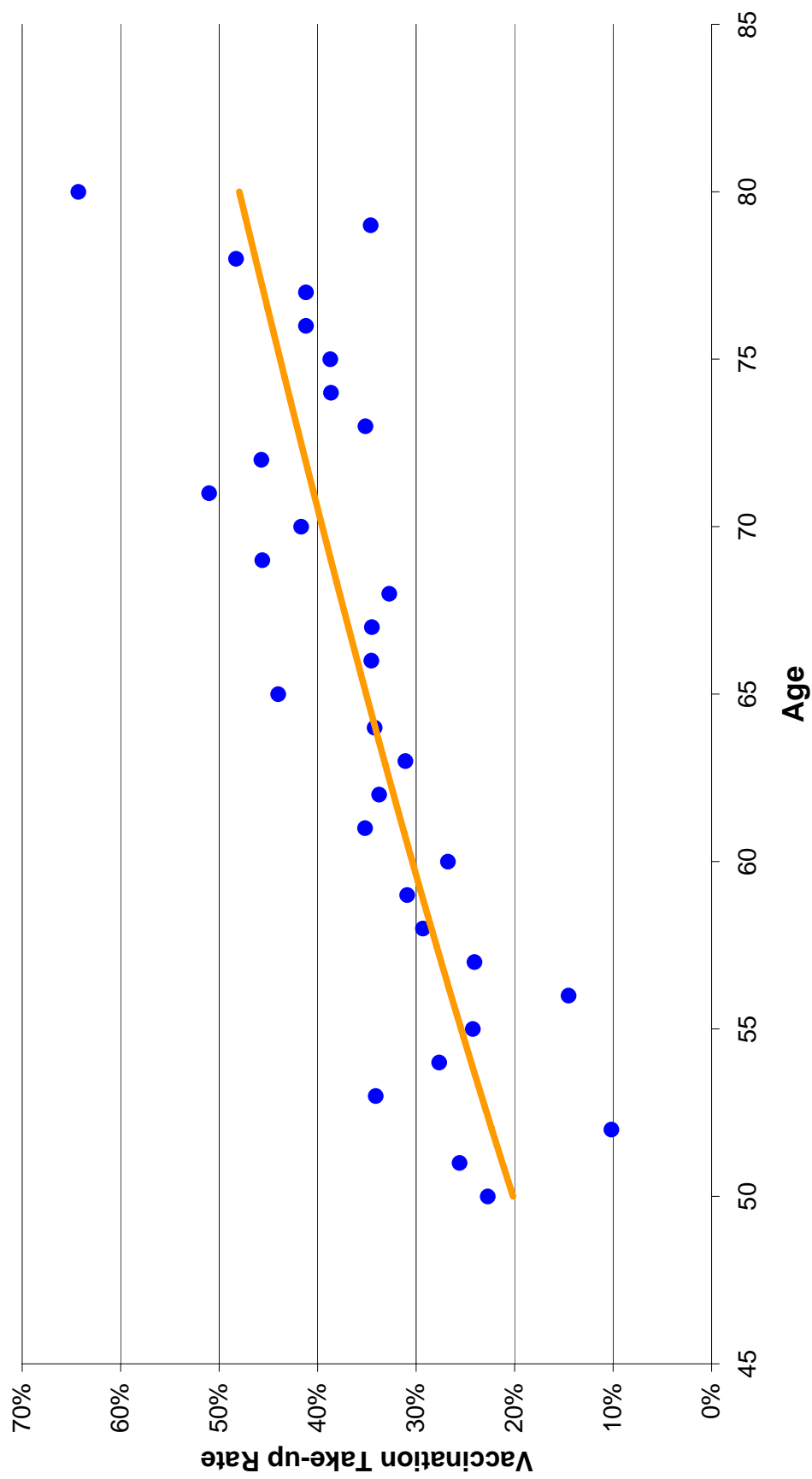
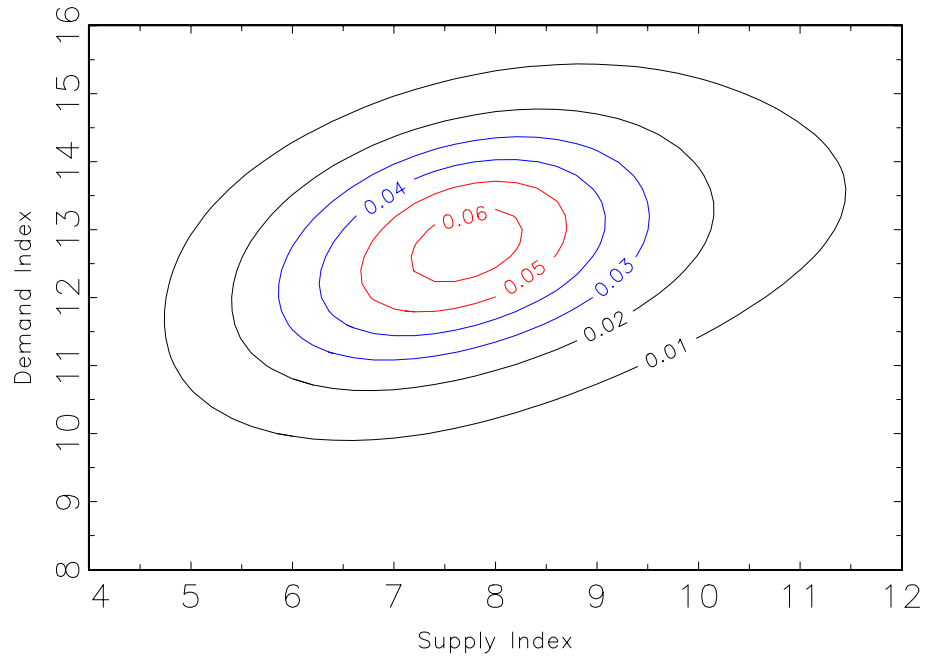


Figure 2: Density and Take-up Probability Plots

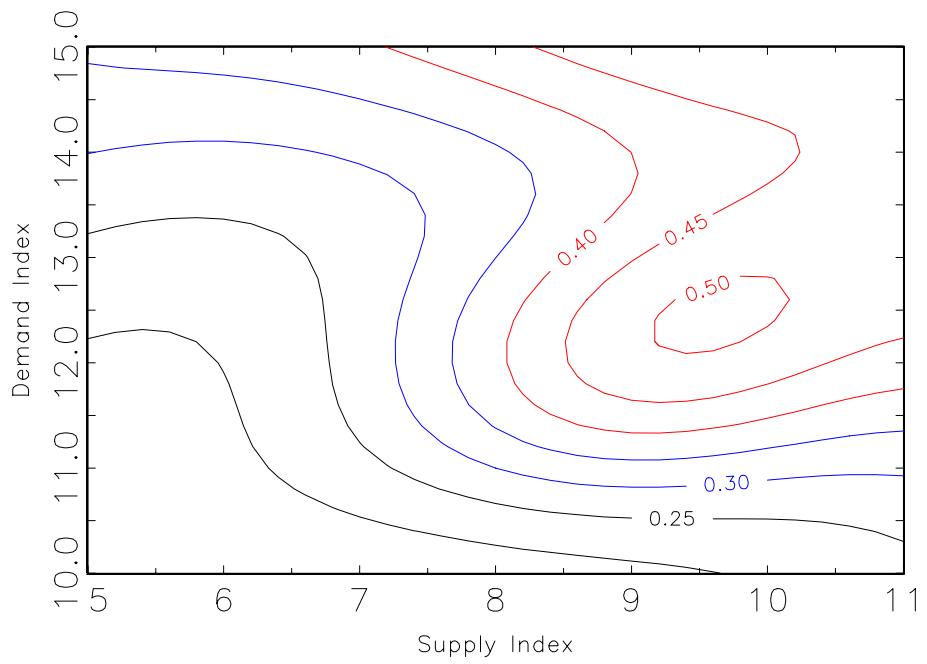
Panel A

Bivariate Density Estimate for the Controls



Panel B

Influenza Vaccination Take-up Probabilities



Panel C

Influenza Vaccination Take-up Probabilities

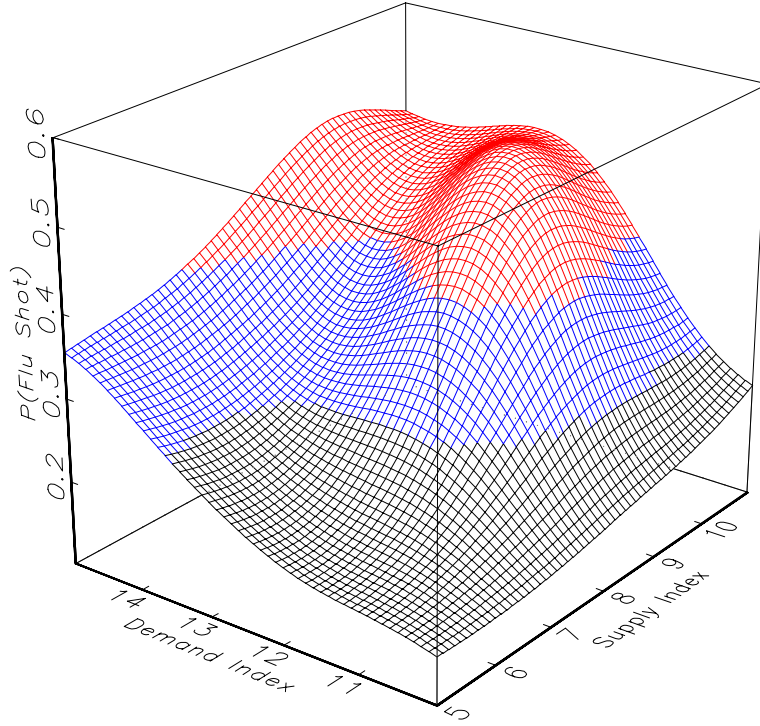
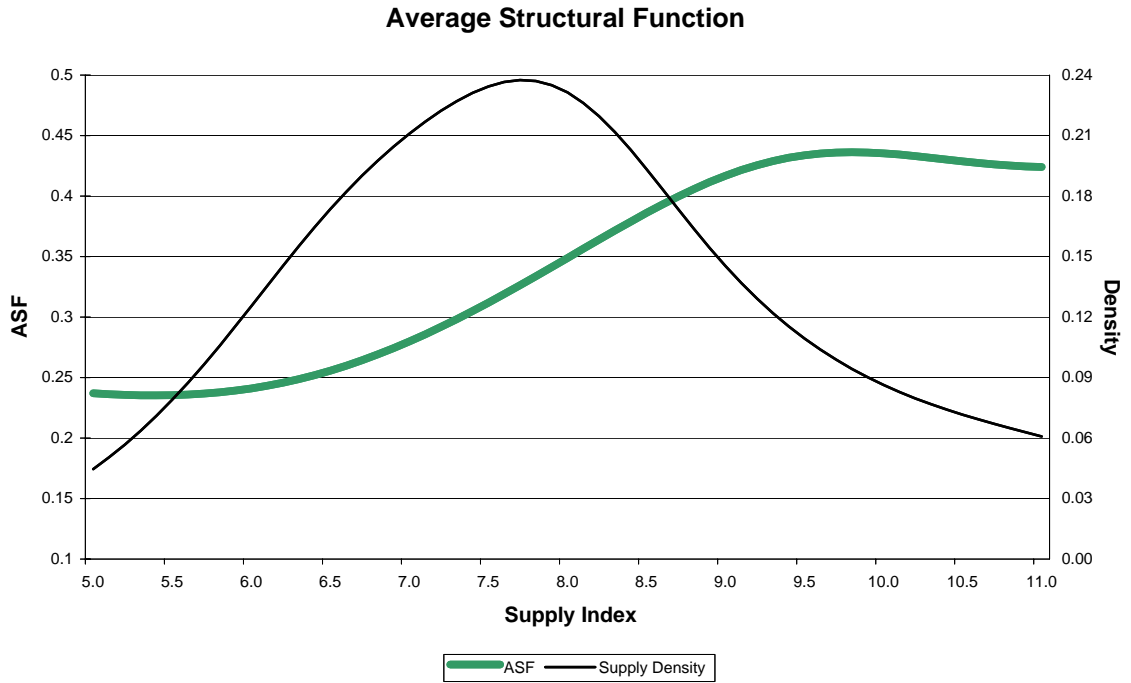


Figure 3: Structural Supply

Panel A



Panel B

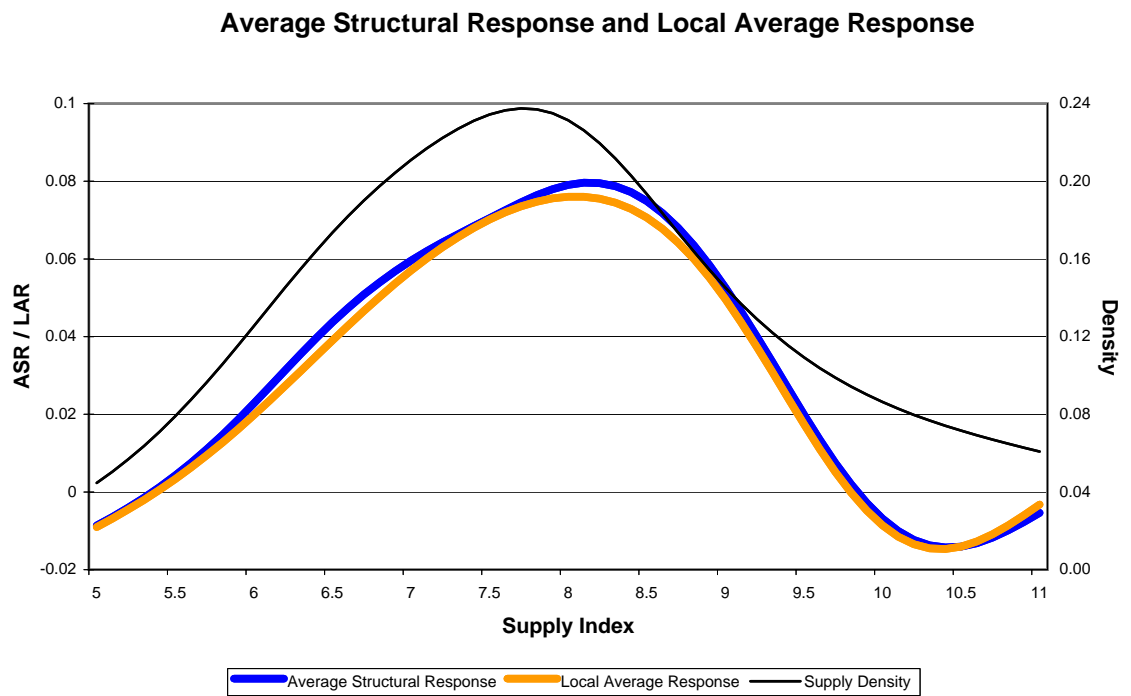
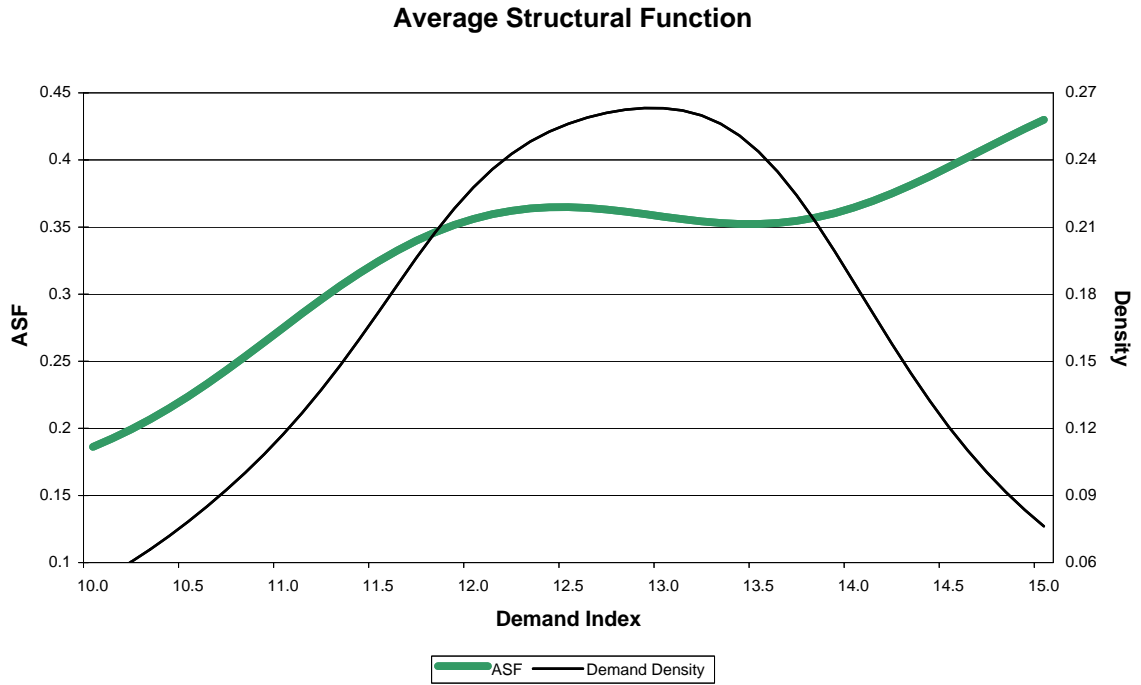
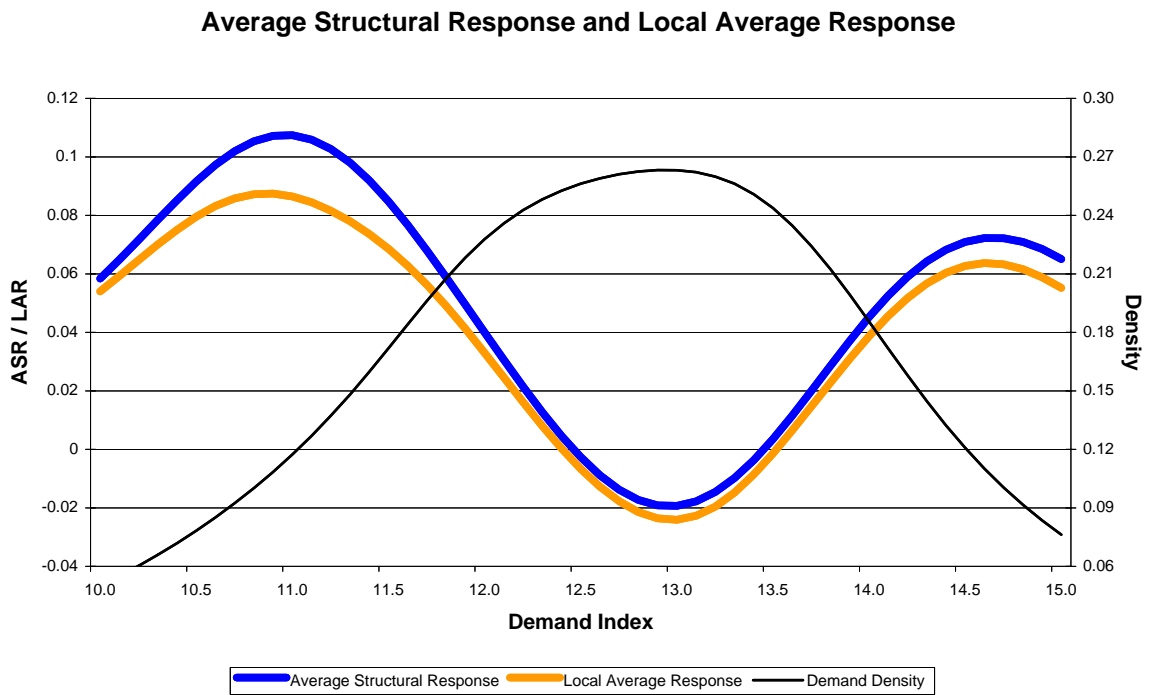


Figure 4: Structural Demand

Panel A



Panel B



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