5-7-2013

Four Essays in Applied Microeconomics

Weiwei Chen

FOUR ESSAYS IN APPLIED MICROECONOMICS

by

Weiwei Chen

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Business Administration

The University of Memphis

August 2013

ACKNOWLEDGEMENTS

I am extremely grateful to my major advisor, Dr. Albert A. Okunade, who always has students on the top of his priority list. I don't remember how much time he spent with students discussing research, let alone the time and energy he devoted to mentoring and guidance in the completion of our Ph.D. degrees.

I would like to thank Dr. Cyril F. Chang, who provided me the opportunity to experience health services research in addition to health care economics. I sincerely appreciate his support and help during my academic development.

I am very thankful to Dr. Andrew Hussey, who introduced me to labor economics. I had chance to work on interesting topics and learned a lot by doing research with him.

I would also like to thank Dr. Julie Heath for advising me on both research and teaching. And I thank Dr. Alex Nikolsko-Rzhevskyy for his econometrics course, helpful comments in department seminars, and great support. I also thank Dr. Ebenezer O. George for being my committee member and giving comments and suggestions on my dissertation.

Lastly, I owe my deepest gratitude to my family for their love, care and support. This dissertation would not have been possible without them.

ABSTRACT

Chen, Weiwei. Ph.D. The University of Memphis. August 2013. "*Four Essays in Applied Microeconomics*." Major Professor: Albert A. Okunade.

This dissertation comprises four essays. The first two essay investigates the sensitivity of two largest components of health care expenditure — hospital care expenditure (HOCEXP) and physician and clinical services expenditure (DOCLNEXP) — to the changes in income and how much of the estimated sensitivity is due to purchasing more care versus purchasing better care. Although the two essays share the same decomposition model, the estimation is different in the second essay due to data limitations. Using 1999 - 2008 panel data of the 50 US states, we estimate and decompose the income elasticity of HOCEXP and DOCLNEXP into its quantity and quality components respectively. Our findings suggest that the both HOCEXP and DOCLEXP rises have more to do with quality than quantity change. The results mimic the literature indicating that both hospital care and physician and clinical services are normal goods and technical necessities at the state level.

The third essay analyzes the effect of insurance coverage on the likelihood of an emergency department (ED) visit being non-urgent or primary-care-sensitive (PCS). We analyze the Tennessee Hospital Outpatient Discharge Data for 2008 and identify non-urgent and PCS ED visits following a widely used ED classification algorithm. Our results of a logit quasi-likelihood model show that noninsurance is associated with higher probability of non-urgent visits and PCS visits when compared to private insurance. The predicted effect of insurance coverage under PPACA depends on the mixed structure of insurance types.

The fourth essay explores the determinants and effects of confidence on academic and labor market outcomes using a rich-informed nationwide survey of graduate Management Admission Test (GMAT) registrants. We discuss several ways to define and measure confidence. Our results suggest that many confidence measures differ by race, gender, observed ability and managerial experience. These confidence measures have some predictive power in eventual academic outcomes and more so for labor market outcomes.

TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 1

INTRODUCTION

This dissertation consists of four essays in applied microeconomics. The first three are in health economics and the fourth integrates economics of education and labor economics. Although each essay addresses different questions and employs various data to empirically analyze the issues and draw policy inferences, they are unified in that microeconomic theories and econometric methods are applied.

The first essay investigates the sensitivity of the U.S. hospital spending to the changes in income and how much of the estimated sensitivity is due to purchasing more care versus purchasing better care quality. Using 1999-2008 panel data of the 50 US states, we estimate and decompose the income elasticity of hospital care expenditure (HOCEXP) into its quantity and quality components. Results from the seemingly unrelated regressions estimation (SUR) model reveal the income elasticity of HOCEXP to be 0.451 (std. error=0.044), with about 0.325 (calculated std. error=0.040) of this due to quality improvements and 0.127 (std. error=0.051) coming from the rise in quantity (or usage volume). Our novel research results suggest that: (a) a greater share of the income-induced rise in hospital care spending has more to do with changes in care quality than quantity; (b) the 0.451 income elasticity of HOCEXP, the largest share of total US health care expenditures, makes hospital care a normal good and a much stronger technical necessity than the aggregate healthcare commodity.

The second essay addresses similar questions on the next important category of health care spending, physician and clinical service expenditure (*DOCLNEXP*). While the same research methodology is used in this essay as the first, the lack of state-level quantity measure requires a different approach to estimate the quantity elasticity. In this case, we first estimate the income and quality elasticity to derive the quantity elasticity using the relationship which exists among them. The seemingly unrelated regressions (SUR) model estimation based on 1999-2008 U.S. state level panel data suggests that the income elasticity of *DOCLNEXP* is 0.743 (std. err.=0.043) with 0.524 (std. err.=0.126) due to quality improvement (measured by the ratio of registered nurses to licensed practical nurses) and 0.219 (calculated std. err.=0.127) arising from quantity usage expansion. Our study findings suggest that the physician and clinical services expenditure rise has more to do with quality than quantity change. The results mimic the literature indicating that the income elasticity of a health care expenditure component may rise with incomes, and physician and clinical services are a normal good and a technical necessity at the state level.

The third essay analyzes the effect of insurance coverage on the likelihood for an emergency department (ED) visit being non-urgent or primary-care-sensitive. Following an ED classification algorithm, we are able to define and derive these likelihoods. We then construct a logit quasi-likelihood model and test it using a statewide hospital outpatient discharge database. Based on the regression results, we further explore how the Patient Protection and Affordable Care Act (PPACA) on the mandates of insurance coverage would affect the likelihood under two scenarios. Our results show that, noninsurance is associated with higher probability of non-urgent visits and higher probability of primary-care-sensitive visits, relative to private insurance. The predicted effect of insurance coverage under PPACA depends on the mixed structure of insurance types. A brief discussion about the impact on ED expenses is also provided.

Finally, the fourth essay explores the determinants and effects of confidence and non-cognitive attributes on academic and labor market outcomes. Drawing evidence from a nationwide survey of Graduate Management Admission Test (GMAT) registrants, this paper addresses the following questions: 1) what make some of these MBA pursuers more confident than others, and 2) whether confidence among MBAs has any impact on academic performance and labor market outcomes. We first discuss several ways to define and measure confidence based on the richness of the survey data. We then present a set of confidence-determination regressions and academic and labor market outcome regressions using different confidence measures. Our results suggest that many confidence measures differ by race, gender, observed ability and managerial experience. Controlling for actual test scores, expectations of verbal test performance are negatively related to later earnings and job satisfaction. Initiative is strongly positively associated with earnings and job satisfaction. Confidence in one's ability to delegate tasks is positively associated with MBA attainment, but negatively associated with obtaining an MBA from a top ranked program. An overall indicator of confidence predicts positive effects on almost all labor market outcomes.

CHAPTER 2

QUALITY-QUANTITY DECOMPOSITION OF INCOME ELASTICITY OF U.S. HOSPITAL CARE EXPENDITURE USING STATE-LEVEL PANEL DATA[1]

1. Introduction

The US national health care expenditures (HEXP) have risen substantially over the past decades. Although its growth rate slowed during the 2007-2009 economic recession and the currently early recovery phase of the business cycle, total HEXP in 2010 surprisingly reached $2.6 trillion and accounted for 17.9% of the GDP, or $8,402 per person. The persistently high US per capita health care expenditure remains the largest for any country in the world. Despite several decades of multi-pronged policy interventions that target cost containments and quality improvements, healthcare economics investigations on the determinants of HEXP and the roles that the multi-dimensioned care quality may play continue to proliferate for their potential implications for policy.

Among the large number of work in this area, publications on the determinants of HEXP debating the magnitude and inference on the nature of the healthcare good from the estimated income elasticities account for a large part of the discussions. While the income elasticity of HEXP has important policy implications, the current investigation advances beyond estimation of the income elasticity by estimating a parsimonious model for decomposing the elasticity of hospital healthcare expenditure, the largest component of total US healthcare spending, into its quantity and quality aspects. The decomposition

[1] I am very grateful to Dr. Albert A. Okunade for his continuous guidance in the completion of this paper. I am further grateful to conference participants at the 2013 annual meetings of Midwest Economics Association (Columbus, Ohio) and seminar participants at the University of Memphis, Economics Department for useful comments on earlier versions of this paper. However, I take full responsibility for any remaining errors.

idea was inspired by a classic work (Hicks and Johnson, 1968) in agricultural economics on the nature of the income elasticity of food demand. There, the authors use a simplified model to determine the composition of income elasticity of food expenditures in terms of quantity changes, measured as calories in the diet, and quality variations, measured as the ratio of calories from non-starchy foods to calories from starchy foods. Similarly, the quantity (i.e., volume) and quality of healthcare consumed could rise as incomes grow due to greater demand with population expansion and ageing and as the discovery and widespread adoption of innovative treatment technologies proliferate. Methodologically, we glean and modify further ideas from Engel curves modeling in agricultural economics on the relationship among expenditure, price, quality and quantity. Using a panel dataset of 50 US states on hospital expenditures for the 1999-2008 period, we propose in this study a two-equation, seemingly unrelated regressions (SUR) system for estimating the hospital expenditure model useful for decomposing the resulting income elasticity into its quantity and quality components.

Hospital care expenditure (*HOCEXP*), and not total HEXP predominantly studied in past research, is the current study focus for many reasons. First, the aggregate HEXP is a largely heterogeneous construct comprising expenditures on hospital care (inpatient and outpatient), physicians and clinical services, prescriptions, nursing homes, and others. The subcategories of HEXP exhibit different patterns of behavior (Sharma and Srivastava, 2011). In effect, estimates of income elasticities are likely to vary by expenditure category types and providers (Costa-Font et al., 2011). Second, the various expenditure sub-categories would require separate quantity (volume) and quality measures in order to properly decompose and obtain theoretically consistent and robust expenditure-specific income elasticities. Consequently, for a sound quality and quantity decomposition, focusing on a major expenditure category and using appropriate quality and quantity measures enhances the reliability and applicability of study findings. Finally, *HOCEXP* accounts for the largest share of the US total HEXP and the relevant data for econometric model estimation tend to be more readily available compared with those of the other components of the aggregate HEXP. During 2010, the US overall spending for hospital services reached $814.0 billion and accounted for 31.3% of total health spending and 5.6% of GDP. Given the continuing rise in HEXP, it is timely to investigate whether quality-based or quantity-based aspects of the growth in this major HEXP category should be policy targets for tighter cost containments. An additional rationale for focusing on *HOCEXP* is the recent (2012) US Supreme Court ruling upholding the constitutionality of the multiple provisions in the 2010 Affordable Care Act (ACA), most notably the individual mandate. Moreover, while the forced expansion of Medicaid was rejected, it left the door open for states to voluntarily participate. While initially resisting the expansion, many states have recently begun to alter that stance and are exploring policy options that would broaden health care access for a greater share of their low-income earners. The expanding insurance coverage is projected to significantly reduce uncompensated hospital care and thus favors hospitals and portends growths in *HOCEXP* for years to come. Full implementation of the 2010 ACA in the US is expected for 2014.

To our knowledge, this current study represents the first attempt to decompose the income elasticity of *HOCEXP* into its quality and quantity components. The US hospital sector is dominated by not-for-profit providers whose utility maximizing behavioral tendencies depend on the amount of quantity and quality of care provided, subject to a constraint (Newhouse, 1970). Today, the hospital sub-sector continues to play a central role in health systems across all countries (Sloan and Hsieh, 2012). Since healthcare economics research touching on quality and value are at the core of policy reform efforts for providers, payers, and consumers the income elasticity of *HOCEXP* estimation and decomposition strategy advanced and implemented here has replication potentials for investigating the other components of aggregate healthcare (and non-health commodity) expenditure for which quality progression occurs in tandem with quantity expansion as incomes rise. The rest of this paper proceeds as follows. Section 2 reviews the literature, Section 3 motivates the theoretical model and empirical strategy along with the data for estimating income elasticity and its quality-quantity decomposition, Section 4 focuses on the estimation results, and Section 5 concludes with the study summary and implications.

2. Literature Review

2.1. Income elasticity of healthcare expenditures

Dating back to the seminal paper by Newhouse (1977), income is consistently one of the core determinants of aggregate healthcare expenditure. The income elasticity of HEXP is important because of its policy implications for whether the healthcare commodity is a technical necessity or luxury. The magnitude of income elasticity of HEXP would differ, depending on the data aggregation level being modeled. Getzen (2000) contends that individual data income elasticities are close to zero while national HEXP elasticities are commonly greater than one. The intuition is that health status plays an important role in individual healthcare spending while this effect attenuates at the macro levels. Moreover, Paluch et al. (2012) indicate that the aggregate elasticity can be very different from the mean of individual elasticities. The difference would depend on the heterogeneity of the population and is quantified by a covariance term, and the magnitude of this difference varies from commodity to commodity.

Even at the same data aggregation level, the income elasticities can be very different depending on other attributes of the data and research methodology. This is the case for empirical papers using state level data. Surprisingly, the estimated state-level income elasticities of HEXP in the existing literature range from near 0 to 1 or more (Di Matteo, 2003). Ringel et al. (2002) and Chernew and Newhouse (2012) claim that studies using long time series or panel data tend to report higher income elasticities. In general, the reported income elasticity estimates in past studies appear sensitive to the data structure (cross-sectional, time-series, panel), regression model specification (functional forms, included and excluded independent variables) and the model estimation methods. Costa-Font et al. (2011) recently use bias-corrected meta-regression analysis to cast doubt on the luxury goods hypothesis in aggregate data models. The meta-regression study places robust estimates of income elasticities of HEXP in the 0.4 to 0.8 range.

Published studies on the numerical magnitude of the income elasticity of *HOCEXP*, the largest component of *HEXP* in the US, are extremely rare. Acemoglu et al. (2011) estimates the income elasticity of *HOCEXP* by instrumenting for local area income with time-series variation in global oil prices interacted with cross-sectional variation in the oil reserves in different areas of the Southern US. The estimated state-level income elasticity using GSP (Gross State Product) as income and for the whole US geographic sample is 0.568. Newhouse and Phelps (1976) estimate the US income elasticity of hospital care utilization at the individual level. The wage income elasticity of length of hospital stay is roughly 0.10 using the two-stage least squares (2SLS) estimation method.

2.2. Quality in healthcare expenditures

Measuring healthcare quality is very difficult, because it is a multi-dimensional concept that encompassing contractable and non-contractable aspects (Sloan and Hsieh, 2012, 275:317). Although there is no lack of hospital-level or disease-specific quality measures, no single commonly accepted quality indicator is capable of capturing all of the many dimensions of care quality. Copnell et al. (2009) identify and classify 383 discrete indicators currently in use to measure the care quality provided by hospitals from 22 sources of organizations or projects. They find 27.2% of the indicators relevant hospital-wide, 26.1% to be applicable to surgical patients, and 46.7% to non-surgical specialties, departments or diseases. Processes of care were measured by 54.0% of the indicators and outcomes by 38.9%. Safety and effectiveness were the domains most frequently represented, with relatively few indicators measuring the other dimensions. They conclude that despite the large number of available indicators, significant gaps in measurement and implementations persist. Whether existing indicators measure what they purport to measure still needs to be evaluated.

There are various methods for eliciting proxies for quality measures in healthcare, including for hospitals (see, e.g., Newhouse, 1970; Akin et al, 1995; Grabowski, 2001; Jappelli et al., 2007; Schneider, 2008; Lichtenberg, 2011). Our paper follows the relatively less controversial method of modeling quality using the modified price. For most goods, high quality means a high cost or a high price. Quality is then measured in “money” terms. This conceptual method for modeling quality in economics literature (Sloan and Hsieh, 2012) is detailed in Section 3 of this study.

2.3. Other determinants of healthcare expenditures

Many studies affirm technological change as another primary determinant of healthcare spending growth (Chernew and Newhouse, 2012). The earliest paper on this is probably Schwartz (1987), who applies the Solow residual approach to healthcare spending growth. Newhouse (1992) comes to a similar conclusion after controlling for more non-technological factors and using data coverage of a longer time period. Smith et al. (2009) report that changes in medical technology explain 27- 48% of the US health spending growth since 1960. Peden and Freeland (1998) use the level of insurance coverage and non-commercial research spending as proxies for technology and attribute 70% of spending growth to changes in the medical technology. Okunade and Murthy (2002) use total R&D and health R&D spending interchangeably to proxy technological change and find significant and stable long-run relationship among per capita real HEXP, per capita real income and broad-based R&D expenditures. More recent papers usually include time trends or year fixed-effects in their regression equations to control for technological change.

The generosity of health insurance coverage also encourages healthcare spending growth. A commonly used control for insurance is the percentage of insurance types in the model. Other explanatory variables include supply-side controls, such as the number of hospital beds, health maintenance organization (HMO) penetration rate, population health status), demographic characteristics (age, gender, ethnicities) and regional factors. More recent papers further include health risk behaviors among the determinants of healthcare spending. Rising obesity rates are shown to be linked to the rise in medical care spending (Finkelstein et al., 2009). Lichtenberg (2011) and Cuckler et al. (2011) include prevalence of obesity and smoking in their models. Lichtenberg finds these two do not appear to influence per capita medical expenditures, however. Interestingly, Cuckler et al. (2011) use the product of the two factors and find its significant effect on healthcare spending. Our current study includes covariates controlling for many of the factors discussed above.

2.4. Decomposing the income elasticity of hospital care expenditure

A comprehensive literature search confirms the lack of studies decomposing the income elasticity of total healthcare expenditure or of its sub-categories into quantity and quality components. However, there are few studies decomposing the expenditure elasticity (with respect to income or other determinants) for commodities other than healthcare. Hicks and Johnson (1968) estimate the quantity and quality components for income elasticities of demand for food using country level cross-sectional data. They use calories in the diet as the quantity measure, and the ratio of calories from non-starchy foods to calories from starchy foods as the quality measure. Moreover, other studies in agricultural economics literature on Engel expenditure curves (e.g., Deaton, 1988; Bils and Klenow, 2001; Gale and Huang, 2007) also yield some insights into modeling the relationship between expenditures and income through price, quality and quantity effects. Archibald and Gillingham (1981) study the decomposition of price and income elasticity of demand for gasoline. Gertler (1985) performs a similar analysis for Medicaid nursing homes. Each nursing home in his paper is solving the optimization problem, and the derived first order condition is then used to perform the decomposition.

Some past studies decomposed healthcare spending into components different from our current study. For example, Bradley and Kominski (1992) decompose the change in average Medicare inpatient costs per case between 1984 and 1987 into input price inflation, changes in costs with diagnostic related groups (DRGs), and changes in case mix across DRGs. Their technology effect is nested in the distribution of cases across DRGs. Bundorf et al. (2009) and some other investigators decompose the health spending growth into quantity growth and price changes. The quality change in these models is presumably excluded or captured using price changes. Our paper innovates by integrating ideas from past work outside of health economics and modifying them for application to the healthcare sector in the specific context of the US hospital healthcare expenditures.

3. Empirical strategy and data

3.1. Motivating the decomposition model

Our modified income elasticity of *HOCEXP* decomposition model is inspired by the agricultural economics literature on Engel curves (Deaton, 1988; Bils and Klenow, 2001; Gale and Huang, 2007) and food demand (Hicks and Johnson, 1968) models.

We start in Eq. (1) with the identity that expenditures on hospital care *HOCEXP* is equal to price P times the quantity Q.

$$\boldsymbol{HOCEXP \equiv P \cdot Q} \tag{1}$$

Quantity Q represents the volume of purchased hospital services, including inpatient and outpatient services. In the empirical part, Q is measured as adjusted inpatient days (that is, inpatient days adjusted higher to reflect an estimate of the volume of outpatient care services). P is an average price paid for all hospital services used, or a unit value (the ratio of expenditures to quantity purchased). We follow existing literature on Engel curves and assume that "quality" comes into play through the unit value P, i.e., different quality level (due to the heterogeneity of hospital services) would result in different unit values. The unit value can increase either because prices of items in a fixed basket rise or because different and better quality (usually more expensive) items are now in the basket. The former is due to a "pure" price effect, and the latter is because of a shift in the composition of services towards premium services. We model this relationship using Eq. (2), which states that the unit value is the product of price of a fixed basket of services and quality. Denote the price of a fixed basket of hospital services as P_f and hospital quality of care as v. We can also interpret it as a base price adjusted by quality. The official price indexes produced by the US Bureau of Labor Statistics (BLS) are indexes such as this (see, Aizcorbe and Nestoriak, 2011) and is thus, used in our empirical modeling.

$$P = P_f \cdot v \tag{2}$$

Plugging Eq. (2) into the *HOCEXP* Eq. (1), one obtains

$$HOCEXP = P_f \cdot v \cdot Q \tag{3}$$

HOCEXP, v, and Q tend to change as income changes. Thus, *HOCEXP*, v and Q are functions of income y. Over a long period of time, the fixed basket price P_f could be correlated with income too, so P_f is also assumed to be a function of y. In empirical application, this study also controls for factors other than income that affect the four variables above. Denote a vector of such factors as X and X=(X_p, X_v, X_Q), where X_p, X_v

and X_Q represent the factors that affect P_f, v and Q respectively. *HOCEXP* equation can be rewritten as

$$HOCEXP(y, \mathrm{X}) = \mathrm{P}_f\left(y, X_p\right) \cdot v(y, \mathrm{X}_v) \cdot Q\left(y, \mathrm{X}_Q\right) \tag{4}$$

Taking the logarithm of both sides of the equation gives

$$\ln HOCEXP(y, \mathrm{X}) = \ln P_f(y, X_p) + \ln v(y, \mathrm{X}_v) + \ln Q(y, \mathrm{X}_Q) \tag{5}$$

Or,

$$\ln \frac{HOCEXP(y,\mathrm{X})}{P_f(y,X_p)} = \ln v(y, \mathrm{X}_v) + \ln Q(y, \mathrm{X}_Q) \tag{6}$$

The left-hand-side in Eq. (6) is simply the log of hospital expenditures adjusted by price index of a fixed basket of hospital care services.

The rationale for moving $P_f(y, X_p)$ to the left-hand side is that: (1) combining *HOCEXP* and P_f into one variable *HOCEXP*/ P_f gives a relation of elasticities among three variables rather than four; (2) the quality elasticity may be derived if the adjusted expenditure elasticity and quantity elasticity are known. If $P_f(y,X_p)$ remains on the right-hand side, there exists the need to estimate one more equation to solve out the quality elasticity, but the requisite data on P_f are not available at the state level.

Taking the derivative of Eq. (6) with respect to ln y on both sides, the income elasticity of adjusted hospital care expenditure has two components:

$$\frac{\partial \ln \frac{HOCEXP}{P_f}}{\partial \ln y} = \frac{\partial \ln V}{\partial \ln y} + \frac{\partial \ln Q}{\partial \ln y} \tag{7}$$

Denote the income elasticity of adjusted hospital care expenditure as ε. It would be the sum of the quality elasticity θ, and the quantity elasticity η. In other words,

$$\varepsilon = \theta + \eta \tag{8}$$

Consequently, if the expenditure and quantity elasticities are known, the quality elasticity is then the difference between them, as follows

$$\theta = \varepsilon - \eta \tag{9}$$

This study empirically models $\frac{HOCEXP}{P_f}(y, \mathrm{X})$ and Q (y, X_Q) in order to estimate the expenditure and quantity elasticities. Following, the quality elasticity is derived as in Eq. (9). Since quality measures of aggregate state level hospital care are either controversial or unavailable for long enough periods, this approach provides an alternative to directly measuring and estimating the quality equation while still capturing the quantity and quality components of the income elasticity of hospital care expenditure.

3.2. Empirical model

First established are the empirical models for $\frac{HOCEXP}{P_f}(y, \mathrm{X})$ and Q (y, X_Q) to estimate the expenditure and quantity elasticities.

For simplicity, functions $\frac{HOCEXP}{P_f}(y, \mathrm{X})$ and Q (y,X_Q) take the following forms:

$$\ln\frac{HOCEXP_{it}}{P_{f_t}} = \alpha_0 + \alpha_1 \ln y_{it} + \alpha_2 \mathrm{X}_{it} + \mathrm{e}_{it} \tag{10}$$

$$\ln \mathrm{Q}_{\mathrm{it}} = \beta_0 + \beta_1 \ln \mathrm{y}_{it} + \beta_2 X_{it}^{Q} + \mathrm{u}_{it} \;, \tag{11}$$

where X_{it} denotes a vector of other control variables for adjusted *HOCEXP* of state *i* in year *t* and X_{it}^{Q} represents other control variables for quantity of hospital care of state *i* in year *t.* In our empirical regression model estimation, X_{it} includes controls for state level health care market characteristics such as hospital capacity, percentage of government owned hospitals; demographic structures, such as population percentage of age 65 and above; health insurance coverage, such as percentage of the uninsured and percentage of Medicaid enrollees; HMO penetration rate; health status of the population, measured by bad health index (defined as smoking rate*obesity rate); and time effects measured by time trend and its time square. X_{it}^{Q} includes covariates that are slightly different from X_{it}. Percentage of government owned hospitals is excluded from Eq. (11) because this market organization measure more likely relates to total expenditure. It is less likely to find any direct link between percentage of public hospitals and adjusted inpatient days.

The price index, P_f, here measured by consumer price index of hospital and related services from BLS, is only available at the national level, so there is no variation for state *i* but only in time t. The error terms e_{it} and u_{it} may be dependent. We therefore, use the seemingly unrelated regressions (SUR) method for joint estimation of the equations and conduct the independent errors test for the model using the Breusch-Pagan procedure.

A possible concern in estimation is potential for reverse causality between the left-hand side variables and some covariates. Greater hospital services use may improve population health outcomes. So, higher *HOCEXP* and *Q* may lead to better behavioral health (e.g., lower smoking rate and obesity rate). Moreover, healthier population can be more productive and earn higher incomes. So, higher *HOCEXP* and *Q* are also likely to increase income. To address this potential endogeneity issue, one-year lag terms of income[2] and bad health index are used in the regression since greater current utilization of hospital services will only affect current or future health outcomes and incomes.

3.3. Data and descriptive statistics

The panel dataset for this study combines published data from several sources. Since many of the relevant state level data only became available relatively recently while some previously available data do not cover more recent years, the final sample period covered by the regression model is from 1999 to 2008 for the 50 US states. Due to few missing values for some states a total of 482 observations are used in the final regression analysis.

HOCEXP

HOCEXP is a major sub-category of personal *HEXP* from the Centers for Medicare &Medicaid Services (CMS). The measure covers all services hospitals provided to the patients. These include room and board, ancillary charges, services of resident physicians, inpatient pharmacy, hospital-based nursing home and home healthcare, and any other services billed by hospitals in the US.[3] The state level *HOCEXP* used here is measured by the state of residence.

[2] We also experimented with using two-year and three-year lag terms for health status measures, but the results do not differ much. In the regressions presented in Table 2, only one-year lag terms are used.

[3] The value of hospital services is measured by total net revenue, which equals gross patient revenues (charges) less contractual adjustments, bad debts, and charity care. It also includes government tax appropriations as well as non-patient and non-operating revenues.

Income

Income is measured as per capita personal income in each state from Bureau of Economic Analysis (BEA). It is then deflated by the national consumer price index (CPI) into 2005 dollars. Alternative income measures (e.g., gross state products and median household income) and price deflators (e.g., gross domestic products deflator and price index for personal consumption expenditures) were also considered. However, their econometric model estimates do not significantly differ from those arrayed in Table 2.

Fixed basket price index for hospital care

Given the theoretical model proposed in the previous section, a price index for *HOCEXP* based on a fixed basket of hospital services is needed. Ideally, it only reflects the "pure" inflation but not the quality change. The index allows us to disentangle the effect of quality change from inflation. In literature discussing the health expenditure price index (Aizcorbe and Nestoriak, 2011), a fixed basket price index is also called service price index (SPI). It answers the question "What would expenditures be today if patients received the same services today as they did in the past?" By design, it does not take into account the effect on expenditures from shifts in the utilization of goods and services in treating medical conditions. It is commonly acknowledged that the price index on hospital and related services developed by BLS is a fixed basket price index. Therefore, this price index is used to adjust *HOCEXP*.

Quantity measure

Quantity Q is measured by adjusted inpatient days. It is derived from dividing total hospital expenditure[4] by adjusted expenses per inpatient day. The data of hospital

[4] State hospital expenditure by providers is used because the quantity measure is also by providers.

adjusted expenses per inpatient day comes from the Kaiser Family Foundation's website *Statehealthfacts.org*[5]. The original data sources are the Hospital Statistics books published by the American Hospital Association. According to their definition of adjusted inpatient days, it is an aggregate figure reflecting the number of inpatient days plus an estimate of the volume of outpatient services expressed in units equivalent to an inpatient day in terms of level of effort.

Supply side characteristics

The estimated models include controls for market organization, such as percentage of hospitals owned by the government (number of public hospitals over number of hospitals of all types). Number of hospital beds is included as hospital capacity control. All data are for community hospitals[6], representing 85% of all US hospitals. The data source for these characteristics is s*tatehealthfacts.org* (Kaiser Family Foundation).

Demand side characteristics

One demographic control utilized is percentage of population age 65 or older. The original data of total population and the population of individuals age 65 or older are from the population estimates released by the US Census Bureau. Also, health insurance and managed care status are controlled for by including percentage of the uninsured

[5] http://www.statehealthfacts.org/comparemaptable.jsp?ind=273&cat=5, Jan 1, 2013.

[6] Community Hospitals are defined as all nonfederal, short-term general, and specialty hospitals whose facilities and services are available to the public. Federal hospitals, long term care hospitals, psychiatric hospitals, institutions for the mentally retarded, and alcoholism and other chemical dependency hospitals are not included.

population, percentage of Medicaid enrollees[7], and HMO penetration rate. The uninsured population data are taken from the U.S. Census Bureau. The number of Medicaid enrollees and HMO data are from s*tatehealthfacts.org* (Kaiser Family Foundation).

Further, the models include a health risk behavior variable—bad health index—to control for smoking and obesity, as in Cuckler et al. (2011). It can also be interpreted as a behavioral related health status index. Formally, it is defined as the smoking rate times the obesity rate in each state (value adjusted into a percentage)[8]. The smoking and obesity rates data are from the Prevalence and Trends Data of the Behavioral Risk Factor Surveillance System (BRFSS). Finally, the District of Columbia (DC), an outlier in personal income, is excluded from our analysis. Table 1 presents the descriptive statistics of the major variables in the estimated model.

4. Empirical estimation results

4.1. Model estimation

In order to obtain the income elasticity of *HOCEXP* and quantity component elasticity, we need to estimate Eqs. (10) and (11). Since the key variables are already in the log form, the coefficient of income in each equation gives the elasticity directly. According to Eq. (9) in our theoretical model, the quality elasticity can then be derived by subtracting the quantity elasticity from income elasticity.

[7] Percentage of Medicare enrollees is not included because it could be a duplicate of the share of population age 65 or older.

[8] We also attempted to keep the smoking rate and obesity rate as two separate variables, but obesity rate is highly correlated with time trend. Therefore, we used the less problematic bad health index as one measure that combines both the obesity and smoking rates.

Table 1

Descriptive statistics (N=482)

Variable	Mean	Std. Dev.
Adjusted *HOCEXP*	2098.638	306.007
Income	33373.41	4940.383
Adjusted inpatient days	1.498378	0.521062
% Public hospitals	0.222947	0.176851
Beds	2.994282	0.936017
% Age 65+	0.126442	0.017773
% Uninsured	0.147687	0.038291
% Medicaid	0.132439	0.042638
HMO penetration rate	0.202561	0.123626
Bad health index	0.0493191	0.0121651

Note: The descriptive statistics are based on non-missing values between 1999 and 2008. Total observations used in the regression are 482. Adjusted *HOCEXP* is per capita hospital care expenditure deflated by CPI of hospital and related services (2005=100). Income is per capita personal income deflated by CPI (2005=100). *Adjusted* inpatient days are in per capita term. Hospital beds are per 1,000 of the population. %Public hospitals, % Age65+, %Uninsured, %Medicaid and HMO penetration rate are all in decimals. The summary statistics for income and bad health index are for the one year lag terms used in the empirical regressions model estimation.

When estimating the two equations, it is expected that the error terms would be correlated. Therefore, seemingly unrelated regression (SUR) is applied to jointly estimate both equations. SUR generates more efficient parameter estimates compared to OLS under the assumption of cross-equation error correlation. This assumption is then tested by the Breusch-Pagan test of independence in the end of the regression table. The SUR estimator is performed in STATA with the iteration option[9]. Under SUR, this iteration converges to the maximum likelihood results. These estimates are arrayed in Table 2.

According to the regression results of Eq. 1, the highly statistically significant and positive income coefficient estimate indicates the income elasticity to be 0.451. (Its implications are discussed in more detail in section 4.2.) The share of public hospitals tends to be negatively associated with adjusted *HOCEXP*. One reason could be that more than half of the services provided by public hospitals were for low-income patients, and public hospitals operate at a lower margin and higher rate of uncompensated care compared to all hospitals nationally (Zaman et al, 2010). Moreover, in the Sloan et al. (2001) study on Medicare enrollees "for-profit hospitals were more expensive to Medicare." Third, one more possibility for the share of public hospitals to reduce *HOCEXP* is their differential effects on hospital sector efficiency. Ozcan et al. (1992) use a national database of urban hospitals and discover that government hospitals more consistently performed in the technical efficient category compared to for-profit hospitals. This efficiency translating into production cost savings can potentially translate to reduction in *HOCEXP*. The effect of hospital capacity, measured by hospital beds, is positive and significant, which could imply the presence of induced demand.

The percentage of population age 65 and older also has the expected positive sign. As it is commonly observed that health care spending during the last few years of life accounts for a large share of the total health care spending in one's entire life, it naturally follows that states with greater proportion of the elderly residents tend to have higher

[9] It iterates over the estimated disturbance covariance matrix and parameter estimates until the parameter estimates converge.

Table 2

Seemingly Unrelated Regressions (SUR) model estimation of *HOCEXP*

	Coef. Est.		Std. Err.	Adj. R^2	χ^2
Equation 1					
log of adjusted *HOCEXP*				0.5629	615.72
log of income $_{t-1}$	0.45127	***	0.04404		
% public hospitals	-0.07266	***	0.024543		
beds	0.073042	***	0.006697		
% 65 years +	1.513859	***	0.342656		
% uninsured	-0.79299	***	0.134127		
% Medicaid	0.897665	***	0.120114		
HMO rate	-0.22496	***	0.054221		
Bad health index $_{t-1}$	1.704504	***	0.471883		
time trend	-0.01257	*	0.007289		
time trend squared	0.0004		0.000618		
constant	2.554453	***	0.468609		
Equation 2					
log of adjusted inpatient days				0.8784	3483.22
log of income $_{t-1}$	0.126731	**	0.05049		
beds	0.297229	***	0.007685		
% 65 years +	0.379322		0.382437		
% uninsured	-1.49329	***	0.153429		
% Medicaid	0.468759	***	0.137954		
HMO rate	-0.28845	***	0.060194		
Bad health index$_{t-1}$	-0.71712		0.541874		
time trend	0.03225	***	0.008346		
time trend squared	-0.00113		0.000709		
constant	-1.79066	***	0.536423		
Derived quality elasticity	0.32454				
Correlation coef. of residuals	0.5810				
Breusch-Pagan test	χ^2=162.691	(Pr.=0)			

Note:

1. Statistical significance level: *:10%, **: 5%, ***:1%.
2. Number of observations in both equations is 482.
3. The calculated standard error of derived quality elasticity is 0.044.
4. The two equations are jointly estimated using SUR. The correlation coefficient of residuals and Breusch-Pagan test of independence confirms the dependence of the two equations.

HOCEXP.[10] Proportion of population without insurance is negatively related to *HOCEXP* whiles percentage of Medicaid enrollees has a positive effect. Uninsured people are likely to limit their own health service use in order to save medical cost. Medicaid enrollees, on the other hand, tend to suffer from the moral hazard problem in which more health service use is encouraged given the low cost. The coefficient of HMO penetration rate shows the effect of managed care on cost saving. The bad health index is positively associated with *HOCEXP*, which means the higher obesity rate or smoking rate the higher the *HOCEXP*, which is as expected. The estimated parameters of the time trend effects are not statistically significant at the 5% level.

The estimation results for Eq. 2 also return a positive and statistically significant income coefficient. The quantity elasticity estimate of 0.127 is as expected numerically smaller than the estimated income elasticity. (Section 4.2 discusses quantity component elasticity further.) The elderly population share and bad health index each has the expected sign but are not significant in Eq. 2. The same as the result of Eq. 1, number of hospital beds has a positive and significant effect, uninsured proportion has a negative and significant effect and Medicaid share and HMO penetration rate have positive and significant effects on the quantity of hospital care used. The time trend and its squared terms have the expected signs. They indicate that the quantity of hospital services tends to rise at an insignificantly decreasing rate over time.

The adjusted R^2 values signal that each of the two equations has a reasonably good fit to the data, and the χ^2 statistic signals the regressions to be jointly significant. The Breusch-Pagan test is also conducted to test the independence of the two equations.

[10] As in Shang and Goldman (2008), we also experimented with 'life expectancy'. While the resulting estimates of the income elasticity of hospital care expenditure (*HOCEXP*) are similar, the model with the population aging factor and bad health index fare is slightly better.

The correlation coefficient of the residuals from the two jointly estimated equations as well as the χ^2 statistics suggests rejecting the independence of the errors hypothesis.

4.2. Estimates of income elasticity and its quantity/quality components

From the SUR system estimates of the Eq. (1) in Table 2, the highly statistically significant income elasticity of adjusted *HOCEXP* estimate of 0.451 (*std. error*=0.044) implies that a 10 percent rise in real per capita income would tend to increase adjusted *HOCEXP* by 4.51 percent. There are extremely few past studies focusing on the hospital expenditure sub-category (*HOCEXP*) of the total healthcare spending (HEXP) for comparison, and none focused on decomposing the income elasticity into its quality and quantity aspects. One recent study on the determinants of US hospital care expenditure (Acemoglu et al. 2011) reports an estimated income elasticity of 0.568 (*std. error* =0.263) based on using state-year observations for the entire US geographic sample. Despite differences in the methodological approaches of the Acemoglu et al.'s study (1970-1990, US state-level data) and our investigation (1999-2008, US state-level data), the numerical magnitude of the difference in the estimated income elasticities of *HOCEXP* is surprisingly small. As earlier discussed in this paper, a longer data span (e.g., as in Acemoglu et al.) would tend to yield a higher income elasticity estimate.

Comparing our study's income elasticity of *HOCEXP* with those of past studies on total HEXP using aggregated data can be interesting. Past study estimates range widely from $\cong 0$ to significantly greater than 1. Costa-Font et al. (2011) use a meta-regression analysis to control for publication selection and aggregation bias and find the corrected estimates to range from 0.4 to 0.8. Our estimate, based on modeling the *HOCEXP* sub-category data, falling in the lower portion of this bound suggests that hospital care is both a normal good and more of a stronger necessity than aggregated healthcare (HEXP) as a commodity. Moreover, our study's highly significant quantity component of the *HOCEXP* income elasticity is 0.127 (*std. error*=0.051) and it represents a smaller share of the entire 0.45 estimated income elasticity of *HOCEXP*. That is, a 10 percent rise in real per capita income can be expected to induce a 1.27 percent increase in adjusted inpatient days (quantity), all else equal.

The implied (see, Eq. 9) estimate of the quality elasticity component of the income elasticity of *HOCEXP* is 0.325 (calculated *std. error*=0.040[11]), the difference between the 0.451 income elasticity and the 0.127 estimated quantity elasticity component. This suggests that, all else equal, a 10 percent increase in real per capita income would tend to raise purchased hospital care quality by 3.25%. Caution, however, that healthcare "… quality is a multi-dimensional concept that incorporates the ability, effort, and time that physicians spend in making a diagnosis and providing treatment, as well as various attributes of the delivery of health services, such as attentiveness, care, and diligence." (Sloan and Hsieh, 2012, p. 279). Moreover, technological sophistication is a core distinguishing attribute of hospitals (ibid, p. 220). Therefore, since heterogeneities characterize hospital care quality and their technological imperatives, it is conceptually challenging to disentangle and isolate their effects. Surprisingly, the 0.325 implied quality portion of the estimated income elasticity of hospital care expenditure model here mimics the 0.323 upper bound estimate of the contribution of technological progress to the rise in US healthcare costs reported in Abrantes-Metz (2012).

[11]Given $\theta=\varepsilon-\eta$ in equation (9), the standard error of the quality elasticity is derived based on $Var(\theta)=Var(\varepsilon)-2cov(\varepsilon,\eta)+Var(\eta)$.

The highly statistically significant estimates of the US income elasticity of hospital healthcare spending and its quality and quantity components in the present study suggest that a greater proportion of the increase in *HOCEXP* induced by a rise in real income is driven by more of the quality than quantity purchase. One rationale is that the opportunity cost of hospital healthcare (e.g., lost work productivity, foregone leisure, etc.,) tends to rise with higher real incomes. Therefore, rational economic actors in the aggregate would prefer to purchase more improved care quality than quantity in order to reduce treatment durations or speed up recovery time to targeted health outcomes. Second, it may further be hypothesized that, due to the US experiencing "flat of the curve" medicine, the quality /technology upgrades yield a greater "bang-for-the-buck" than the quantity increases.

5. Summary discussion and implications

This study is innovative in several dimensions. First is using the most currently available panel data of the 50 US states and a SUR equations system to estimate an econometric model of the determinants of hospital healthcare expenditure, the largest component of the US aggregate healthcare spending. Second, for the first time in this line of work we successfully decomposed the US income elasticity of hospital care expenditure into its quantity and quality components with the goal of providing estimates for benchmarking the implications for hospital cost containment policies in the context of the expansion of hospital care coverage following the full implementation of the 2010 US healthcare law.

Using 1999-2008 US state-level panel data, we estimate the relations among adjusted hospital healthcare expenditures, quantity of care measure and real income using the SUR method. The variable measuring quantity is adjusted inpatient days that reflects the volume of both inpatient and outpatient services. Given the controversy on various quality measures for hospital care, we model it in a way that no quality measure needs to be explicitly specified. Instead, income and quantity elasticities are first estimated and the quality elasticity is then derived as the difference between the two. Pure price effect is also controlled for in the model by introducing the price index of a fixed basket of hospital services, measured by CPI in hospital and related services. The estimated income elasticity is about 0.451 (*std. error*=0.044), and the quantity elasticity is about 0.127 (*std. error*= 0.051). The derived quality elasticity is about 0.325 (*std. error*=0.040). Our study findings reveal that a significantly larger share of hospital care expenditure rise has more to do with quality than quantity of care purchases as income grows. This finding is consistent with the theory that the income elasticity of (a major component of) health care spending can be expected to rise with income and that hospital care is both a normal good and a stronger technical necessity than the aggregate healthcare commodity, using a panel data of the US states.

One of the study policy implications is that, as the economies of the US states grow, demand for higher quality hospital care is expected to outpace the rise in the volume (or quantity) of care. This is consistent with the recent commentary in Dubois et al. (2012) that the US healthcare economy is evolving from volume-based (quantity) to value-based (quality and cost) to achieve the triple goal of better healthcare for individuals, improved health for populations and slower cost growth. As a consequence, hospitals and their regulators at the state level might consider strategies that consistently target reimbursable cost-containing quality improvements and produce services more efficiently as the quantity of hospital care demanded (volume) is poised to also grow with the implementation mandates of the 2010 Affordable Care Act.

CHAPTER 3

DECOMPOSING THE U.S. INCOME ELASTICITY OF PHYSICIAN AND CLINICAL SERVICES EXPENDITURE INTO QUANTITY AND QUALITY COMPONENTS[1]

1. Introduction

The number of physician office visits shows a declining trend for the recent recessionary years[2]. The uninsured reduced their frequency and intensity of physician office visits and clinical services. Healthcare quantity and quality consumed would tend to fall as income declines. Just as what some physicians noticed,[3] patients presenting at doctor offices tend to ask about less costly treatment options. This paper investigates the responsiveness of the physician and clinical services expenditure to an income change using 1999- 2008 panel data of the 50 U.S. states, and partitions the income-induced expenditure change into quantity and quality components. Specifically, as income changes how much of the change in *DOCLNEXP* is due to quantity fluctuation and how much is attributable to quality variation? We seek an answer this question by constructing a model describing the relationship among *DOCLNEXP*, income, quality and quantity of physician and clinical services, and estimate them in a seemingly unrelated regression (SUR) equations system.

---

[1] I am very grateful to Dr. Albert A. Okunade for his continuous guidance in the completion of this paper. I am further grateful to seminar participants at the University of Memphis, Economics Department for their useful comments on earlier versions of this paper. However, I take full responsibility for any remaining errors.

[2] See, IMS Institute for Healthcare Informatics report on The Use of Medicines in the United States: Review of 2010, 2011.

[3] See, http://www.ama-assn.org/amednews/2012/04/23/bisb0423.htm, on “Physicians feeling pressure from patients’ financial problems.”

DOCLNEXP is the second largest expenditure component (after hospital care expenditure) of the aggregate healthcare expenditure (*HEXP*) and it accounts for 20.3% of the total in 2009[4]. Compared with the volume of research on prescription drugs and other components of *HEXP*, *DOCLNEXP* is surprisingly less well studied. Despite the wider scope, magnitude, and the gate-keeping importance of physicians and reimbursements for insured clinical services, an exhaustive literature search confirms that only few studies estimated the income elasticity of physician and clinical services expenditure. The estimates are mostly dated and differ across studies. Silver (1970) estimates the elasticity of physician expenses with respect to family income to be 0.85. Andersen and Benham (1970)'s estimate of the elasticity is 0.4. Fuchs and Kramer (1972) use 33 US. States' data in 1966 and estimates the income elasticity of expenditures for physician services to be 0.9. A more recent paper (Acemoglu et al., 2011), in an appendix, reports an estimate of 0.365 as the income elasticity of physician and clinical services expenditure. Past studies share the common finding of a positive elasticity estimate less than one, which suggests that physician and clinical services are a normal good and a technical necessity at the individual or aggregate state level data.

According to our knowledge, there is no study in existence that decomposes the income elasticity of *DOCLNEXP* into its quality and quantity components. The ongoing implementation of the 2010 Affordable Care Act (ACA, the US health care system reform) makes our current research idea more relevant and timely, as the expected health sector resource reallocation is projected to affect the quality and quantity mix in the physician and clinical services expenditure. As the implementation of the ACA unfolds,

[4]From FactStats Homepage of health expenditures. Oct 21,2012. http://www.cdc.gov/nchs/fastats/hexpense.htm.Orginal source is Health, United States, 2011, Table 128: http://www.cdc.gov/nchs/data/hus/hus11.pdf#128

the expanding insurance coverage would encourage greater use of physician and clinical services. On the supply side, however, the current and rising shortage of the healthcare providers, especially in primary care, may constrict health care access. Although the ACA aims to expand the number of primary care physicians by offering bonus incentives, it remains unclear whether the rise will be able to keep up with increased health care demand. A further concern on the quality of physician and clinical services is whether the impact of Medicaid expansion on physicians (e.g., from reduced reimbursement rates) would induce low care quality (e.g., in the form of shorter visits, less doctor face time and compromised care). Based on the US panel data, our study reveals that a significantly larger share of the income elasticity of *DOCLNEXP* is due to quality variation and a smaller share is due to quantity change. If this trend persists, an implication is that a focused target of the ACA should be on preventing care quality attrition under an expanded quantity of care regime.

Our modified income elasticity of *DOCLNEXP* decomposition model is inspired by the agricultural economics literature on Engel curves (Deaton, 1988; Bils and Klenow, 2001; Gale and Huang, 2007) and food demand (Hicks and Johnson, 1968) models. Hicks and Johnson (1968), for instance, use a simplified model to determine the composition of income elasticities of food expenditures in terms of quantity and quality changes. Similarly, the quantity and quality of health care expenditure could rise as incomes grow due to greater demand as population ages and demographic mix shifts and as the use of innovative treatment technologies proliferates. Moreover, the literature on Engel curve estimation provides a framework useful for modeling expenditures, price, quality and quantity. In our study, we combine and modify the related approaches and apply the seemingly unrelated regressions (SUR) method to estimate *DOCLNEXP* model (using 1999-2008 US panel data) for decomposing the income elasticity into its quantity and quality components.

Some of the challenges in performing a quantity-quality decomposition of the income elasticity of *DOCLNEXP* include choosing a suitable quality measure and finding appropriate quantity data at the state level for the sample years. While there is no consensus on the best measure of the quality of physician and clinical services,[5] we differentiate such services in terms of the human capital embodied in the different health care workers. More specifically, registered nurses (RNs) have about twice as many years of training as the licensed practical nurses (LPNs). Therefore, healthcare services requiring RN skills are taken as involving improved care quality. The quality proxy used in this study is the ratio of number of RNs to the number of LPNs. The greater the ratio is, the higher the level of skills mix (higher quality) entailed in the medical care process. Over the sample years, employments of the RNs and LPNs implicitly reflect the demand for their differentiated services. It may also correlate with the differentiation of the demand for physician and clinical services in other dimensions. For example, physician offices that hire more RNs than LPNs may also use more advanced medical devices in practice. Basically, if there is a "true" quality level in the equilibrium outcome, we expect the ratio used here to be proportional to the "true" level, if not a close proxy to it. One caveat is that this proxy is by no means a normative quality measure, but it is one of the few possible measures that can be constructed using the currently available published

[5] According to the CMS website of Talking Quality, "The development of physician quality measures that meet the needs of consumers is in a nascent stage. Consequently, the measures are neither very refined nor stable." https://www.talkingquality.ahrq.gov/content/create/physician/whatscoming.aspx

data. Esparza et al. (2012) find evidence from California hospitals supporting the conjecture that the higher the RN proportion of the total nursing hours of care, the lower the length of stay and the lower the odds of hospitalized patients developing urinary tract infections. In addition, Acemoglu et al. (2011) recently employed a similar method for differentiating health care services of the RNs and LPNs. For the quantity of physician and clinical services, unfortunately, the commonly used measure --- total number of physician office visits—is unavailable at the state level for the sample data years of our study. However, the model we develop in this paper motivates a way to estimate the income elasticity of the health care expenditure and its quality/quantity components. Given the relationship among the variables in this model, income and quality elasticities are first estimated and the quantity elasticity is then derived as the difference between the two (see, for details, section 2).

Our SUR estimation model results indicate that the US state level income elasticity of physician and clinical services spending is 0.743 (*std. err.* = 0.043), with 0.524 (*std. err.* = 0.126) attributable to quality progress (measured by the ratio of RNs to LPNs) and 0.219 (*calculated std. err*. = 0.127) due to quantity expansion. The income elasticity estimate suggests that physicians and clinical services are a normal good and a technical necessity. This agrees with a host of earlier studies on aggregate *HEXP* as well as a limited number of studies on *DOCLNEXP*, which estimate income elasticities to be positive and less than one. Our 0.743 estimate falls in the 0.4 to 0.8 range for the bias-corrected estimates of income elasticity of aggregate healthcare suggested by Costa-Font et al. (2011), who use a Meta-regression analysis to control for publication selection and aggregation bias. Moreover, our model controls for "pure" price effect and incorporates time trend and time trend square to allow nonlinear time effects.

The balance of this paper proceeds as follows. Section 2 develops the model and estimation strategy, Section 3 describes the dataset and presents the empirical results, and Section 4 discusses findings with implications and concludes.

2. Model and estimation methods

2.1. Motivating the decomposition model

Our decomposition model takes a cue from the agricultural economics literature on Engel curves (Deaton, 1988; Bils and Klenow, 2001; Gale and Huang, 2007) and from the work of Hicks and Johnson (1968) on food demand.

We start with the identity that expenditure on physician and clinical services *DOCLNEXP* is a product of price *P* and quantity Q.

$$DOCLNEXP \equiv \mathrm{P} \cdot \mathrm{Q} \tag{1}$$

Quantity Q represents the volume of physician and clinical services. P is an average price paid for all the physician and clinical services used, or a unit value (the ratio of expenditure to quantity purchased). We follow the literature on Engel curves and assume that "quality" comes in to play through the unit value P. i.e., different quality level (due to the heterogeneity of physician and clinical services) would result in different unit values. The unit value can increase either because prices of items in a fixed basket increase or because different and better quality (usually more expensive) items are now in the basket. The former is due to a "pure" price effect, and the latter is because of a shift in the composition of services towards premier or more advanced services. We model this relationship using Eq. (2), which asserts that the unit value is the product of price of a fixed basket of services and quality. Denote the price of a fixed basket of physician and clinical services as P_f and the quality as v. We can also interpret it as a base price adjusted by quality. The official price indexes produced by the Bureau of Labor Statistics (BLS) are indexes like this (Aizcorbe and Nestoriak, 2011) and thus used in the empirical part.

$$P = P_f \cdot v \tag{2}$$

In this context, quality v is measured by the differences in the skill mix of two types of healthcare workers. In particular, v is the ratio of RNs to LPNs. The RNs have about twice as many years of training as the LPNs, and the RNs are paid substantially higher hourly wages (Acemoglu and Finkelstein, 2008). It is reasonable to think that the human capital embodied in the RNs is higher than those of the LPNs and that the health care services provided by the RNs are of better quality in terms of skills mix and care outcome. It is reasonable to assume that, quality differences in other dimensions of physician and clinical services are also correlated with this ratio. For example, clinics that hire more RNs may also have more skilled physicians or use more advanced medical devices or techniques. Over the sample years, the realized employment of these two types of nurses is expected to reflect patients' demand for the differentiated services.

Plugging Eq. (2) into *DOCLNEXP* Eq. (1), we obtain

$$DOCLNEXP = P_f \cdot v \cdot Q \tag{3}$$

where *DOCLNEXP*, v and Q tend to change as income changes. Thus, *DOCLNEXP*, v and Q are functions of income y. Over a long time period, the fixed basket price P_f could be correlated with income too, so we assume P_f is also a function of y. In empirical application, we also control for factors other than income that affect the above four variables. Denote a vector of such factors as X and X= (X_p, X_v, X_Q), where X_p, X_v and X_Q representing the factors that affect P_f, v and Q respectively. The *DOCLNEXP* equation can be rewritten as

$$DOCLNEXP(\mathrm{y}, \mathrm{X}) = \mathrm{P_f}\big(\mathrm{y}, X_p\big) \cdot \mathrm{v}(\mathrm{y}, \mathrm{X}_v) \cdot \mathrm{Q}\big(\mathrm{y}, \mathrm{X}_Q\big) \tag{4}$$

Taking the logarithm of both sides of the equation gives

$$\ln DOCLNEXP(\mathrm{y}, \mathrm{X}) = \ln \mathrm{P_f}(\mathrm{y}, X_p) + \ln \mathrm{v}(\mathrm{y}, \mathrm{X}_v) + \ln \mathrm{Q}(\mathrm{y}, \mathrm{X}_Q) \tag{5}$$

Or,

$$\ln \frac{DOCLNEXP(\mathrm{y},\mathrm{X})}{\mathrm{P_f}(\mathrm{y}, X_p)} = \ln \mathrm{v}(\mathrm{y}, \mathrm{X}_v) + \ln \mathrm{Q}(\mathrm{y}, \mathrm{X}_Q) \tag{6}$$

By moving $P_f(y, X_p)$ to the left, the left-hand side becomes the log of physician and clinical service expenditures adjusted by price index of a fixed basket of such services. This adjusted expenditure is then expressed in terms of quality and quantity on the right-hand side.

Taking derivative of Eq. (6) with respect to $\ln y$ on both sides, the elasticity of adjusted physician and clinical service expenditure has two components:

$$\frac{\partial \ln \frac{DOCLNEXP}{\mathrm{P_f}}}{\partial \ln y} = \frac{\partial \ln V}{\partial \ln y} + \frac{\partial \ln Q}{\partial \ln y} \tag{7}$$

Denote the elasticity of adjusted physician and clinical expenditure as ε. It would be the sum of the quality elasticity θ, and the quantity elasticity η:

$$\varepsilon = \theta + \eta \tag{8}$$

So, if the expenditure and quality elasticities are known, the quantity elasticity can be obtained as the difference between the expenditure and quality elasticities, as follows

$$\eta = \varepsilon - \theta \tag{9}$$

In the empirical part, we model functions $\frac{DOCLNEXP}{\mathrm{P_f}}(\mathrm{y}, \mathrm{X})$ and v (y, X_v) to estimate the income and quality elasticities. Then, the difference of the two yields the quantity elasticity as in Eq. (9). This model provides a tractable approach for decomposing the estimated income elasticity of adjusted spending of physician and clinical services into quality and quantity components, even though the state level quantity measure is not explicitly available for the sample years of the study.

2.2. Empirical model

In this part, we set up empirical models for $\frac{DOCLNEXP}{\mathrm{P_f}}(\mathrm{y}, \mathrm{X})$ and v (y, X_v) in order to estimate the income and quality elasticities. As earlier justified, the quality of care is measured as the ratio of RNs to LPNs.

For simplicity, suppose functions $\frac{DOCLNEXP}{\mathrm{P_f}}(\mathrm{y}, \mathrm{X})$ and v (y, X_v) take the following forms:

$$\ln \frac{DOCLNEXP_{\mathrm{it}}}{\mathrm{P_{f_t}}} = \alpha_0 + \alpha_1 \mathrm{lny_{it}} + \alpha_2 \mathrm{X_{it}} + \mathrm{e_{it}} \tag{10}$$

$$\ln v_{it} = \beta_0 + \beta_1 \mathrm{lny_{it}} + \beta_2 \mathrm{X}_{v_{\mathrm{it}}} + \mathrm{u_{it}} \tag{11}$$

where X_{it} denotes a vector of other control variables for adjusted *DOCLNEXP* of state i in year t and $\mathrm{X}_{v_{\mathrm{it}}}$ represents other control variables for quality of physician and clinical services of state i in year t. In our estimation, X_{it} and $\mathrm{X}_{v_{\mathrm{it}}}$ include controls for state level health care market characteristics (such as number of health care providers, measured by the sum of physicians, RNs, LPNs and PAs or physician assistants); demographic structures (such as percentage of people age 65 and older); health insurance coverage (such as percentage of uninsured people and percentage of Medicaid enrollees); HMO penetration rate; population health status, measured by bad health index (defined as = smoking rate*obesity rate); and time effects measured using time trend and its square (controls for non-linearity).

The price index, P_f, which measured by consumer price index of physician services from BLS, is only available at the national level, so there is no variation for state i but only in time t.

The error terms e_{it} and u_{it} may not be independent. We therefore use the seemingly unrelated regression (SUR) to estimate the two equations together. This hypothesis is then tested by Breusch-Pagan test of independence in the estimated regressions.

Another concern about the estimation is the potential for reverse causality between the left-hand side variables and some covariates. More or better physician and clinical services may improve population health outcomes. Therefore, higher *DOCLNEXP* and v may lead to better behavioral health (e.g., reduced smoking rate and obesity prevalence). In addition, a healthier population can be more productive and earn higher income. In order to partially control for this endogeneity tendency, we use one-year lag terms of income and bad health index in the regression. Potential for a reverse causality is likely to be reduced since the use of physician and clinical services in year t (either more or better quality services) may only affect current or future incomes, but not income in t-1.

3. Data and empirical results

3.1. Data

The panel data for the study merged published information from multiple sources. Since many of the relevant state level data only became available relatively recently while some previously available data do not cover the most recent years, our final sample period used in the empirical regression model is from 1999 to 2008 for the 50 US states. Due to missing values for some states, 448 observations were eventually used for estimating the regression models.

DOCLNEXP

DOCLNEXP is a major sub-category of personal *HEXP* data obtained from the Centers for Medicare &Medicaid Services (CMS). It covers services provided in establishments operated by Doctors of Medicine (M.D.) and Doctors of Osteopathy (D.O.), outpatient care centers, plus the portion of medical laboratories services that are billed independently by the laboratories[6]. The state level *DOCLNEXP* used here is measured by the state of residence.

Income

The income measure is state level per capita personal income, obtained from the Bureau of Economic Analysis (BEA). It is then deflated using the US consumer price index (CPI) with 2005 as the base year.

[6] This category also includes services rendered by a doctor of medicine (M.D.) or doctor of osteopathy (D.O.) in hospitals, if the physician bills independently for those services. Clinical services provided in freestanding outpatient clinics operated by the U.S. Department of Veterans' Affairs, the U.S. Coast Guard Academy, the U.S. Department of Defense, and the U.S. Indian Health Service are also included.

Fixed basket price index for physician services

Given the theoretical model developed in the previous section, a price index for *DOCLNEXP* based on a fixed basket of physician and clinical services is needed. Ideally, it only reflects the “pure” inflation but not the quality change. It allows us to disentangle the effect of quality change from inflation. In the literature that discussing the health expenditure price index (Aizcorbe and Nestoriak, 2011 and so on), a fixed basket price index is also called service price index (SPI). It answers the question “What would expenditures be today if patients received the same services today as they did in the past?” By design, it does not take into account the effect on expenditures from shifts in the utilization of goods and services in treating medical conditions. It is commonly known that the price index on physician services developed by BLS is a fixed basket price index. We therefore use this price index to adjust *DOCLNEXP*.

Quality measure

Quality v, measured as the ratio of RNs to LPNs, proxies the level of supply side skills mix. The data are from the occupational employment estimates released by the Bureau of Labor Statistics (BLS).

Supply side characteristics

Supply side controls include the number of major healthcare providers consisting of the total number of physicians, RNs, LPNs, and PAs. Physicians comprise anesthesiologists, family and general practitioners, general internists, obstetricians and gynecologists, general pediatricians, psychiatrists, surgeons, and all other physicians and surgeons. These data are from the Occupational Employment estimates released by the Bureau of Labor Statistics (BLS).

Demand side characteristics

The percentage of population age 65 years and older is included as a demographic control. The original data source is the U.S. Census Bureau.

We control for health insurance and managed care status by including the percentage of uninsured population, percentage of Medicaid enrollees[7] and HMO penetration rate. Data on the uninsured population are taken from the U.S. Census Bureau. Data on the number of Medicaid enrollees and HMO enrollment rate are from s*tatehealthfacts.org* (Kaiser Family Foundation).

As in Cuckler et al. (2011), a health risk behavioral variable—bad health index—is used to control for the smoking rate and obesity prevalence. This measure can also be interpreted as a behavioral health status index, defined as the smoking rate times the obesity rate in each state (value adjusted into a percentage)[8]. The smoking and obesity rates data are from the Prevalence and Trends Data of the Behavioral Risk Factor Surveillance System (BRFSS).

Finally, the District of Columbia (D.C.), an outlier in personal income, is excluded from our analysis. Table 3 presents descriptive statistics of the major variables in the estimated model.

3.2. Model estimation

Eqs. (10) and (11) are estimated in order to obtain the income elasticity of *DOCLNEXP* and quality elasticity. Since the key variables are already in the log form,

---

[7] Percentage of Medicare enrollees is not included because of its potential collinearity with the share of population age 65 or older.

[8] We also tried keeping the smoking rate and obesity rate as two separate variables, but obesity rate is highly correlated with time trend. We therefore still used the bad health index as a combined measure.

the coefficient of income in each equation yields the elasticity estimate. According to Eq. (9) in our theoretical model, the quantity elasticity can then be derived by subtracting the estimated quality elasticity from that of the income elasticity.

Table 3

Descriptive Statistics (N=448)

Variable	Mean	Std. Dev.
Adjusted *DOCLNEXP*	1325.202	201.4697
Income	33421.73	5028.728
RN/LPN	3.760633	1.541408
# Physicians and nurses	12.27248	2.191292
% Age 65+	0.126891	0.016308
% Uninsured	0.147952	0.0382
% Medicaid enrollees	0.133146	0.043088
HMO penetration rate	0.200846	0.122903
Bad health index	0.049615	0.01233

Note: Total number of non-missing observations used in the analysis is 448. Adjusted *DOCLNEXP* is per capita expenditure on physician and clinical services deflated by CPI of physician services (2005 =100). *Income* is per capita personal income deflated by CPI (2005 =100). The number of physicians and nurses is per 1,000 of the population. Percentage of the uninsured and the population of age 65 and over are in decimals.

When estimating Eqs. (9) and (10), the error terms are expected to be correlated. The seemingly unrelated regressions (SUR) estimation method is, therefore used for joint estimation of the equations system. The SUR would generate more efficient estimates, under the assumption of cross-equation error correlation, compared to the ordinary least squares (OLS). This assumption is then tested using the Breusch-Pagan test of independence (see, Table 4). The SUR estimation is performed in STATA with iteration option[9]. Under SUR, the iteration converges to the maximum likelihood estimates. The results are shown in Table 4. The respective adjusted R^2 statistics suggest the two

[9] It iterates over the estimated disturbance covariance matrix and parameter estimates until the parameter estimates converge.

equations have a reasonable fit. The χ^2 statistic confirms that the regression equations are jointly significant. The Breusch-Pagan test is also conducted to test for the independence of the two equations. The *p*-value of the χ^2 statistic suggests rejecting the independence hypothesis of the residuals across equations.

Eqs. (9) and (10) include controls for the time effect using a time trend and its squared term (to capture any nonlinear time effects on *DOCLNEXP* and quality). [10]

According to the results of the first regression in Table 4, income has a positive and statistically significant sign. The coefficient indicates an income elasticity of 0.74 (see further discussion in section 3.3). The effect of the number of healthcare providers, measured as the number of physicians, RNs, LPNs and PAs, is negative and significant. One possible explanation could be that healthcare workers play beneficial roles in the population management of diseases to stay healthy, thus reducing expenditures on physician and clinical services. The positively signed elderly population agrees with the expectation that medical services are demanded more intensely as population ages. The share of Medicaid enrollees positively associated with *DOCLNEXP* implies that Medicaid coverage tends to encourage the use of the physician and clinical services. The

[10] Regression without the time trends has also been tried. The log ratio test result suggests using the model with time trends instead of without time trends. In addition, an earlier version of this paper used state fixed effects and year fixed effects in each equation. They tend to pick up much of the explanatory power of income differences across states. When using the state and year fixed effects in the current model, they generate much smaller income elasticity and negative quality elasticity. The small income elasticity when including fixed effects is consistent with those in earlier studies. For example, some of the income elasticity estimates in Acemoglu et al. (2011) are close to zero but statistically insignificant when including state fixed effects as additional determinants. They suspect that the insignificant estimates are due to the existence of the endogeneity problem between income and expenditures leading to biased OLS estimates. In our case here, the explanation can be that using the one year lag of income could not fully control for the endogeneity problem. Although finding a plausible instrumental variable for income can improve the estimation result, it is not an easy task to do in addition to our primary goal in this paper. Therefore, it can be one limitation of our paper that is admittedly common to many empirical econometric models.

Table 4

Seemingly Unrelated Regressions (SUR) model estimation of *DOCLNEXP*

	Coef.		Std. Err.	Adj R^2	Chi^2
Equation 1					
log of adjusted *DOCLNEXP*				0.6346	778.03
log of income,t-1	0.743147	***	0.043451		
#physicians and nurses	-0.00586	**	0.002965		
% 65 years +	1.513061	***	0.33167		
% uninsured	0.165392		0.142842		
% Medicaid	0.393817	***	0.118136		
HMO rate	0.018174		0.04679		
Bad health index,t-1	2.569894	***	0.476154		
time trend	0.03994	***	0.007333		
time trend squared	-0.00237	***	0.000618		
constant	-1.01436	**	0.456785		
Equation 2					
log of RN/LPN				0.4489	364.86
log of income,t-1	0.524336	***	0.126389		
#physicians and nurses	-0.07255	***	0.008625		
% 65 years +	0.490213		0.964748		
% uninsured	-3.50235	***	0.415494		
% Medicaid	-0.85828	**	0.343629		
HMO rate	0.27153	**	0.1361		
Bad health index,t-1	-2.87357	**	1.385018		
time trend	0.031112		0.02133		
time trend squared	0.00043		0.001798		
constant	-2.84357	**	1.328679		
Derived quantity elasticity	0.218811		0.1267		
Correlation coef. of residuals	0.1643				
Breusch-Pagan test	Chi2=12.088	Pr=0.0005			

Note:

1. Statistical significance level: *:10%, **: 5%, ***:1%.
2. Number of observations in both equations is 448.
3. Derived quantity elasticity has the calculated standard error as 0.1267.
4. The two equations are jointly estimated using SUR. The correlation coefficient of residuals and Breusch-Pagan test of independence confirms the dependence of the two equations.

bad health index is positively related to *DOCLNEXP* confirms that the higher the obesity rate or smoking rate is, the more physician and clinical services are purchased. The respective coefficients of time trend and its quadratic effect imply that *DOCLNEXP* is increasing over time at a decreasing rate. The uninsured rate and HMO penetration rate are insignificant in the first regression.

The second regression in Table 4 also indicates a positive and significant income coefficient. The quality elasticity coefficient is 0.52, which is over half of the estimated income elasticity (see further discussion in the next section). The number of total physicians and nurses is negatively correlated with the quality measure, which means a larger size of the healthcare workforce is associated with a lower ratio of RNs to LPNs. It might indicate there is a trade-off between the total employment of healthcare workers and the skill mix of the healthcare workers. The aging population is positively correlated with the quality measure, but the effect is not significant. The percentage of the uninsured and that of the Medicaid enrollees are both negatively associated with quality. This possibly reflects the tendency for care quality attrition that associated with low Medicaid reimbursement rates. The coefficient of HMO penetration rate suggests that increased HMO enrollments raise quality (the ratio of RNs to LPNs). However, it is unclear why a high HMO penetration rate is related to a higher skill mix ratio. Moreover, bad health index tends to be negatively associated with quality. It appears that a higher proportion of smokers and obese people do not translate into a higher demand for better skills mix of the nursing staff.

3.3. Income elasticity and quantity\quality components

From estimation results of the first equation in Table 4, the income elasticity of adjusted *DOCLNEXP* is 0.74. This implies that a 10 percent rise in per capita income tends to raise the adjusted *DOCLNEXP* by 7.4 percent. Compared with the few past research that estimated such an elasticity, our estimate is within the values they reported. Nonetheless, our current estimate using state level data implies that physician and clinical services expenditure behaves as a normal good and a technical necessity.

The quality elasticity estimate 0.52 accounts for more than half of the income elasticity, and it suggests that a 10 percent rise in real per capita income leads to a 5.2 percent increase in the RN to LPN ratio.

The difference in these two elasticities is the quantity elasticity, and is 0.22, according to Eq. (9). The calculated standard error of this estimate is 0.13[11]. It indicates that a 10 percent rise in the real per capita income increases the quantity of physician and clinical services by 2.2 percent.

The three estimated elasticities signal that the increase in DOCLNEXP emanating from a rise in income is largely attributable to purchased quality increase than the quantity increase. One rationale is that the opportunity cost of physician office visits (e.g., lost work productivity, foregone leisure, etc.) would tend to rise with incomes and higher income patients would prefer higher quality care that reduces the follow-up office visits given the desired health outcome sought. We could also hypothesize that, due to the US experiencing a "flat of the curve" medicine, the quality/technology upgrades give a greater bang-for-the-buck than quantity increases.

[11] Given $\eta = \varepsilon - \theta$ in Eq. (9), derivation of the standard error of the quantity elasticity is based on the expression$\mathrm{Var}(\eta)=\mathrm{Var}(\varepsilon)-2\mathrm{cov}(\varepsilon, \theta)+\mathrm{Var}(\theta)$.

4. Summary conclusion

This paper attempts to address the question of the sensitivity of US expenditure on physician and clinical services (*DOCLNEXP*) to a change in income, using 1999-2008 US state level panel data. One of the novel contributions of this study is decomposing the income elasticity *DOCLNEXP* into portions due to purchasing greater care quantity and improved care quality. We modeled the relationship among *DOCLNEXP*, income, quantity and quality based on past studies of Engel curves and food demand. In addition to the theoretical model, we also faced and surmounted empirical challenges such as the choice of an appropriate quality measure and finding the relevant quantity measure and data for physician and clinical services at the state level. The quality measure used in the paper is based on the skills mix of two types of nurses --- RNs versus LPNs. For quantity, however, the commonly used measure -- number of physician office visits---is not available at the state level. We construct a model for deriving the quantity elasticity once the income and quality elasticities are estimated. We are, therefore, still able to estimate and decompose the income elasticity into quality and quantity components in the absence of explicitly measured quantity data.

Using 1998-2008 US state-level panel data, we estimate the relation among the adjusted expenditures on physician and clinical services, quality and real income using a SUR model estimation. Pure price effect is also controlled for by a price index of a fixed basket of physician and clinical services y-- CPI in physician services. The estimated income and quantity elasticities are about 0.743 (*std. error*=0.043) and 0.524 (*std. error*= 0.126) , which lead to the derivation of the quantity elasticity estimate as 0.219 (calculated *std. error*=0.127). Our findings reveal that a significantly larger share of the income elasticity is due to higher quality than quantity consumption components. This finding is consistent with the theory that the income elasticity of (a major component of) health care spending can be expected to rise with income and it is both a normal good and a technical necessity using a panel dataset of the US states.

One potential policy implication is the expectation of greater consumption of physician and clinical services as the economies of the US states recover and grow, and that more of the rise in this spending is likely to emanate from *greater* quality *than* quantity. If continuance of this trend is assumed, our findings suggest that a sharper focus of the emerging health care system reform should be on preventing care quality attrition under an expanded quantity of care. This policy prescription is consistent with the recent claim in Dubois et al. (2012) that the US healthcare economy is evolving from volume-based (quantity) to value-based (quality and cost) to achieve the triple goal of better healthcare for individuals, improved health for populations and slower cost growth.

CHAPTER 4

EFFECTS OF INSURANCE COVERAGE ON EMERGENCY DEPARTMENT USE[1]

1. Introduction

The uninsured population in the United States has been a focus of the Health care debate over the years. The group, which represents 16.3% of the US population in 2010, has frequently been blamed for driving up the nation's health bill, overcrowding the health care delivery, and even impairing of the quality and effectiveness of America's health care system. As a consequence, providing coverage for the uninsured has been suggested as a major way to cut health care cost and a primary goal of the health care reform. Among the problems caused by the uninsured, the overuse and misuse of ED care has been one of the major concerns.

Given that the uninsured do not have access to primary care, there could be two possibilities when they visit ED. One is that they use ED as a source of regular care, which results in unnecessary ED visits. Another possibility is that they go to ED as they had unmet needs earlier and their diseases have developed into more severe problems, which results in very urgent ED visits. The primary goal of this paper is to investigate the effect of insurance coverage on ED visits that can be considered "non-urgent" or "primary-care-sensitive" (PCS) cases. Our primary research question is whether changes in insurance coverage would affect the likelihood of an ED visit being non-urgent or primary care sensitive. We will follow the definitions used by the well-known New York University ED Classification Algorithm (NYU Algorithm) and define "non-urgent" ED

[1] I am very grateful to Dr. Cyril F. Chang for his continuous guidance in the completion of this paper. I am further grateful to seminar participants at the University of Memphis, Economics Department for their helpful comments on earlier versions of this paper. However, I take full responsibility for any remaining errors.

visits as those that are non-emergent (that is, no ED care needed) or emergent (ED care needed) but primary care treatable. Primary care sensitive or "PCS" ED visits, on the other hand, are a broader definition that includes all non-urgent cases as well as cases that require immediate ED care but could have been avoided had effective primary care been delivered earlier (and hence sensitive to the effective delivery of primary care). Formal definitions of "non-urgent" and "PCS" ED visits will be provided in section 3.

Unlike previous studies that have developed dichotomized dependent variables based on the NYU Algorithm (Ballard et al., 2010; Tsai et al., 2011), we will use the actual probabilities generated by the NYU Algorithm as the dependent variables and use an econometric model for fractional responses to estimate the effects of noninsurance as well as other control factors. We adopt the logit quasi-likelihood regression developed by Papke and Wooldridge (1996) and applied it to a statewide dataset from Tennessee hospital discharge data, supplemented by hospital and county information from Tennessee Joint Annual Report of Hospitals and the Area Resource File.

Based on the regression results, we further explore how the PPACA on the mandates of insurance coverage would affect the non-urgent and PCS likelihood. In addition, we provide a brief discussion on the potential changes in ED expenses. This simulated cost analysis assumes two scenarios: (1) every uninsured patient gets private insurance coverage and (2) every insured patient gets public insurance (primarily Medicaid). The reality then represents a mix of these two scenarios. We predict the changes in the average likelihood of being non-urgent and PCS over all visits given the changes in the insurance coverage.

Our results show that on the whole, noninsurance is associated with higher probability of ED visits being non-urgent and higher probability of being PCS, relative to private insurance. These effects are different for male and female and across race groups. The effects are also different according to insurance type. Specifically, if all uninsured patients get private insurance, the average probabilities of an ED visit being non-urgent and being PCS would decrease. If all uninsured patients get public insurance (Medicaid), the average probability of an ED visit being non-urgent and being PCS would increase. The mixed effect of the two would depend on the proportion of previously uninsured patients who later enroll in Medicaid relative to the proportion who later purchase private insurance. In terms of ED expenses, the net effect depends on the mixed structure of the insurance types as well. When the effect of private insurance outweighs that of Medicaid, the average ED expenses tend to increase as the average non-urgent and PCS likelihood increase.

For policy makers, this discussion would provide additional information on the potential changes in ED use under health care reform.

The rest of the paper is organized as follows. Section 2 reviews the background and relevant literature. We describe the data used for the analysis in the third section. Section 4 introduces our empirical model. And the estimation results are discussed in section 5. We further predict the changes under the assumption that everybody gets insurance coverage in section 6. And section 7 concludes the paper with a discussion of policy implications of our study.

2. Background and relevant literature

Lack of insurance coverage and the resulting difficulties in accessing the needed basic health services have often been cited as a major contributing factor in driving uninsured patients to seek care at hospital EDs (Paradise and Dark, 2009; Weber et al., 2005; Gindi et al., 2012). However, a number of recent studies have shown that most of the growth in ED volume has been driven by the insured, with Medicaid insured individuals being more likely to have had multiple ED visits than those with private insurance and the uninsured (Garcia et al., 2010; Newton et al., 2008).

Studies have also shown that persons with and without a usual source of medical care are equally likely to have one or more ED visits in a 12-month period, a reality contrary to the common perception that a lack of access to primary care contributes to the overuse of ED services (Cunningham 1995; Garcia et al., 2010). Also contrary to expectation has been the realization that immigrants, particularly illegal immigrants, as a group are not a major contributor to the overcrowding of hospital EDs (Cunningham 2006, Cunningham and Artiga 2009). In the last few years, attention on ED overcrowding has shifted to the questions of why people use ED for non-urgent medical conditions and how much money can be saved by an effective counter policy.

Non-urgent ED visits are typically defined as visits for conditions for which a delay of several hours would not increase the likelihood of an adverse outcome. However, each study tends to vary in its definition of non-urgent visits given the specific context. Uscher-Pines et al. (2013) claimed in their recent literature review article that no two studies (among the selected review articles) used the same exact definition of non-urgent visits. In the clinical setting, the level of urgency of ED visits is usually determined by triage staff upon a patient’s arrival at the hospital ED. For research and public policy discussion, non-urgent visits are often defined retrospectively from medical record review or by patient self-report. Compare to the prospective determination at triage, retrospective definition takes into account the patient’s medical condition and the broader underlying predisposing and enabling factors closely associated with the patient’s health (Chang, 2013). One of the retrospective classifications that has been used by the Center for Disease Control and Prevention (CDC) to describe the characteristics of high safety-net burden EDs and has been used by several states and municipalities to track ED visits patterns is New York University (NYU) ED Algorithm developed by the NYU center for Health and Public research (Ballard et al., 2010). This algorithm has the added advantage of empirically linking the admitting diagnoses to the role of the primary care physician and the capacity of the community health system in which the patient lives (Weinick et al., 2007). We applied this NYU Algorithm to the Tennessee outpatient discharge data for 2008 to identify and analyze ED visits for this paper.

Most papers that have focused on this critical health system issue followed a descriptive approach to explain of who the non-urgent ED users are and why they use ED for less than urgent purposes. Among a limited number of quantitative and predictive studies published, most were using a dichotomized non-urgent visit as the dependent variable. In addition, very few empirical studies took advantage of the ED classification determined by NYU Algorithm. A couple of papers classified their ED visits by NYU Algorithm were conducted using data from a foreign country such as Kuwait (Shah et al., 1996) and Taiwan (Chan et al., 2000; Tsai et al., 2010). This paper contributes to the literature by adding a quantitative analysis of the likelihood of an ED visit being non-urgent or PCS, based on NYU Algorithm. We use an econometric model developed for fractional dependent variables and applies it to a statewide hospital outpatient discharge dataset. It also provides a timely study on how the changes in insurance coverage under PPACA would affect the non-urgent and PCS ED use and expenses.

3. Data

Our main data source is the Tennessee Hospital Discharge Data Set (HDDS) that contained detailed patient discharge records of all inpatient and outpatient visits to licensed hospitals in Tennessee. This study uses all ED discharge records in 2008 for the analysis. Two additional data sources that provide information for hospitals and patient's county are The Tennessee Joint Annual Report of Hospitals (JAR-H) and the Area Resource File (ARF).

We base the construction of our two key study variables -- non-urgent and PCS ED visits -- on the NYU Algorithm developed by the New York University Center for Health and Public Service Research. This widely-used ED classification algorithm was designed with advice from a panel of ED and primary care physicians who examined a sample of almost 6,000 full ED records from patients treated in Bronx, New York, hospitals in 1994 and 1999. The abstracted information from the patient records included data on such variables as the initial complaint, presenting symptoms, vital signs, medical history, age, gender, diagnoses, procedures performed, and resources used in the ED. The NYU Algorithm has recently been verified by a team of researchers from Kaiser Permanente, University of California San Francisco, and Harvard University using ED use data from a total of close to three million patients enrolled in an integrated health care delivery system in northern California (Ballard et al., 2010).

Our initial analysis of the outpatient HDDS data identified a total of 2,807,874 ED visits in 2008. We took these visits with ICD-9 codes as input and applied the NUY Algorithm. It output a new set of variables to the original data set, and the names of the new variables are: “ne” (non-emergent), “epct” (emergent/primary care treatable) , “edcnpa” (emergent/ED care needed/preventable and avoidable), “edcnnpa” (emergent/ED care need and not preventable/avoidable), “injury” (injury principal diagnoses), “psych” (mental health principal diagnoses), “alcohol” (alcohol-related health principal diagnoses), “drug” (drug-related health principal diagnoses, excluding alcohol) or “unclassified” (not in one of the above categories). The relationship among the categories is shown in Figure 1. For each ED encounter with a valid diagnostic code, the data values created by the NYU Algorithm for the nine new fields represent “… the relative percentage of cases for that diagnosis falling into the various classification categories” according to the online version of documentation for the NYU Algorithm (Center for Health and Public Service Research). These can also be interpreted as probabilities for being in the specified categories. The average probabilities of each category in the original sample are shown in Figure 2.

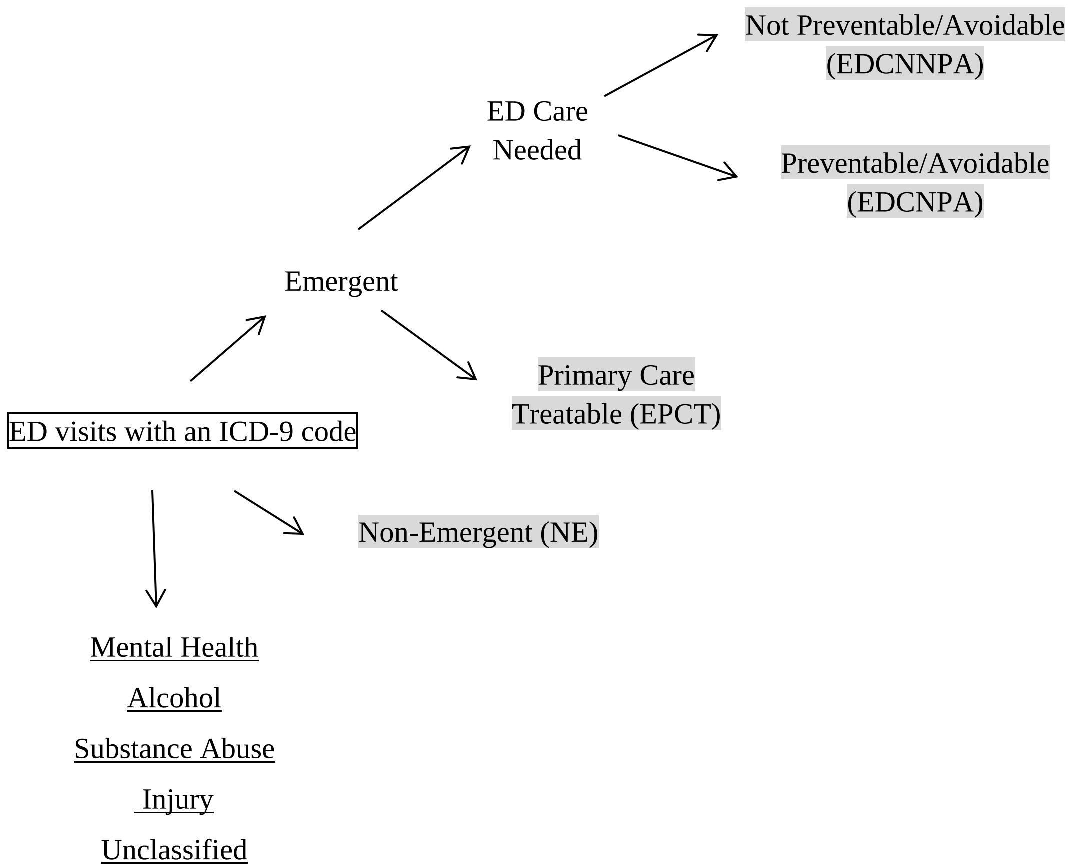

Figure 1. NYU Algorithm for Classifying Diagnoses
(adapted from NYU Algorithm documentation and "Figure 1" from Ballard et al. (2010))

According to the suggestion by NYU Algorithm, cases involving a primary diagnosis of injury, mental health problems, alcohol, substance abuse or unclassified cases are separated from the standard classification scheme. We therefore excluded those visits from the sample. This resulted in 1,772,428 ED visits as remaining observations. Then, the remaining visits are classified into four categories: "ne" (non-emergent), "epct" (emergent/primary care treatable), "edcnpa" (emergent- ED care needed- preventable and avoidable), and "edcnnpa" (emergent - ED care need- not preventable/avoidable). For each remaining visit, the probabilities of being in the four categories would sum up to 1.

For example, in the case of urinary tract infections (ICD-9-CM code 599.0), each case is assigned 66% "non-emergent," 17% "emergent/primary care treatable," and 17% "emergent - ED care needed - preventable/avoidable."

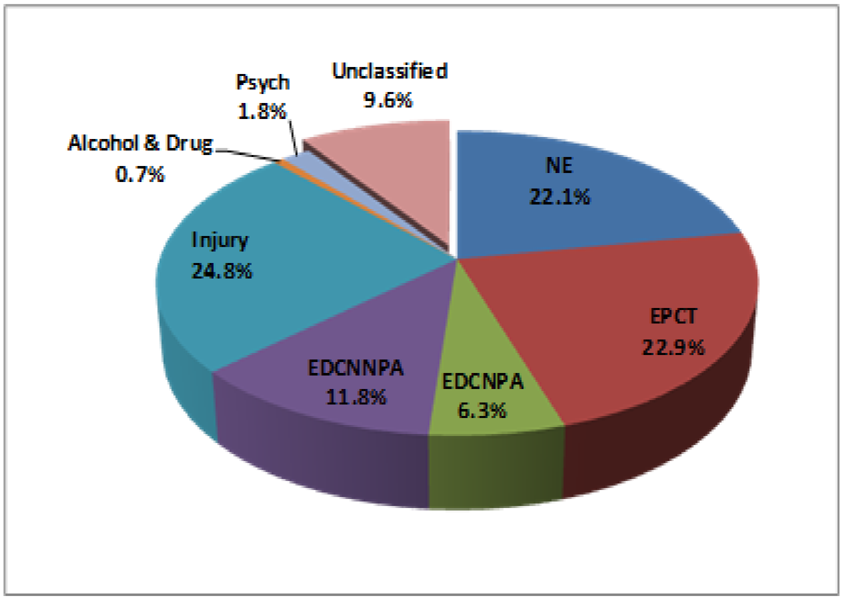

Figure 2. Classification of ED visits in Tennessee (based on original sample), 2008

We further exclude visits made by non-Tennessee residents from the analysis to focus on ED use by Tennessee residents. The remaining data include 1,657,030 visits. Lastly, since some variables, such as race or gender, have unknown or missing values, the final sample size used in the regression is 1,574,403. The step-by-step changes of sample size are illustrated in Figure 3.

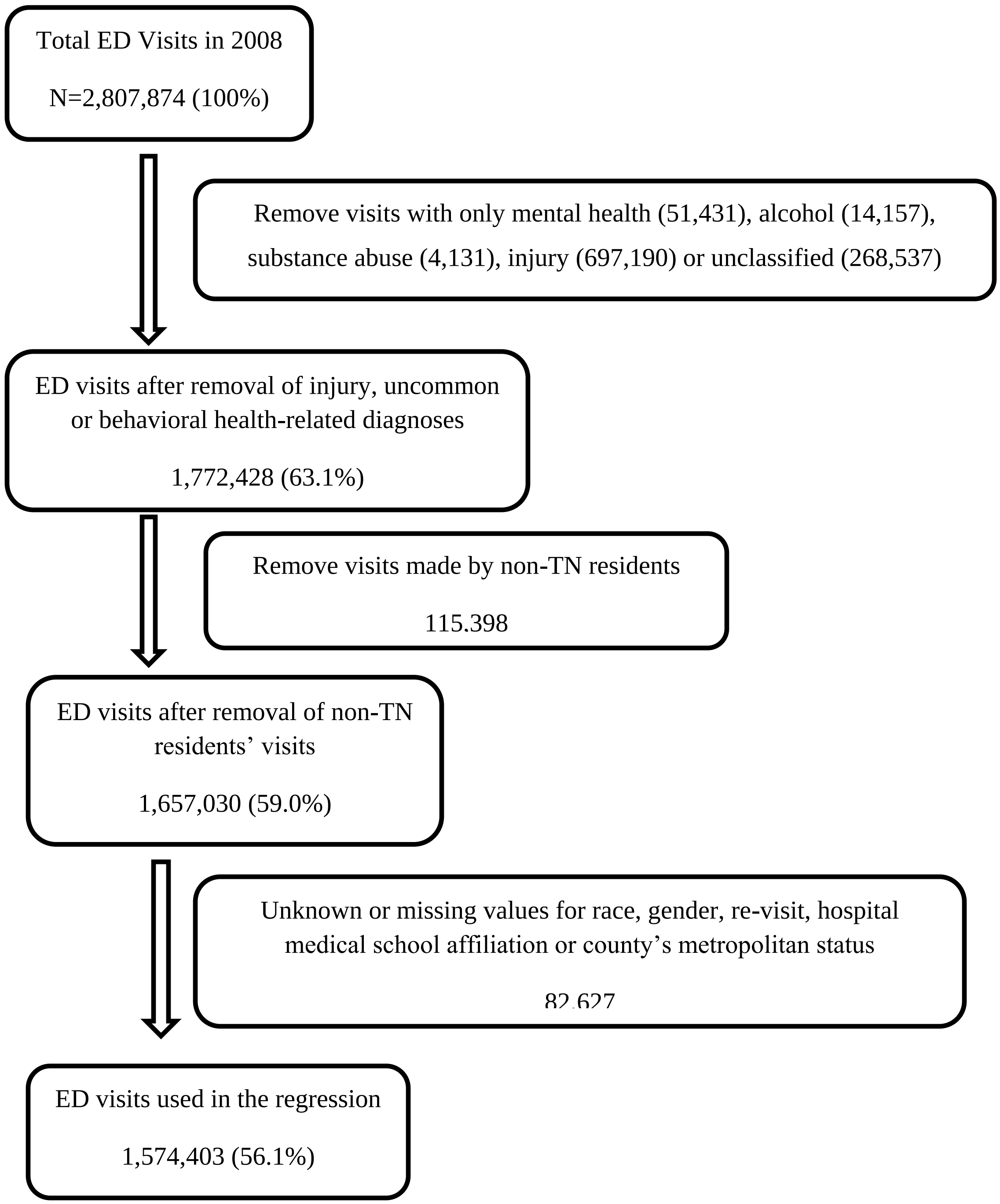

Figure 3. Data for the Study
(the number of observations removed in each step depends on the order of removal)

The descriptive statistics of the sample used in the regression are presented in Table 5. An average ED visit would have a probability of being non-urgent as high as 0.713 and a probability of being PCS as high as 0.813. Compared to the statewide population average (as in the last column), this ED sample is deviated in mean of many variables. This difference from the general population may indicate the self-selection nature of the ED visitors. In terms of insurance coverage, public insured (Medicaid and Medicare) patients represented the largest share of 55 percent of the total number of ED visits by Tennessee residents and this is much larger than the number of total enrollees as a percentage of the total population in Tennessee (Kaiser Family Foundation). In contrast, uninsured patients represented 17 percent of the total ED visits and this is close to the 15 percent representation in the total general population.

Dependent Variables

There are two dependent variables used in two regressions respectively, one is the likelihood of an ED visit being non-urgent and the other is the likelihood of being PCS. The definitions are based on the NYU ED Algorithm output.

As explained above, each visit is assigned probabilities of being in four categories respectively (see Figure 1). We regrouped and combined the first two category ("ne" and "epct") probabilities into one probability[2] and called it "non-urgent". Non-urgent cases mean that they do not need to be seen in a hospital ED and therefore are unnecessary for ED care. Common examples of reasons for non-urgent and potentially unnecessary ED visits include sore throat and back problems. The non-urgent probability, thus, refers to the likelihood of a case being unnecessary for ED care. In the first regression, we

[2] The way of combining the two category probabilities has been used by Ballard et al. (2010), except they dichotomized it the called it "non-emergent" when $P_{NE}+P_{EPCT}>0.5$.

examine how the probability of being non-urgent is explained by insurance coverage, other patient and visit characteristics, hospital attributes and county level variables.

We then added the third category probability to the first two category probabilities and it gives us the so-called "primary-care-sensitive" category[3]. It includes all non-urgent ED visits defined above plus all ED visits that require immediate ED care but the emergent nature of the condition is potentially avoidable had timely and effective primary care been received earlier by the patient before going to the hospital for ED. This category is thus sensitive to (or modifiable by) the effective delivery of primary care outside the hospital. In other words, they are potentially avoidable by the delivery of effective primary care and can serve as an indicator of problems with access to primary care within a patient subgroup or in a local area (Chang 2013). The PCS probability (sum of the three category probabilities) refers to the probability of a visit being primary-care-sensitive. This is used as the second dependent variable, and a relationship between this probability and independent variables are estimated in a similar way in a separate regression.

It is also worth noticing that, the primary-care-sensitive probability also equals to 1 minus the fourth category ("edcnnpa") probability, since the four category probabilities sum up to 1 (after excluding the other categories) as designed by the NYU ED Algorithm. Therefore, the regression can also be interpreted as the opposite side of the relationship between the fourth category and the independent variables. In fact, the fourth category

[3] Such a definition has been widely used the ED literature. For example, Utah Office of Health Care Statistics, 2004.

Table 5

Descriptive Statistics (N=1,574,403)

Variable	Mean	Std. Dev.	TN mean*
Dependent Variables			
Non-urgent (ne+ epct)	0.712599	0.27909	
Primary-care-sensitive (ne+	0.812504	0.267419	
Patient-visit Characteristics			
Charlson Score	0.191772	0.617687	
Age	34.32853	22.05868	
Female	0.607162	0.488381	0.52
Black	0.23617	0.424728	0.2
Hispanic	0.036703	0.188031	0.07
White (reference)			
Other race	0.091611	0.288476	0.03
Uninsured	0.169919	0.375562	0.15
Medicaid/care	0.549074	0.497586	0.31
Private insurance (reference)			
other insurance	0.034141	0.18159	0.02
Revisit	0.399181	0.48973	
# visits	3.575337	6.634233	
Hospital characteristics			
Medical school	0.323664	0.467874	
Public hospital	0.204192	0.40311	0.15
For-profit hospital (reference)			
Nonprofit hospital	0.517564	0.499692	0.43
County characteristics			
Primary care providers/ 1k pop	1.28147	0.683592	2.25
% 65+	0.136864	0.030039	0.14
Professional shortage area, part	0.44763	0.49725	
Professional shortage area, whole	0.166586	0.372606	
No professional shortage area			
% poor	0.159259	0.035708	0.20
Metropolitan area	0.685118	0.464469	
East TN	0.405461	0.490981	
Central TN (reference)			
West TN	0.238488	0.426159	

Note: TN mean column presents the mean values of the general population in Tennessee. The data came primarily from the Kaiser Family Foundation State Health Facts Website and they were supplemented by data from such sources as US Department of Agriculture and the Census Bureau.

represents the cases that are the least likely to be prevented with access to primary care or other medical interventions. It is the most urgent and necessary cases among all categories in the regression analyses.

Independent Variables

Our independent variables are drawn from three major conceptual domains: patient-visit characteristics, hospital characteristics, and the external access-to-care environment. Patient-visit characteristic variables are selected from the Tennessee HDDS dataset and include patient age, gender, race and ethnicity, insurance status, Charlson Co-morbidity Score (calculated from the patient's ICD-9-CM codes and the related procedure codes), whether it is a repeated visit and the total number of ED visits in 2008.

Hospital characteristics are represented by such familiar variables as hospital ownership (public, non-profit, and for-profit) and medical school affiliation. Finally, the external access-to-care environment is represented by county-level measures of the number of primary care physicians per 1,000 population, proportion of population over 65 years of age, percentage of population under the federal poverty line, whether the county was designated as a Health Professional Shortage Area (HPSA) partially or entirely[4], where the county is in a Metropolitan Statistical Area (MSA), and whether the county is in the eastern, central or the western section of Tennessee.

In order to allow the effects of insurance to be heterogeneous across gender and race groups, interaction terms among insurance types, gender and race are included.

[4] For health planning purposes, the federal Health Resources and Services Administration (HRSA) categorizes counties into one of the three HPSA designations: entire county HPSA, part of the county HPSA, and none of the county HPSA.

4. Empirical model

We first analyze how insurance status affects the probability of an ED visit being non-urgent. Then we explore how it is related to the likelihood of an ED visit being PCS. Since these two variables are measured in terms of probabilities, our dependent variables can take any values between zero and one including zero and one. The bounded nature of such variables can give rise to estimation issues. Standard linear regression models, such as OLS regression, would have two problems: (1) the predicted values can never be guaranteed to lie in the unit interval. (2) its variance must be heteroskedastic since the variance will approach zero as the mean approaches either boundary point (Papke and Wooldridge, 1996; Kieschnich and McCullough, 2003). Previous studies usually dichotomize it and define a visit to be non-urgent or primary-care-sensitive if the probability is above a predetermined cutoff. Although this is certainly one way to do it, it tends to lose a lot of information in the probabilities. In this paper, we use the original values of the probabilities and model it using an econometric method developed for fractional or proportional dependent variables by Papke and Wooldridge (1996).

We begin with a probabilistic function taking the following form:

$$E(y_i|X_i) = G(\beta_0 + V_i\beta_V + H_i\beta_H + N_i\beta_N) \quad (1)$$

The observation unit is the i^{th} hospital ED visit (i = 1, 2, 3, …, N). The dependent variable y_i represents the probability of a visit i being non-urgent in the first regression and being PCS in the second regression. In other words, the two regressions share the same function form, and the regressions are run separately. The conditional expectation of y_i can be expressed as a function G of independent variables. As in Papke and Wooldridge (1996), G(.) is a known function satisfying 0< G(.) < 1. This ensures that the predicted values of y_i lie in the interval (0, 1). Following Papke and Wooldridge (1996), we assume G(z)≡exp(z)/[1+exp(z)], which is the logistic function. The independent variables, denoted as a vector Xi, includes V (a vector of patient-visit characteristics including age, gender, race, insurance status, Charlson comorbidity score, whether this ED visit is at least a second time visit in 2008, total ED visits in 2008), H (hospital characteristics, such as whether the hospital is affiliated with a medical school, whether it is a public hospital or a nonprofit hospital), and N (neighborhood characteristics, such as primary care physicians per 1000 population in the county where the patient lives, percentage of population age 65 or older, whether part of or the whole county is a health professional shortage area, percentage of population in poverty, whether the county is in an metropolitan statistical area, whether it is in eastern, central or western Tennessee). We also include interaction terms between race and gender, and among insurance types, race and gender. It is likely that the effect of gender is different across race groups. Similarly, insurance types could be affecting the left-hand side variable differently across gender and race groups.

We then use the logit quasi-maximum likelihood estimator proposed by Papke and Wooldridge (1996)[5] to estimate the non-linear model (1). The model is first estimated for ED visit probability of being non-urgent, and is then estimated for ED visit probability of being PCS. The quasi-likelihood estimation is performed in Stata[6], with

[5] Papke and Wooldridge (1996) use the following log-likelihood function $l_i(b) \equiv y_i \ln[G(X_i\beta)] + (1 - y_i)\ln[1 - G(X_i\beta)]$. Because this equation is a member of the linear exponential family, the quasi-maximum likelihood estimator of β obtained from the maximization problem $max \sum_{i=1}^{N} l_i(b)$ is consistent for β provided that equation (1) holds.

[6] It is done in Stata by using *glm* commend with the option of binomial distribution and logit link function.

error terms clustered at patient levels. It is observed that a large proportion of the ED visits are repeated visits[7]. The clustered errors terms could control for any correlation among multiple visits by the same patient.

5. Estimation results

The estimation results are shown in Table 6. Regression 1 (for an ED visit being non-urgent) and regression 2 (for an ED visit being PCS) are presented side by side for ease of comparison. Standard errors in both regressions are adjusted for 947,799 clusters by patient ID. The chi-square statistics of the two equations are both significant with p-value equals to 0, suggesting the overall significance of the models. The log of pseudo likelihood and deviance are also presented. The two types of deviance[8] are similar to the concept of total squared error. The deviances over the degree of freedom are about 0.4 in both regressions, which suggests they are reasonable fit.

The key variable of interest, "uninsurance" (noninsurance status) is shown to have a significant positive effect on the likelihood of an ED visit being non-urgent and PCS, comparing to the private insurance. This agrees with the expectation that patients who face severe barriers to access to regular care are more likely to have non-urgent ED visits for primary care treatable or potentially avoidable conditions. However, when compared with public insurance, the impact of noninsurance status is not as large in magnitude as that of public insurance. Medicaid and Medicare enrollees tend to have the highest probability among the four insurance types to be non-urgent and PCS. This may have

[7] Among the 1,574,403 total observations used in the regression, 947,799 have different patient IDs. The rest are visits made by repeated patients.

[8] They measure the difference between the log-likelihood value of a saturated model (i.e., a model that estimates one parameter for each observation and thus perfectly replicates the observed data) and the log-likelihood value of the estimated generalized linear model.

something to do with the nationwide observation that Medicaid patients visit ED more than patients with other types of insurance. One rationale for the high probability of non-urgent or PCS visits may be that, the low or zero cost of the public insurance encourages patients to take less care of themselves and use emergency care at their convenience. Another possible explanation may be that Medicaid patients have limited health care access due to physicians' refusal to accept Medicaid which gives a below-market reimbursement rate. As reported in Cheung et al. (2012), Medicaid patients were almost twice as likely to face barriers that limit their access to primary healthcare as people with private insurance. The difficulty in access to primary care then tends to send the Medicaid patients to EDs. Visits made by patients with other types of insurance[9], are also more likely to be non-urgent or PCS compared to visits made by privately insured patients.

[9] Other types of insurance: any insurance types that do not belong to private insurance, Medicaid, Medicare or noninsurance. It includes other government insurance, worker compensation and others.

Table 6

Estimation results

	Non-urgent				Primary-care-sensitive			
	Coef.		Robust Std. Err.	Marginal effect	Coef.		Robust Std. Err.	Marginal effect
Patient-visit characteristics								
Charlson Score	-0.34365	***	0.002959	-0.06959	0.063703	**	0.003228	0.009334
Age	-0.01108	***	6.03E-05	-0.00224	-0.01735	**	7.35E-05	-0.00254
Female	0.198667	***	0.005336	0.040585	0.243557	**	0.006528	0.036297
Black	0.261608	***	0.007931	0.051329	0.519231	**	0.010036	0.069627
Hispanic	0.073928	***	0.015983	0.014744	0.113293	**	0.019562	0.016044
White (reference)								
Other race	0.069467	***	0.01075	0.013891	0.061915	**	0.013265	0.008925
Uninsured	0.258231	***	0.007225	0.050286	0.421114	**	0.009303	0.056351
Medicaid/care	0.31937	***	0.005502	0.065049	0.540286	**	0.006923	0.080619
Private insurance (reference)								
Other insurance	0.280939	***	0.011784	0.053526	0.382587	**	0.015125	0.049828
Black*female	-0.01185		0.007201	-0.0024	-0.17984	**	0.009535	-0.02743
Hispanic*female	-0.01948		0.013322	-0.00396	-0.06612	**	0.016908	-0.00989
Other race*female	-0.02428	***	0.009188	-0.00494	-0.0174		0.012014	-0.00256
Uninsured*female	-0.05097	***	0.008439	-0.01041	-0.01133		0.010819	-0.00167
Medicaid/care*female	-0.05986	***	0.00639	-0.01217	-0.09537	**	0.008064	-0.0141
Other insurance*female	-0.09492	***	0.014646	-0.0196	-0.13677	**	0.018642	-0.02089
Uninsured*black	-0.1294	***	0.01008	-0.02687	-0.16149	**	0.012621	-0.0248
Uninsured*Hispanic	-0.07247	***	0.021412	-0.0149	-0.14989	**	0.026159	-0.02302
Uninsured*other race	-0.01847		0.013658	-0.00375	-0.02677		0.017817	-0.00396
Medicaid/care*black	-0.24051	***	0.007835	-0.05045	-0.29597	**	0.009984	-0.04635
Medicaid/care*Hispanic	-0.08748	***	0.016196	-0.01803	-0.08657	**	0.019989	-0.01302
Medicaid/care*other race	0.010975		0.010727	0.002218	0.023709	*	0.013502	0.00345

(Continue)

Table 6 (continue)

	Non-urgent				Primary-care-sensitive			
	Coef.		Robust Std. Err.	Marginal effect	Coef.		Robust Std. Err.	Marginal effect
Other insurance*black	-0.12659	***	0.018803	-0.02632	-0.15806	**	0.02295	-0.02433
Other insurance*Hispanic	0.015311		0.047088	0.00309	-0.01163		0.054373	-0.00171
Other insurance*othr race	0.001277		0.029841	0.000259	-0.00085		0.037766	-0.00013
Revisit	0.010196	***	0.003371	0.002064	0.032792	**	0.004356	0.004795
# visit	0.000892		0.000732	0.000181	-0.00607	**	0.00089	-0.00089
Hospital characteristics								
Medical school	-0.01111	***	0.003309	-0.00225	-0.05608	**	0.004289	-0.00827
Public hospital	-0.01604	***	0.004107	-0.00325	-0.09439	**	0.005296	-0.01408
Nonprofit hospital	-0.02596	***	0.003614	-0.00526	-0.05549	**	0.004686	-0.00813
For-profit hospital (reference)								
County characteristics								
Primary care providers	0.03612	***	0.002652	0.007314	0.062173	**	0.00351	0.00911
% 65+	1.87166	***	0.072285	0.379001	0.900658	**	0.093576	0.131967
Prof short area, part	-0.01076	***	0.003986	-0.00218	-0.04018	**	0.005126	-0.00589
Prof short area, whole	0.02581	***	0.00472	0.005207	0.003989		0.006034	0.000584
No prof short are (reference)								
% poor	0.51924	***	0.0537	0.10514	0.121236	*	0.06858	0.01776
Metropolitan area	0.031472	***	0.004531	0.006389	-0.03715	**	0.005832	-0.00542
East TN	0.008098	*	0.004303	0.001639	0.091028	**	0.005556	0.013265
West TN	-0.09764	***	0.004169	-0.01999	0.006811		0.005263	0.000997
Central TN (reference)								
Constant	0.660632	***	0.013562		1.424946	**	0.017261	

(Continue)

Table 6 (continue)

	Non-urgent			Primary-care-sensitive		
	Coef.	Robust Std. Err.	Marginal effect	Coef.	Robust Std. Err.	Marginal effect
Chi-2	79902.4	p=0		76773.4	p=0	
Log pseudolikelihood	-725081			-612087		
Deviance	606891.3			690473.2		
(1/df) Deviance	0.385483			0.438573		
Pearson	552575.6			685961.1		
(1/df) Pearson	0.350983			0.435707		
AIC	0.921136			0.777596		
BIC	-2.19E+07			-2.18E+07		

Note: number of observations in both equations is 1,574,403. ***, **, and * indicate that the coefficient is statistically significantly different from zero at the 1, 5 and 10 percent levels, respectively. Primary care providers are per 1000 population. Standard errors are adjusted for 947799 clusters in patient ID.

Considering the potential heterogeneous effect of noninsurance, visits by uninsured patients of different gender and race may have different likelihood to be non-urgent or PCS. We therefore allow insurance types to interact with gender and race. The results indicate that the interaction effect of female with insurance types reduces the likelihood of non-urgent or PCS visits. This effect is consistent across all three insurance types. The interaction effect of race with insurance is similar. Most interaction terms of insurance with race groups have negative signs and are statistically significant while the ones with positive signs are not significant. Among the race groups, blacks have the largest negative interaction effects.

Some other factors that have significant effects in the model include Charlson score, age, gender and their interactions, revisit indicator, total visits, and many of the hospital and county characteristics. Charlson score (which measures comorbidity) is negatively correlated with non-urgent likelihood, suggesting that the higher the Charlson score, the less likely it is to be non-urgent. This agrees with prior expectation that ED patients with more severe comorbid conditions are more likely to have urgent instead of non-urgent conditions. On the contrary, Charlson score is positively correlated with PCS likelihood, which means patient with more severe comorbid conditions are more likely to be primary care treatable or potentially preventable. This is unexpected since patients with more severe comorbid conditions are usually thought to be more difficult to treat and more urgent. It is unclear, however, whether there is any other study that has similar findings.

In terms of age, the older the patient is, the less likely the visit to be non-urgent or PCS. It indicates that young patients are more likely to have non-urgent or PCS ED visits.

This agrees with several previous studies which found younger adults were more likely to have non-urgent visits compared with older adults (Liu et al., 1999; Davis et al., 2010; Sarver et al., 2002). This may due to the inexperience of younger patients. Females, are more likely to visit ED for non-urgent and PCS conditions than males. And all three races—black, Hispanic and others – tend to be more likely to visit ED for non-urgent and PCS cases compared to white patients. We also allow the effect of race to be different for male and female. It appears that, the interaction effects of female and race are all negative. However, some of the interaction terms are not significant.

We also include among the independent variables an indicator for whether it is a repeated visit within year 2008. If a patient visited ED multiple times, this indicator would be 1 starring from his or her second visit. And another variable is also included to count the total number of ED visits during the year 2008, to distinguish visits made by frequent users. The result shows a mixed story. On the one hand, a repeated visit is more likely to be non-urgent or PCS. This tend to link to patients who overestimated their severity and overused ED, or patients who did not have access to other medical care and sought ED for regular or primary care. On the other hand, as the patients made more and more ED visits within the year, the current visit is less likely to be PCS. This may link to patients who suffered from various severe diseases. These patients might have difficulty in controlling and maintaining their condition and had to go back ED for any relapse.

Among the hospital characteristics, public hospitals are more likely to have ED visits for non-urgent or PCS cases. This result also applies to nonprofit hospitals.

The county where a patient lives also affects the likelihood of non-urgent or PCS visits. The density of primary care providers has surprising positive signs for both non-urgent visits and PCS visits. It seems to suggest that more primary care providers failed to lower the non-urgent or PCS cases. One earlier article by Cunningham et al. (1995) had some results relate to this. It is found there that persons with non-urgent ED visits actually had higher average number of physician visits in an outpatient setting other than the ED. It is questionable that whether more primary care providers or more care services received necessarily means more effectively primary care delivery.

The proportion of people aged 65 and above in patient's county tends to relate to higher likelihood of non-urgent visits and PCS visits. This appears to be different from the negative relationship between patient's own age and the likelihood of non-urgent and PCS. The marginal effect is greater on the non-urgent visits. Partially professional shortage area is negatively associated with non-urgent and PCS cases, which again disagrees with expectation but is consistent with the discussed results for primary care provider density. However, if the whole county is in professional shortage area, patients from the county are more likely to visit ED for non-urgent reasons. The effect on PCS is not significant.

The percentage of poor people tends to increase the likelihood of non-urgent visits and PCS visits. This result implies that people with insufficient income are probably using ED as an alternative of regular care. Patients that live in metropolitan areas are significantly more likely to have non-urgent ED visits but less likely to have PCS visits, compared to those from non-metropolitan areas. Lastly, patients that live in eastern Tennessee are most likely to have non-urgent ED visits, followed by those from central Tennessee and least likely for those from western Tennessee. For PCS cases, it is also eastern Tennessee from where patients are most likely to have PCS ED visits. Western

Tennessee tends to have slightly higher likelihood than central Tennessee. The difference is not significant at 5% level. Patients in central Tennessee have the least primary-care-sensitive ED visits. Marginal effects at the means of each independent variable are also presented.

6. Predicting the effects of covering uninsured patients

In this section, we simulate the effect of insurance mandates under PPACA in 2014 and address the question: if everybody gets insurance, how would the average likelihood of non-urgent and PCS ED visits change? We explore two scenarios in which uninsured patients get covered by either private insurance or public insurance (primarily Medicaid). According to the empirical results in the last section, these two types of insurance coverage would generate different outcomes. In addition, we attempt to predict the direction of change in the corresponding ED expenses. The details are discussed as below.

Scenario 1: Every uninsured patient gets private insurance

Suppose all uninsured patients got private insurance, and everything else stays the same. Given the model estimation, we change those uninsured patients' insurance type to private insurance and predict the likelihood of their visits being non-urgent and PCS. The mean of the likelihood over the whole sample is then updated and presented in Table 7. It appears that, under the condition that all uninsured patients get private insurance, the sample average likelihood of an ED visit being non-urgent is reduced from 0.713 to 0.706. For the likelihood of being PCS, the average likelihood decreases from 0.813 to 0.803. The decreases in both cases are significant at 1 percent level based on t-test results.

One question following the changes in the probability of being non-urgent or PCS is that, how would the expenses on that ED visit being affected due to the probability change. Here, expenses of an ED visits mean the hospital revenue of that ED visit. It is approximated by charge price of the ED visit adjusted by outpatient revenue charge ratio. Data are from the Tennessee HDDS dataset and JAR-H data. Notice that, insurance type changes can affect the expenses through the reimburse rate. Even if the same emergency care service is provided, hospital revenue would differ because of different reimbursement rate provided by different insurers. The discussion here, however, only focuses on the differences in expenses caused by the changes in the likelihood of being non-urgent or PCS. We provide a rough comparison of the ED expenses according the levels of the non-urgent and PCS likelihood in order to predict the direction of change in the expenses. In Table 8, variable non-urgent and PCS are divided into five groups based on their quintile points. It is clear that from low non-urgent probabilities to high non-urgent probabilities, the expenses are decreasing. Similar decreasing pattern shows in mean expenses as PCS probabilities increase. According to the discussion above, the non-urgent and PCS probabilities are going to decrease if every uninsured patient gets private insurance. This tends to be associated with an increase in mean expenses.

In sum, the mean likelihoods of ED visit being non-urgent and PCS would be reduced if the uninsured are covered by private insurance. The mean expenses tend to increase due to the reduction in average non-urgent and PCS likelihoods.

Table 7

Comparison of estimated (or observed) and predicted likelihood of being non-urgent and primary-care-sensitive

	Non-urgent		Primary-care-sensitive	
	Mean	Diff (estimated-predicted)	Mean	Diff (estimated-predicted)
Estimated (or observed)	0.7125994		0.8125044	
predicted, uninsured get private insur	0.7057172	0.0068822***	0.8025211	0.0099833***
predicted, uninsured get Medicaid/care	0.7136551	-0.0010557***	0.8138003	-0.00112959***

Note: *** indicate the difference is significant at 1 percent level based on t-test.

Table 8

Expenses mean and standard deviation by non-urgent quintiles and by PCS quintiles

non-urgent	Expenses Mean	Expenses Std. Dev.	PCS	Expenses Mean	Expenses Std. Dev.
0~0.5	943.4775	1038.937	0~0.670	993.5649	1043.557
0.5~ 0.758	699.4035	788.8095	0.670~0.870	476.4171	526.1188
0.7582~0.835	411.0502	480.2506	0.870~1	379.4021	556.7149
0.835~0.942	346.695	448.3544	1~1	-	-
0.942~1	319.656	661.4426	1~1	-	-

Note: 1. the 4th quintile point of PCS is the same as the 3rd quintile point (=1), so there are only three groups of PCS values.
2. Expenses are in 2008 dollars.

Scenario 2: Every uninsured patient gets Medicaid/Medicare

If all uninsured patients got covered by Medicaid, the effect is the opposite to that of private insurance. The average likelihood of an ED visit being non-urgent is raised from 0.713 to 0.714. The average likelihood of an ED visit being PCS is increased by 0.001 with respect to the original condition. The differences in both cases are significant suggested by t-test results. However, the magnitude of the increase in the average likelihoods is much smaller than the decrease when all uninsured get private insurance.

Measured in dollars of expenses, the increase in the mean of non-urgent and PCS likelihood tends to associate with a decrease in the mean expenses, given the relationship summarized in Table 8. Therefore, if every uninsured patient got Medicaid, the mean likelihoods of ED visits being non-urgent and PCS would increase and the mean expenses caused by the likelihood changes tend to decrease.

The reality: A mix of scenario 1 and 2

In reality, by the time PPACA is fully phased in, more than 30 million people nationwide without insurance will be eligible to get either public insurance through Medicaid expansion or private insurance through insurance exchange. In Tennessee, about 14.7% of the population, or over 900,000 people are without insurance (three-year average over 2008 to 2010 from US Census Bureau data). It is expected that 330, 932 to 474, 240 people would be new enrollees in Medicaid by 2019 (Holahan and Headen, 2010). And, there would still be a positive uninsured rate (Chang et al., 2012). Therefore, about one third to half of the uninsured people would enroll in Medicaid, and the rest would get coverage through insurance exchange or remain uninsured.

As discussed in the two scenarios, the effect of private insurance coverage on the average non-urgent or PCS likelihood (as in scenario 1) is the opposite of that of public insurance coverage (as in scenario 2). Therefore, the net effect would depend on the mixed structure of insurance types. Also notice that the magnitude of the effect of private insurance is about seven times of that of public insurance on the average non-urgent likelihood and about nine times on the average PCS likelihood (see Table 7). If the proportion of uninsured patients who get public insurance is about the same or slightly higher than the proportion of uninsured patients who get private insurance, the effect of private insurance tends to outweigh the effect of public insurance and results in lower average likelihood of being non-urgent and PCS. If the proportion of uninsured patients who get public insurance is more than seven (or nine) times of the proportion of those who get private insurance, the effect of public insurance is likely to outweigh the effect of private insurance and results in higher non-urgent (or PCS) likelihood.

Similarly, expense changes caused by the likelihood changes depend on the mixed structure of insurance types too. If the effect of private insurance (as described in scenario 1) outweighs the effect of public insurance (as described in scenario 2), the total impact caused by lower average non-urgent or PCS likelihood would increase ED expenses. When the effect of public insurance outweighs the effect of private insurance, the total impact caused by higher average non-urgent or PCS likelihood would reduce ED expenses.

7. Conclusion

The main purpose of this paper is to investigate the effect of insurance coverage on ED use. In particular, how the change in insurance coverage would affect the likelihood of an ED visit being non-urgent and being PCS. It mimics the effect of insurance mandates under PPACA and also relates to the hot debates on how uninsured patients are attributing to the overcrowded ED. Following NYU Algorithm, we are able to define and derive the likelihood of an ED visit being non-urgent or PCS. We then construct a logit quasi-likelihood model and test it using a statewide hospital outpatient discharge database. The results of this study support the finding that uninsured patients are associated with higher probabilities of non-urgent visits and PCS visits compared to private insured patients, but not as high as that of public insured (Madicaid/Medicare) patients. Based on the estimation, we predict that average non-urgent or PCS likelihood can change in either way depending on relative proportions of each insurance type. We further discuss the impact of these changes on expenses.

This paper is different from previous research in three ways: (1) it provides a quantitative analysis of both non-urgent ED visits and PCS visits; (2) instead of using an zero-one dependent variables for non-urgent or PCS ED visits, we keep the original probabilities generated by NYU Algorithm and model it by logit quasi-likelihood regression; (3) we further predict the changes in the likelihood and discussed the changes in expenses assuming everybody gets insurance coverage in two scenarios.

Our results show that noninsurance is associated with higher probability of non-urgent visits and higher probability of PCS visits compared to private insurance. These effects are different for male and female and across race groups. If all uninsured patients got private insurance, the average probability of being non-urgent and PCS would decrease. If all uninsured patients got public insurance (Medicaid), the average probability of being non-urgent or PCS would increase. The total effect of the insurance coverage change on the average likelihood would depend on the mixed structure of insurance types. If the proportion of uninsured patients who get public insurance is about the same or only slightly higher than the proportion of uninsured patients who get private insurance, the effect of private insurance would outweigh the effect of public insurance and results in lower average likelihood of being non-urgent and PCS. This is further associated with a higher average ED expenses.

The analysis of the assumed scenarios would provide valuable information to policy makers on the potential changes in ED use under recently enacted health insurance coverage expansions. A lower average likelihood of non-urgent or PCS ED visits would occur when the proportion of uninsured people who will be covered by Medicaid is about the same or only slightly greater than the proportion of uninsured people who will purchase private insurance. However, the average ED expenses tend to increase as the likelihoods decrease.

CHAPTER 5

DOES SELF-CONFIDENCE AFFECT MBA SUCCESS?[1]

1. Introduction

In recent years, economists have begun to go beyond the traditional, human capital centered view of earnings determination. While formal and informal education and training certainly matter for one's job market success, other factors, such as personal preferences, expectations, and noncognitive abilities, are also likely to be important (Borghans et al., 2008). Several recent studies investigate the effects of noncognitive abilities and psychological traits on employment and wages, many in the context of estimating gender gaps (Braakman, 2009; Long, 1995; ter Weel, 2008; Thiel and Thomsen, 2009).

Researchers have also become interested in role that expectations play in determining outcomes, especially insofar as those expectations may be either irrational or inaccurate. A stream of studies have either empirically documented (Benoit and Dubra, 2011; Mobius et al., 2011; Moore and Healy, 2008) or theoretically motivated (Compte and Postlewaite, 2004; Koszegi, 2006; Santos-Pinto and Sobel, 2005; Van den Steen, 2004; Zabojnik, 2004) the existence of individuals' overconfidence in their own abilities or likelihood of success.

Most economic papers define confidence or overconfidence as an inaccurate expectation or imperfect information about one's ability, performance or chances of success. In psychology, however, the preferred terms are self-esteem, self-efficacy and

[1] I am very grateful to Dr. Andrew Hussey for his continuous guidance in the completion of this paper. I am also grateful to Dr. Wayne Grove for his valuable inputs. I further thank seminar participants at the University of Memphis, Economics Department for helpful comments on earlier versions of this paper. However, I take full responsibility for any remaining errors.

optimism[2], as confidence is a multi-dimensional concept. What confidence means in economics is therefore mostly related to self-esteem and self-efficacy in psychology. In our paper, we attempt to incorporate expectation, bias in expectation and optimism to develop three measures for confidence. We are able to study these types of confidence by using the data of GMAT Registrant Survey, which has four waves and tracked the GMAT registrants between 1990 and 1998. The first measure is a set of values that measure confidence as personal perception of own ability on 16 specific managerial skills and expectation of personal performance in two GMAT sections (verbal and quantitative). The second one is a single-value measure that changes the verbal and quantitative expectation into average bias in expectation by comparing the expected score levels with actual score levels. The last one is a single-value index based on optimism, measuring confidence as a general attitude and view someone has regarding the likelihood of future positive outcomes. In our case, it is reflected in choosing self-favoring outcomes in most of survey questions that involve future expectation. Hereafter, we refer to it as an overall confidence indicator.

We first explore the determinants of confidence among the survey respondents. A wide range of variables covering individual demographics, academic records, career history and family background are used in the regressions to explain the variation in the three confidence measures respectively.

Our second goal is to investigate the effect of confidence, measured in three ways, on academic progression and career success of business professionals. We focus specifically on outcomes related to the attainment of a Master's of Business

---

[2] Carol Craig, "Confidence", Centre for Confidence and Well-being, Oct 26, 2012. http://www.centreforconfidence.co.uk/pp/overview.php?p=c2lkPTYmdGlkPTAmaWQ9MTgx

Administration (MBA) degree, as well as subsequent earnings and job quality measures. This is a particularly important area of study for several reasons. First, the self-confidence of managers and other business leaders can have large implications for employment and overall success of their firms. For example, Malmendier and Tate (2008) find evidence that overconfident CEOs are more likely to take value-destroying mergers and to overpay for the target companies. On the other hand, Englmaier (2011) highlights the benefit to firms of hiring overconfident managers. Additionally, overconfidence is believed to play an important role in entrepreneurship and opening new business (Koh, 1996; Koellinger et al., 2007; Asoni, 2011). Second, if confident business man is more competent, business schools that offer MBA program should start by looking for more confident MBA applicants. Third, it also addresses the question of how an MBA program can boost one's confidence in managerially related skills and make a significant difference in post program labor outcomes.

There are limited empirical studies that have investigated the labor market effects of self-confidence. Studies that focus on similar concepts such as internal control, self-esteem, optimism are also considered. Kalachek and Raines (1976) find that a worker's sense of internal (versus external) control, a measure of self-confidence, positively affects their wage. Groves (2005) carries out a similar study for white women in US and UK. The variable, locus of control (measuring personal sense of internal versus external control), also has a significant effect on wage. Tsui (1998) finds that, among individuals in the business management field, an indicator of leadership self-confidence, but not social self-confidence, affects income. Drago (2011) shows that self-esteem in 1980 has a sizeable impact on wages 8 years later after controlling for a wide set of individual characteristics. Mobius and Rosenblat (2006) indirectly show that confidence matters when they study the physical attractiveness and job search outcomes. They found that physically attractive workers are more confident and higher confidence increases wages. Kaniel et al. (2010) study MBA students at a major midatlantic university and find "dispositional optimists" experience significantly better job search outcomes than pessimists with similar skills. Our study differs from theirs by using a nationwide survey, developing several confidence measures, investigating determinants for levels of confidence and also studying the effect of confidence on MBA related academic outcomes.

There is also some limited evidence that self-confidence affects academic performance. Lent, Brown and Larkin (1986) find that beliefs of self-efficacy help predict grades and retention in college. Other papers find overconfidence in academic performance may negatively relate to actual performance (Yang et al., 2009; Potgieter et al., 2010; Chiu and Klassen, 2010). This may due to the fact that overconfidence causes students to prepare less than they need to in order to perform well.

Our findings indicate that all three confidence measures are influenced by several background and demographic variables, most notably race, gender, managerial status and actual GMAT scores. These confidence measures in turn have some predictive power for eventual academic outcomes and more so for labor market outcomes. Initiative is most strongly associated with earnings and job quality indicators. Confidence in one's verbal skills (beyond actual verbal test scores) negatively impact earnings several years later. Confidence based on average verbal and quantitative bias has little predictive power for both academic and labor market outcomes. And overall confidence is shown to strongly improve almost all labor market outcomes.

The rest of this paper proceeds as follows. Section 2 discusses the data and our empirical strategy. Section 3 presents the results. Section 4 concludes.

2. Empirical Strategy and Data

The data used in our analysis comes from the GMAT Registrant Survey, a longitudinal survey of individuals who registered for the Graduate Management Admission Test (GMAT), an admission requirement for the vast majority of MBA programs in the United States. The survey, sponsored by the Graduate Management Admission Council (GMAC), was mailed to the same individuals in four waves, between 1990 and 1998, whether or not they took the GMAT. The Wave I survey occurred from April 1990 to May 1991, shortly after test registration, but prior to MBA enrollment. Of the 7,006 registrants initially surveyed, 5,885 responded to the first survey, 4,327 to the third survey, and 3,771 to the fourth in 1998.

The GMAT Registrant Survey contains a wealth of information about an individual's background, their education experiences, work experience and earnings. Useful for our purposes, in the first survey wave (prior to MBA enrollment and prior to taking the GMAT) is included a set of 16 self-assessed skills or traits deemed important for success in business. We include variables for responses ranging from 1 ("not at all" having the characteristic or skill) to 4 ("very much" having the characteristic or skill) for each of the following: initiative; high ethical standards; communication abilities; ability to work with people from diverse backgrounds; shrewdness; ability to organize; physical attractiveness; assertiveness; ability to capitalize on change; ability to delegate tasks;

ability to adapt theory to practical situations; understanding business in other cultures; good intuition; ability to motivate others; being a team player; and knowing the right people. In the context of estimating the gender wage gap, Montgomery and Powell (2003) combined all of these responses into a single variable, which they refer to as a "confidence index", and include it as a control. Instead, we focus on each variable individually and consider a large number of academic and work related outcomes, as well as investigating the determinants of these self-assessed skill responses.

In addition to investigating the effects of self-confidence in these managerial related skills, we include variables intended to represent one's confidence in their quantitative and verbal abilities. Immediately after registering to take the GMAT but before taking the exam, respondents were asked, in the first survey wave, how well they expected to do on the quantitative and verbal sections of the GMAT. Responses include 1 ("excellent"), 2("above average"), 3("average"), 4("below average") and 5 ("poor") which we reversed so that a higher number means greater confidence. Importantly, because the survey data were linked to actual testing records, we have an accurate measure of individual verbal and quantitative abilities. Since actual GMAT scores are controlled for in all of the specifications where we include these expectations, we interpret these expectations of verbal and quantitative performance as indicating confidence in one's own abilities, beyond their eventual realized scores. In sum, the 16 self-assessed skills or traits plus the expectations of verbal and quantitative performance make up our first set of confidence measures. The second confidence measure is a single-value index based on the bias of expectation, rather than expectation itself, on the quantitative and verbal scores and abilities. Since the choice set in the survey question indicates five levels of performance, we also divide actual scores into quintiles and take the difference between expected performance levels (5 to 1 corresponding to “excellent”, “above average”, “average”, “below average” and “poor”) and actual quintile levels. If expected score level is higher than actual score quintile, the respondent shows overconfidence in his or her verbal or quantitative ability. And, the greater the difference is, the more over-confident the individual is. We further take the average of verbal difference and quantitative difference and use it as a combined measure of confidence on verbal and quantitative abilities.

We also construct a single-value overall confidence indicator that mimics psychological scales and comprehensively assesses the level of respondents’ confidence. Searching through the psychological literature, we find several psychological tests that relate to confidence --- the Locus of Control questionnaire that tests internal versus external control, the Life Orientation Test-Revised that measures optimism, and the Rosenberg or LAWSEQ Self-Esteem Questionnaire for self-esteem. Depending on the definition and interpretation of confidence, each of these tests evaluates self-confidence from different angle. Among the three tests, we find the Life Orientation Test for optimism is closer to how we define our confidence, and the questions and measurement in the Life Orientation Test are more replicable in our context. We therefore select 40 questions in wave 1 survey that imitate the questions in the Life Orientation Test-Revised and follow their scales by defining overconfidence (or over optimism) as expecting good or positive results (rather than bad or negative outcomes) in over 70% of the selected survey questions. The detail definition and comparison of the questions in the Life Orientation Test and questions selected from wave 1 survey are in the Appendix.

Our analysis begins by investigating the determinants of each of our 20 variables that reflect self-confidence. Because 19 of these variables can take on multiple values that are on a scale but have no quantitative meaning on their own, we run ordered probits. The overall confidence indicator only takes on values of 0 and 1, so we apply the probit model for it. Included in these regressions are a large number of variables that correspond to prior work experience and academic achievement, family background, and demographics. Specifically, we include: indicator variables representing whether or not the individual (at the time of the first survey wave) had between 1 and 3 years of total full-time work experience, between 3 and 5 years, between 5 and 7 years, and more than seven years; indicator variables for race and gender; age; whether or not the individual is married; variables for mother's and father's education (in years); actual quantitative and verbal GMAT scores; undergraduate GPA, indicator variables representing selectivity of undergraduate institution attended[3]; whether the individual had an advanced degree at the time of the first survey; and variables reflecting current employment, including job tenure (in years), whether the individual was unemployed, whether they were in school as a full-time student, whether they considered themselves an entry level manager or a mid/upper level manager (versus non-manager), and indicator variables for broad classes of industries.

After investigating the determinants of the self-confidence measures, we turn to analyzing their effects on academic and career outcomes. The dependent variables we consider for academic outcomes are: (1) whether or not the individual obtains an MBA

[3] These measures were obtained from Barron's *Profiles of American Colleges*. We collapsed the various undergraduate admission selectivity categories as designated in Barron's into the following three categories: Highly Selective (19% of our sample), Moderately Selective (26%), and the omitted category representing the least selective schools and those not included in the Barron's guide (55%).

sometime within the sample period; (2) conditional on MBA attainment, whether that MBA was obtained from a top 25 program, according to *U.S. News & World Report* 1992 rankings; (3) the individual's GPA within the MBA program; (4) whether the individual reports concentrating their MBA studies in finance; and (5) whether the individual reports concentrating their studies in marketing. For career related outcomes, we utilize the fourth (and final) survey wave. We first run earnings regressions (both log of hourly wage and log of annual salary, each calculated from survey responses about earnings and weeks and hours worked). We then consider self-reported managerial status as the dependent variable. This variable is defined as being zero if the individual was a non-manager, 1 if the individual reports being an entry-level manager, and 2 if the individual reports being a mid- to upper-level manager. We also consider a Wave 4 self-employment status as a labor market outcome. This variable is equal to 1 if the individual is self-employed. Finally, Wave 4 of the survey also contains three of the five Job Descriptive Index surveys (excluded are the Supervision and the Coworkers surveys) and the related Job in General survey, used primarily in the field of industrial organizational psychology.[4] Each survey asks respondents to indicate whether particular words or phrases describe their current employment situation. If a "yes" response was indicated and the job attribute was positive, 3 points were given. If "can't decide" was indicated, 1 point was given. If the job attribute was negative and "no" was indicated, zero points were given. In order to investigate effects on quality of job (beyond earnings), we include as dependent variables the resulting total points for each section of these surveys.

[4] See Smith et al. (1987) and the JDI website.: http://showcase.bgsu.edu/IOPsych/jdi/index.html

We use ordinary least squares (OLS) in cases where the dependent variable may be considered continuous (log of wage, log of earnings, MBA GPA, and each JDI measure). In cases where the dependent variable is binary (MBA, Top 25 MBA, Study Finance, Study Marketing, Self-employed, Overall Confidence Indicator), we use probit estimation. Finally, for managerial status, we carry out an ordered probit. In each case, we include a full set of covariates corresponding to the initial characteristics of individuals (at the time or prior to skill self-assessment).

Our sample contains a maximum of 3,788 individuals and observations. We rely on individuals with non-missing values of the large number of control variables, including actual GMAT scores. Of this sample, 1,157 obtained an MBA by the end of the sample period, while 2,631 did not. Descriptive statistics of our sample are presented in Table 9, for the full sample and also for the MBA and non-MBA subsamples.

3. Results

Table 10 presents estimates from ordered probit regressions of individuals' confidence in their managerial skills or traits and GMAT expectations. Because the dependent variables have no objective values, we focus merely on the sign and significance levels of regressors. Several variables predict confidence in a wide set of indicators, while other variables are either consistently insignificant or are significant in a small number of regressions. Not surprisingly, actual quantitative GMAT scores are

Table 9

Descriptive statistics

	Full Sample		MBA Sample		Non-MBA Sample	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Wave 1 Confidence Indicators:						
Verbal Expectations	3.459	0.741	3.499	0.732	3.441	0.744
Quant Expectations	3.647	0.864	3.718	0.857	3.616	0.865
Average Verbal & Quant expectation bias	0.621	1.085	0.306	1.002	0.761	1.092
Overall Confidence Indicator	0.635	0.481	0.650	0.477	0.629	0.483
Initiative	3.592	0.530	3.598	0.534	3.589	0.528
Ethical Standards	3.684	0.515	3.694	0.511	3.679	0.516
Communication Skills	3.366	0.610	3.378	0.603	3.360	0.613
Work with Diversity	3.600	0.571	3.594	0.571	3.603	0.572
Shrewdness	2.724	0.748	2.712	0.727	2.729	0.758
Ability to Organize	3.483	0.623	3.513	0.604	3.470	0.632
Physical Attractiveness	3.060	0.590	3.055	0.588	3.063	0.590
Assertiveness	3.185	0.657	3.164	0.634	3.194	0.667
Capitalize on Change	3.193	0.661	3.196	0.639	3.192	0.671
Delegate Tasks	3.238	0.688	3.253	0.681	3.231	0.690
Adapt Theory to Practice	3.168	0.686	3.160	0.689	3.171	0.684
Understanding Cultures	2.617	0.886	2.592	0.869	2.628	0.893
Intuition	3.336	0.640	3.323	0.650	3.342	0.636
Motivate Others	3.300	0.642	3.284	0.629	3.307	0.648
Team Player	3.592	0.604	3.606	0.575	3.586	0.616
Connections	2.575	0.791	2.548	0.769	2.587	0.800
Wave 1 Covariates:						
Age	27.784	5.832	27.549	5.814	27.887	5.839
1 yr. < Experience < 3 yrs.	0.244	0.430	0.262	0.440	0.236	0.425
3 yrs. < Experience < 5 yrs.	0.188	0.391	0.195	0.397	0.185	0.389

(Continue)

Table 9 (continue)

	Full Sample		MBA Sample		Non-MBA Sample	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
5 yrs. < Experience < 7 yrs.	0.128	0.334	0.118	0.323	0.133	0.339
Experience > 7 yrs.	0.278	0.448	0.268	0.443	0.282	0.450
Asian	0.175	0.380	0.147	0.354	0.187	0.390
Black	0.122	0.327	0.097	0.296	0.133	0.340
Hispanic	0.158	0.365	0.148	0.355	0.163	0.369
Female	0.411	0.492	0.368	0.483	0.430	0.495
Married	0.318	0.466	0.322	0.467	0.316	0.465
Mother's Edu.	14.031	3.803	14.376	3.722	13.879	3.829
Father's Edu.	13.320	3.450	13.586	3.370	13.203	3.479
Quant GMAT	28.982	8.748	31.298	8.109	27.963	8.826
Verbals GMAT	27.983	8.097	30.282	7.416	26.973	8.178
Undergrad. GPA	3.017	0.424	3.072	0.411	2.993	0.427
Selective Undergrad	0.246	0.431	0.260	0.439	0.240	0.427
Highly Selective Undergrad	0.198	0.398	0.241	0.428	0.179	0.383
Other Advanced Degree	0.059	0.236	0.049	0.217	0.064	0.245
Industry: Agricultural	0.119	0.324	0.105	0.306	0.125	0.331
Industry: Manufacturing	0.191	0.393	0.227	0.419	0.176	0.381
Industry: Service	0.189	0.392	0.178	0.383	0.194	0.396
Industry: Finance, Real Estate	0.144	0.351	0.151	0.358	0.141	0.348
Industry: Public Administration	0.087	0.281	0.080	0.271	0.090	0.286
Tenure	2.217	3.469	2.324	3.384	2.170	3.505
Unemployed	0.173	0.378	0.133	0.340	0.190	0.393
In School	0.155	0.362	0.156	0.363	0.155	0.362
Hours (per week)	30.874	21.861	32.867	21.559	29.998	21.938

(Continue)

Table 9 (continue)

	Full Sample		MBA Sample		Non-MBA Sample	
	mean	std. dev.	mean	std. dev.	mean	std. dev.
Entry Level Manager	0.170	0.376	0.178	0.383	0.167	0.373
Mid/Upper-Level Manager	0.125	0.331	0.137	0.344	0.120	0.326
Wave 4 Outcomes:						
Hourly Wage	29.124	51.050	31.641	62.508	27.361	41.098
Annual Salary	69158	114147	77641	138570	63212	92898
Entry Level Manager	0.212	0.409	0.238	0.426	0.194	0.396
Mid/Upper-Level Manager	0.374	0.484	0.411	0.492	0.348	0.477
Work JDI	38.180	10.458	38.659	10.131	37.841	10.673
Pay JDI	18.882	7.007	19.542	6.623	18.421	7.231
Promotion JDI	15.534	8.923	16.492	8.749	14.860	8.985
General JDI	39.965	10.018	40.153	9.419	39.833	10.418
Observations	3788		1157		2631	

Notes: Source of data is the GMAT Registrant Survey. MBA Sample includes individuals known to have completed an MBA sometime within the sample period (ie., by Wave 4). Numbers of observations correspond to non-missing values of Wave 1 covariates. Actual sample sizes in regressions may differ due to some additional missing values of confidence indicators and wave 4 outcomes.

strongly related to expectations of quantitative GMAT performance, and the same is true for verbal scores. Thus, individual expectations are more accurate than not. Interestingly, however, quantitative scores are negatively related to verbal expectations, and verbal scores are also negatively related to quantitative scores. This is despite the fact that actual verbal and quantitative scores are rather highly and positively correlated. Along the same line, higher quantitative scores negatively predict self-confidence in most of the managerial self-confidence indicators as well as the overall confidence indicator. This is also mostly true for verbal scores, but verbal scores positively predict confidence in ethical standards, communication skills, and ability to work with people from diverse backgrounds.

In general, blacks and Hispanics report higher confidence than whites, while Asians report lower self-confidence. A notable exception is confidence in connections, which blacks and Hispanics report lower than whites. As expected, actual managers, especially mid- to upper-level managers, are significantly more likely to report confidence in their abilities. Interestingly, few of the broad industry of employment variables predict self-confidence.

The last two columns of Table 10 report ordered probit regression result of individuals' confidence based on average verbal and quantitative expectation bias and probit regression result of overall confidence indicator. Similar to the result using the first set of confidence measures, blacks tend to be more confidence using the second and third measures of confidence. And higher quantitative or verbal scores tend to lower average quantitative and verbal expectation bias. However, verbal score is positively associated with overall confidence while quantitative score is negatively associated with overall

Table 10

(Ordered) Probit estimates of confidence indicators

	Verbal Expectations	Quant Expectations	Initiative	Ethical Standards	Communica -tion Skills	Work with Diversity	Shrewdness
Age	0.002	-0.011*	-0.014*	0.029***	-0.002	0.002	-0.007
	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)
1 yr. < Experience < 3	0.005	-0.072	0.094	0.043	-0.101	-0.059	0.022
	(0.075)	(0.076)	(0.082)	(0.085)	(0.078)	(0.084)	(0.076)
3 yrs. < Experience < 5	0.153*	-0.073	0.080	-0.070	-0.041	0.025	0.084
	(0.084)	(0.085)	(0.091)	(0.094)	(0.087)	(0.093)	(0.084)
5 yrs. < Experience < 7	0.191**	-0.137	0.200**	-0.103	-0.062	-0.127	0.162*
	(0.094)	(0.094)	(0.100)	(0.103)	(0.094)	(0.101)	(0.092)
Experience > 7 yrs.	0.250**	-0.193*	0.289**	-0.158	0.005	0.046	0.108
	(0.112)	(0.109)	(0.117)	(0.120)	(0.110)	(0.115)	(0.106)
Asian	-0.01	0.108*	-0.187***	-0.232***	-0.300***	0.080	0.118**
	(0.055)	(0.057)	(0.060)	(0.062)	(0.058)	(0.062)	(0.055)
Black	0.172***	0.305***	0.044	0.110	0.263***	0.501***	0.010
	(0.064)	(0.064)	(0.074)	(0.075)	(0.066)	(0.072)	(0.064)
Hispanic	0.001	0.067	-0.031	0.078	-0.037	0.510***	0.103*
	(0.054)	(0.053)	(0.060)	(0.065)	(0.057)	(0.066)	(0.053)
Female	-0.137***	-0.342***	0.039	0.362***	0.070*	0.061	-0.267***
	(0.040)	(0.041)	(0.045)	(0.047)	(0.042)	(0.045)	(0.039)
Married	-0.076	-0.005	0.167***	0.134**	-0.015	-0.067	-0.017
	(0.048)	(0.047)	(0.053)	(0.054)	(0.048)	(0.050)	(0.045)
Mother's Education	0.003	0	-0.006	0.005	0.014**	0.020***	-0.012*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)

(Continue)

Table 10 (continue)

	Verbal Expectations	Quant Expectations	Initiative	Ethical Standards	Communica -tion Skills	Work with Diversity	Shrewdness
Father's Education	0.013*	-0.01	0.014*	0.007	0.018**	-0.004	0.018***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.007)
Quantitative GMAT	-0.037***	0.105***	-0.018***	-0.004	-0.027***	-0.013***	-0.005
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Verbal GMAT	0.085***	-0.024***	0.003	0.015***	0.029***	0.009**	0.004
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
Undergraduate GPA	0.138***	0.05	0.168***	0.083	0.030	0.032	0.038
	(0.050)	(0.049)	(0.053)	(0.055)	(0.051)	(0.052)	(0.047)
Selective Undergrad	-0.099**	-0.011	0.037	0.063	0.016	0.081	0.064
	(0.047)	(0.046)	(0.051)	(0.054)	(0.048)	(0.050)	(0.045)
Highly Selective	0.089*	-0.05	0.187***	0.055	0.089*	0.200***	0.182***
	(0.053)	(0.053)	(0.058)	(0.061)	(0.053)	(0.059)	(0.052)
Other Advanced Degree	0.118	0.197**	0.068	-0.070	0.121	-0.031	-0.010
	(0.092)	(0.089)	(0.097)	(0.097)	(0.087)	(0.091)	(0.076)
Industry: Agricultural	0.221***	-0.048	-0.014	0.083	0.025	0.025	-0.073
	(0.067)	(0.071)	(0.074)	(0.076)	(0.069)	(0.077)	(0.069)
Industry: Manufacturing	0.065	0.218***	-0.012	0.025	0.082	0.017	-0.016
	(0.062)	(0.060)	(0.067)	(0.069)	(0.063)	(0.065)	(0.057)
Industry: Service	0.031	0.092	0.004	0.031	0.081	0.029	-0.086
	(0.061)	(0.061)	(0.065)	(0.069)	(0.063)	(0.066)	(0.058)
Industry: Finance, Real Estate	0.079	0.013	0.006	0.037	0.126*	0.083	0.058
	(0.065)	(0.063)	(0.071)	(0.075)	(0.067)	(0.072)	(0.062)
Industry: Public Administration	0.039	0.171**	0.000	0.076	0.111	0.071	0.044
	(0.078)	(0.076)	(0.086)	(0.086)	(0.079)	(0.084)	(0.071)
Tenure	-0.033***	-0.012	-0.008	0.012	-0.002	-0.013*	-0.017***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.008)	(0.007)

(Continue)

Table 10 (continue)

	Verbal Expectations	Quant Expectations	Initiative	Ethical Standards	Communica-tion Skills	Work with Diversity	Shrewdness
Unemployed	0.062	0.154	0.339***	0.077	0.177	0.178	0.024
	(0.109)	(0.111)	(0.116)	(0.119)	(0.110)	(0.112)	(0.097)
In School	0.009	0.212**	0.278**	0.127	0.069	0.218**	0.143
	(0.105)	(0.106)	(0.113)	(0.115)	(0.105)	(0.108)	(0.091)
Hours (per week)	0.002	0.003	0.008***	0.004	0.002	0.004*	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Entry Level Manager	0.091*	-0.029	0.136**	-0.061	0.090	0.056	0.102**
	(0.054)	(0.052)	(0.060)	(0.063)	(0.056)	(0.059)	(0.051)
Mid/Upper-Level Manager	0.072	0.037	0.205***	-0.147**	0.192***	-0.036	0.125**
	(0.069)	(0.066)	(0.076)	(0.075)	(0.069)	(0.072)	(0.062)
Observations	3607	3598	3757	3758	3759	3753	3740
(Pseudo) R2	0.119	0.199	0.029	0.037	0.048	0.029	0.013

	Ability to Organize	Physical Attractive-ness	Assertive-ness	Capitalize on Change	Delegate Tasks	Adapt Theory to Practice	Understanding Cultures
Age	-0.009	-0.022***	-0.013**	-0.003	-0.016**	-0.003	0.002
	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
1 yr. < Experience < 3 yrs.	-0.050	-0.066	-0.051	0.011	0.025	0.137*	0.045
	(0.080)	(0.078)	(0.076)	(0.078)	(0.077)	(0.073)	(0.073)
3 yrs. < Experience < 5 yrs.	0.010	0.026	0.032	0.057	-0.058	0.124	0.128
	(0.090)	(0.085)	(0.085)	(0.086)	(0.085)	(0.081)	(0.079)
5 yrs. < Experience < 7 yrs.	-0.052	-0.044	-0.028	-0.001	0.033	0.165*	-0.018
	(0.097)	(0.094)	(0.092)	(0.094)	(0.091)	(0.092)	(0.089)

(Continue)

Table 10 (continue)

	Ability to Organize	Physical Attractive -ness	Assertive -ness	Capitalize on Change	Delegate Tasks	Adapt Theory to Practice	Understand ing Cultures
Experience > 7 yrs.	-0.039	-0.093	0.018	0.004	0.153	0.234**	0.116
	(0.110)	(0.110)	(0.109)	(0.110)	(0.106)	(0.107)	(0.099)
Asian	-0.122**	-0.302***	-0.173***	-0.099*	-0.028	-0.001	0.458***
	(0.058)	(0.060)	(0.055)	(0.054)	(0.055)	(0.054)	(0.053)
Black	0.025	0.355***	0.204***	0.164**	0.201***	0.174***	-0.017
	(0.066)	(0.071)	(0.066)	(0.066)	(0.065)	(0.066)	(0.062)
Hispanic	-0.022	-0.130**	0.201***	0.128**	0.124**	0.047	0.355***
	(0.057)	(0.058)	(0.055)	(0.056)	(0.056)	(0.054)	(0.056)
Female	0.288***	0.130***	-0.005	-0.119***	-0.095**	-0.135***	-0.120***
	(0.043)	(0.042)	(0.040)	(0.041)	(0.041)	(0.040)	(0.039)
Married	0.061	-0.025	0.078*	-0.003	0.087*	-0.010	-0.040
	(0.048)	(0.049)	(0.046)	(0.046)	(0.047)	(0.046)	(0.044)
Mother's Education	0.002	0.006	-0.004	0.007	0.007	0.008	0.011*
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
Father's Education	0.008	0.012	0.006	0.002	-0.000	-0.007	-0.008
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Quantitative GMAT	-0.009***	-0.011***	-0.016***	-0.014***	-0.011***	-0.001	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Verbal GMAT	-0.010***	-0.004	0.001	-0.006*	-0.008***	-0.001	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Undergraduate GPA	0.241***	0.037	0.011	0.041	0.011	0.075	0.074
	(0.051)	(0.051)	(0.049)	(0.047)	(0.049)	(0.048)	(0.046)
Selective Undergrad	0.100**	0.026	0.042	0.011	0.019	-0.043	0.031
	(0.048)	(0.048)	(0.046)	(0.047)	(0.047)	(0.045)	(0.044)
Highly Selective	0.118**	0.111**	0.033	0.079	0.059	-0.071	0.125**
	(0.057)	(0.054)	(0.054)	(0.053)	(0.053)	(0.054)	(0.051)

(Continue)

Table 10 (continue)

	Ability to Organize	Physical Attractive-ness	Assertive-ness	Capitalize on Change	Delegate Tasks	Adapt Theory to Practice	Understanding Cultures
Other Advanced Degree	0.028	-0.153*	0.003	0.100	-0.001	0.150*	0.126
	(0.085)	(0.091)	(0.085)	(0.089)	(0.081)	(0.082)	(0.082)
Industry: Agricultural	0.103	-0.058	0.012	0.010	0.043	0.022	-0.106
	(0.073)	(0.071)	(0.067)	(0.069)	(0.069)	(0.067)	(0.065)
Industry: Manufacturing	0.006	-0.013	-0.045	-0.076	-0.039	-0.033	-0.049
	(0.061)	(0.062)	(0.060)	(0.060)	(0.059)	(0.060)	(0.057)
Industry: Service	0.077	-0.127**	-0.101*	-0.096	0.014	0.028	-0.071
	(0.063)	(0.062)	(0.060)	(0.060)	(0.061)	(0.060)	(0.057)
Industry: Finance, Real Estate	0.059	-0.036	0.018	-0.006	-0.066	0.100	0.067
	(0.067)	(0.068)	(0.064)	(0.064)	(0.066)	(0.064)	(0.061)
Industry: Public Administration	0.105	-0.013	-0.051	-0.027	0.020	0.132*	-0.031
	(0.081)	(0.081)	(0.077)	(0.077)	(0.076)	(0.078)	(0.075)
Tenure	-0.011	-0.005	-0.020***	-0.014*	-0.008	-0.007	-0.008
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
Unemployed	-0.095	0.137	0.133	0.154	-0.043	-0.013	0.132
	(0.110)	(0.111)	(0.102)	(0.101)	(0.107)	(0.101)	(0.099)
In School	0.050	0.015	0.092	0.135	0.086	0.107	0.236**
	(0.105)	(0.105)	(0.099)	(0.096)	(0.102)	(0.097)	(0.096)
Hours (per week)	-0.001	0.003	0.004*	0.004*	-0.003	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Entry Level Manager	0.028	-0.030	0.189***	0.063	0.133**	0.020	0.115**
	(0.055)	(0.055)	(0.056)	(0.055)	(0.055)	(0.055)	(0.052)
Mid/Upper-Level Manager	0.256***	0.096	0.350***	0.340***	0.422***	0.178***	0.072
	(0.067)	(0.069)	(0.065)	(0.068)	(0.067)	(0.066)	(0.064)
Observations	3756	3754	3742	3754	3754	3742	3754
(Pseudo) R2	0.026	0.039	0.025	0.018	0.021	0.008	0.029

(Continue)

Table 10 (continue)

	Intuition	Motivate Others	Team Player	Connections	Average Verbal & Quant expectation	Overall Confidence Indicator
Age	-0.005	-0.010	-0.017***	-0.013**	-0.005	-0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
1 yr. < Experience < 3 yrs.	-0.069	-0.061	-0.038	-0.025	-0.035	0.005
	(0.079)	(0.079)	(0.084)	(0.075)	(0.071)	(0.084)
3 yrs. < Experience < 5 yrs.	0.045	-0.021	-0.013	-0.030	0.031	0.028
	(0.087)	(0.088)	(0.093)	(0.082)	(0.077)	(0.094)
5 yrs. < Experience < 7 yrs.	-0.003	0.014	-0.057	-0.150*	0.085	0.001
	(0.094)	(0.093)	(0.100)	(0.090)	(0.085)	(0.102)
Experience > 7 yrs.	0.060	-0.010	-0.120	-0.204**	0.047	-0.083
	(0.109)	(0.108)	(0.113)	(0.103)	(0.101)	(0.119)
Asian	-0.134**	-0.205***	-0.227***	-0.021	0.012	-0.141***
	(0.056)	(0.057)	(0.061)	(0.054)	(0.051)	(0.063)
Black	0.125*	0.175***	0.187**	-0.141**	0.154***	0.240***
	(0.065)	(0.067)	(0.073)	(0.062)	(0.059)	(0.074)
Hispanic	0.126**	0.169***	0.028	-0.101*	0.049	-0.000
	(0.057)	(0.057)	(0.063)	(0.053)	(0.049)	(0.063)
Female	0.041	-0.002	0.100**	-0.097**	-0.241***	-0.156***
	(0.041)	(0.041)	(0.044)	(0.038)	(0.038)	(0.046)
Married	-0.076	0.087*	0.097*	0.017	-0.05	-0.016
	(0.047)	(0.047)	(0.051)	(0.043)	(0.044)	(0.053)
Mother's Education	0.005	0.021***	0.018**	0.018***	-0.002	0.007
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Father's Education	0.016**	0.003	-0.010	0.002	0	0.015*
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
Quantitative GMAT	-0.014***	-0.021***	-0.009***	-0.008***	-0.101***	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

(Continue)

Table 10 (continue)

	Intuition	Motivate Others	Team Player	Connections	Average Verbal & Quant expectation	Overall Confidence Indicator
Verbal GMAT	-0.006*	-0.009***	-0.008**	-0.021***	-0.114***	0.011***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Undergraduate GPA	0.066	0.031	-0.117**	0.035	0.125***	0.272***
	(0.049)	(0.049)	(0.053)	(0.047)	(0.046)	(0.055)
Selective Undergrad	0.136***	0.042	0.063	-0.061	-0.07	-0.003
	(0.047)	(0.048)	(0.051)	(0.044)	(0.043)	(0.053)
Highly Selective Undergrad	0.121**	0.116**	0.068	-0.059	0.025	0.021
	(0.054)	(0.054)	(0.058)	(0.051)	(0.049)	(0.061)
Other Advanced Degree	0.060	0.110	-0.091	0.005	0.182**	0103
	(0.084)	(0.086)	(0.087)	(0.085)	(0.085)	(0.099)
Industry: Agricultural	-0.080	0.005	0.134*	0.019	0.082	0.034
	(0.069)	(0.070)	(0.075)	(0.066)	(0.063)	(0.075)
Industry: Manufacturing	-0.039	-0.060	0.042	0.051	0.129**	0.220***
	(0.061)	(0.061)	(0.066)	(0.057)	(0.055)	(0.070)
Industry: Service	-0.062	-0.045	0.014	-0.032	0.035	0.083
	(0.061)	(0.060)	(0.065)	(0.056)	(0.056)	(0.068)
Industry: Finance, Real Estate	0.021	0.029	0.115	0.090	0.029	0.133***
	(0.064)	(0.066)	(0.071)	(0.061)	(0.059)	(0.074)
Industry: Public Administration	-0.074	0.111	-0.063	-0.119	0.075	0.216**
	(0.079)	(0.081)	(0.080)	(0.076)	(0.072)	(0.088)
Tenure	-0.005	-0.015**	0.001	0.009	-0.028***	0.001
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)

(Continue)

Table 10 (continue)

	Intuition	Motivate Others	Team Player	Connections	Average Verbal & Quant expectation	Overall Confidence Indicator
Unemployed	0.093	0.239**	0.032	0.007	0.101	0.010
	(0.103)	(0.109)	(0.109)	(0.101)	(0.108)	(0.117)
In School	0.054	0.282**	-0.022	0.042	0.131	-0.041
	(0.100)	(0.110)	(0.105)	(0.097)	(0.103)	(0.113)
Hours (per week)	0.001	0.005**	0.003	0.001	0.004*	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Entry Level Manager	0.064	0.111**	0.203***	0.084*	0.042	0.122*
	(0.055)	(0.054)	(0.062)	(0.051)	(0.049)	(0.063)
Mid/Upper-Level Manager	0.174***	0.380***	0.102	0.230***	0.085	0.311***
	(0.067)	(0.068)	(0.070)	(0.061)	(0.062)	(0.077)
Observations	3757	3754	3759	3759	3597	3788
(Pseudo) R2	0.017	0.036	0.027	0.023	0.274	0.03

Notes: Reported are coefficients (and standard errors) from ordered probits except that overall confidence indicator regression coefficients (and standard errors) are from probit. Included are observations from Wave 1 of the GMAT Registrant Survey. ***, **, and * indicate that the coefficient is statistically significantly different from zero at the 1, 5 and 10 percent levels, respectively.

confidence. Undergraduate GPA tends to boost confidence when using the second and third measures. Unlike the result using the first set of confidence measures, females are significantly less confident and people working in a manufacturing industry are significantly more confident using the second and third measures of confidence.

Table 11 reports estimates of the effects of three confidence measures on academic outcomes respectively. According to the first part of Table 11, which presents the effects of confidence in skills, confidence in one's ability to delegate tasks is positively related to MBA attainment and GPA within graduate school. However, condition on obtaining an MBA, this measure is negatively related to obtaining an MBA from a top ranked program. Confidence in connections is positively related to obtaining a top rated MBA. Individuals appear to sort into marketing and away from finance on the basis of confidence in communication skills. It is interesting that verbal and quantitative expectations have little predictive power on these outcomes beyond that offered by actual GMAT scores.

In the second and third part of Table 11, the academic outcome regressions are repeated using the single-value measures --- average verbal and quantitative expectation bias and overall confidence indicator. In order to investigate differences by gender, we also include the interaction between confidence and gender in the model. A female being confident overall enhances the confidence effect by having higher probability of studying marketing and receiving MBA from top 25 programs. Average verbal and quantitative expectation bias tends to negatively relate to the probability of obtaining a MBA degree. Finally, overall confidence is negatively associated with chances of choosing to concentrate on marketing.

Table 11

Effects of confidence indicators on MBA outcomes

	MBA	Top 25 MBA	MBA GPA	Study Finance	Study Marketing
Verbal Expectations	-0.097**	-0.097	0.005	-0.045	0.028
	(0.040)	(0.095)	(0.014)	(0.057)	(0.073)
Quant Expectations	-0.094**	0.002	0.033**	-0.105**	-0.09
	(0.038)	(0.090)	(0.013)	(0.053)	(0.065)
Initiative	0.035	0.094	0.013	0.074	-0.081
	(0.053)	(0.115)	(0.018)	(0.075)	(0.100)
Ethical Standards	-0.012	0.066	0.016	-0.01	0.017
	(0.052)	(0.120)	(0.018)	(0.069)	(0.095)
Communication Skills	0.017	0.043	-0.003	-0.126*	0.278***
	(0.047)	(0.108)	(0.017)	(0.067)	(0.093)
Work with Diversity	-0.082*	0.121	-0.002	0	0.216**
	(0.049)	(0.114)	(0.016)	(0.074)	(0.097)
Shrewdness	-0.052	0.084	-0.007	0.02	0.098
	(0.037)	(0.082)	(0.013)	(0.055)	(0.070)
Ability to Organize	0.035	-0.048	0.007	0.117*	0.113
	(0.044)	(0.098)	(0.015)	(0.063)	(0.081)
Physical Attractiveness	0.007	-0.099	-0.014	-0.005	0.004
	(0.046)	(0.099)	(0.015)	(0.067)	(0.084)
Assertiveness	-0.003	0.011	-0.004	0.021	-0.151*
	(0.045)	(0.112)	(0.015)	(0.059)	(0.080)
Capitalize on Change	0.059	-0.036	-0.01	0.023	0.076
	(0.046)	(0.100)	(0.015)	(0.065)	(0.078)
Delegate Tasks	0.088**	-0.221**	0.052***	0.005	0.024
	(0.043)	(0.097)	(0.015)	(0.060)	(0.077)
Adapt Theory to Practice	-0.047	-0.103	-0.001	0.036	-0.208***
	(0.042)	(0.101)	(0.014)	(0.062)	(0.079)
Understanding Cultures	0.074**	-0.055	-0.005	0.011	0.033
	(0.033)	(0.079)	(0.011)	(0.047)	(0.059)
Intuition	-0.032	0.036	-0.012	-0.057	-0.097
	(0.045)	(0.104)	(0.016)	(0.066)	(0.076)
Motivate Others	0.012	0.191	-0.003	-0.002	0.039
	(0.047)	(0.118)	(0.018)	(0.067)	(0.093)
Team Player	0.081*	-0.091	-0.017	0.043	0.058
	(0.046)	(0.113)	(0.016)	(0.066)	(0.084)

(Continue)

Table 11 (continue)

	MBA	Top 25 MBA	MBA GPA	Study Finance	Study Marketing
Connections	-0.005	0.208**	-0.003	-0.007	-0.093
	(0.035)	(0.084)	(0.012)	(0.050)	(0.058)
Observations	2820	1076	957	2539	2555
(Pseudo) R^2	0.056	0.325	0.21	0.092	0.127
	MBA	Top 25 MBA	MBA GPA	Study Finance	Study Marketing
Avg Verbal & Quant expect bias	-0.129***	-0.097	0.022	-0.071	-0.06
	(0.046)	(0.107)	(0.015)	(0.063)	(0.082)
Female*Avg Verbal & Quant expect bias	-0.028	0.012	0.021	0.049	0.022
	(0.046)	(0.122)	(0.016)	(0.072)	(0.083)
Observations	2917	1105	984	2620	2639
(Pseudo) R^2	0.05	0.311	0.191	0.078	0.086
	MBA	Top 25 MBA	MBA GPA	Study Finance	Study Marketing
Overall Conf Indicator	-0.026	-0.139	0.009	-0.049	-0.273***
	(0.065)	(0.133)	(0.021)	(0.089)	(0.118)
Female*Overall Conf Indicator	0.108	0.352	-0.006	0.092	0.399**
	(0.099)	(0.248)	(0.034)	(0.157)	(0.176)
Observations	3061	1156	1026	2764	2784
(Pseudo) R^2	0.046	0.316	0.180	0.085	0.094

Note: Reported are coefficients (and standard errors) from probits (columns 1, 2, 4, 5) and OLS (column 3). Each regression also included all covariates from Table 1. Included are observations from Wave 1 of the GMAT Registrant Survey. Regressions in columns 2-5 are conditional on MBA attainment. ***, **, and * indicate that the coefficient is statistically significantly different from zero at the 1, 5 and 10 percent levels, respectively.

Table 12 reports estimates of the effects of our confidence indicators on labor market outcomes. These outcomes are measured roughly 8 years after the self-confidence indicators were reported. Despite this time lag, several confidence indicators appear to have lasting effects on labor market outcomes. Verbal expectations negatively affect earnings and attitudes about earnings (through the Pay JDI), beyond the effect of actual verbal scores. The coefficients on quantitative expectations are positive, though not statistically significant. We find that one of the strongest predictors of career success is confidence in one's initiative. This variable is strongly significantly related to all labor market outcome variables (except, perhaps surprisingly, being self-employed). Interestingly, ethical standards negatively affect earnings, though they positively affect general job satisfaction and the probability of being self-employed. Assertiveness is also positively related to earnings, managerial status, and being self-employed. Being self-employed is also positively associated with confidence in intuition. Confidence in one's ability to motivate others and in connections positively affects job satisfaction, but not earnings.

The last two parts of Table 12 show the labor market outcome regressions using second and third confidence measures. Based on the result, the second measure of confidence tends to have little explanatory power for most outcomes. On the contrary, overall confidence indicator positively correlates with almost all labor market outcomes (except the effect on self-employment is insignificant). The gender interaction terms fail to be significant for most outcomes.

Table 12

Estimates of confidence indicators on labor market outcomes

	Log(Wage)	Log(Salary)	Managerial Status	Self-Employed	Work JDI	Pay JDI	Promotion JDI	General JDI
Verbal expectations	-0.035**	-0.047**	0.046	-0.006	-0.458	-0.576**	-0.18	-0.749**
	(0.017)	(0.019)	(0.044)	(0.010)	(0.386)	(0.246)	(0.321)	(0.376)
Quant Expectations	0.005	0.009	-0.033	-0.01	0.291	0.121	0.245	0.059
	(0.016)	(0.018)	(0.040)	(0.009)	(0.371)	(0.236)	(0.297)	(0.356)
Initiative	0.068***	0.104***	0.118**	0.019*	1.674***	0.846***	1.388***	1.446***
	(0.023)	(0.024)	(0.054)	(0.011)	(0.490)	(0.320)	(0.408)	(0.469)
Ethical Standards	-0.041*	-0.051**	0.012	0.018*	0.689	-0.273	-0.104	0.864*
	(0.022)	(0.024)	(0.055)	(0.011)	(0.501)	(0.326)	(0.406)	(0.485)
Communication Skills	-0.003	0.009	0.04	-0.002	-0.303	-0.241	-0.467	-0.236
	(0.019)	(0.023)	(0.049)	(0.011)	(0.453)	(0.288)	(0.368)	(0.442)
Work with Diversity	0.02	0.009	-0.028	-0.012	-0.291	0.115	0.087	0.003
	(0.021)	(0.024)	(0.051)	(0.011)	(0.459)	(0.310)	(0.382)	(0.438)
Shrewdness	0.004	0.006	-0.006	-0.013	-0.731**	-0.03	-0.072	-0.42
	(0.014)	(0.017)	(0.039)	(0.008)	(0.357)	(0.230)	(0.286)	(0.337)
Ability to Organize	-0.031*	-0.043**	0.01	-0.028***	-0.184	-0.297	-0.393	-0.157
	(0.019)	(0.021)	(0.046)	(0.011)	(0.394)	(0.279)	(0.354)	(0.403)
Physical Attractiveness	0.031	0.043**	-0.083*	0.002	0.007	0.148	0.854**	0.556
	(0.019)	(0.021)	(0.048)	(0.010)	(0.443)	(0.297)	(0.363)	(0.441)
Assertiveness	0.038**	0.041**	0.080*	0.015*	0.24	-0.218	0.22	0.029
	(0.019)	(0.020)	(0.046)	(0.009)	(0.423)	(0.271)	(0.346)	(0.412)

(Continue)

Table 12 (continue)

	Log(Wage)	Log(Salary)	Managerial Status	Self-Employed	Work JDI	Pay JDI	Promotion JDI	General JDI
Capitalize on Change	-0.018 (0.019)	-0.024 (0.023)	0.001 (0.047)	0.011 (0.011)	0.274 (0.444)	0.189 (0.287)	-0.126 (0.365)	0.408 (0.435)
Delegate Tasks	-0.022 (0.019)	-0.026 (0.022)	0.032 (0.043)	0.012 (0.009)	-0.003 (0.402)	-0.083 (0.267)	-0.167 (0.328)	-0.145 (0.378)
Adapt Theory to Practice	0.022 (0.019)	0.028 (0.021)	-0.026 (0.043)	-0.008 (0.010)	0.241 (0.373)	0.402 (0.268)	0.256 (0.323)	0.359 (0.363)
Understanding Cultures	0.003 (0.014)	0.021 (0.016)	0.022 (0.035)	0.006 (0.007)	-0.078 (0.317)	-0.117 (0.209)	0.09 (0.269)	-0.085 (0.305)
Intuition	-0.034* (0.020)	-0.039* (0.022)	-0.076 (0.048)	0.018** (0.009)	0.294 (0.431)	-0.074 (0.284)	-0.14 (0.362)	-0.326 (0.421)
Motivate Others	0.016 (0.020)	0.031 (0.022)	0.047 (0.049)	0.005 (0.010)	1.066** (0.442)	0.381 (0.293)	0.858** (0.362)	1.095*** (0.420)
Team Player	0.008 (0.021)	0.015 (0.023)	-0.057 (0.049)	-0.017 (0.010)	-0.041 (0.437)	0.437 (0.304)	0.366 (0.364)	0.389 (0.452)
Connections	0.006 (0.015)	0.015 (0.017)	0.077** (0.037)	0.002 (0.009)	0.804** (0.348)	0.305 (0.227)	0.253 (0.288)	0.659* (0.346)
Observations	2013	2013	2107	2244	2043	2062	2072	2071
(Pseudo) R^2	0.179	0.223	0.065	0.038	0.057	0.076	0.091	0.057

	Log(Wage)	Log(Salary)	Managerial Status	Self-Employed	Work JDI	Pay JDI	Promotion JDI	General JDI
Avg Verbal & Quant expect bias	0.004 (0.019)	0.003 (0.021)	0.023 (0.049)	-0.019* (0.011)	0.848* (0.458)	-0.025 (0.290)	0.706* (0.368)	0.335 (0.459)

(Continue)

Table 12 (continue)

	Log(Wage)	Log(Salary)	Managerial Status	Self-Employed	Work JDI	Pay JDI	Promotion JDI	General JDI
Female*Avg Verbal & Quant expect bias	0.005	0.009	0.013	0.006	0.039	0.065	-0.341	0.343
	(0.018)	(0.021)	(0.048)	(0.011)	(0.447)	(0.281)	(0.362)	(0.435)
Observations	2071	2071	2170	2314	2102	2123	2136	2136
(Pseudo) R^2	0.169	0.206	0.057	0.024	0.032	0.063	0.074	0.030

	Log(Wage)	Log(Salary)	Managerial Status	Self-Employed	Work JDI	Pay JDI	Promotion JDI	General JDI
Overall Conf Indicator	0.057**	0.094***	0.158**	0.012	3.089***	0.778**	1.425***	2.856***
	(0.029)	(0.030)	(0.068)	(0.015)	(0.623)	(0.396)	(0.501)	(0.622)
Female*Overall Conf Indicator	-0.018	-0.025	-0.098	-0.018	-1.629*	0.539	-0.790	-1.445
	(0.043)	(0.049)	(0.104)	(0.022)	(0.944)	(0.630)	(0.770)	(0.904)
Observations	2165	2165	2267	2415	2197	2219	2232	2232
(Pseudo) R^2	0.164	0.204	0.059	0.023	0.042	0.066	0.077	0.039

Note: Reported are coefficients (and standard errors) from OLS (column 1, 2, 5-8) and ordered probit (column 3) regressions. Each regression also included all covariates from Table 1, plus a dummy variable indicating whether or not the individual obtained an MBA sometime in the sample period. Regressions included observations from the 4th (final) survey wave of the GMAT Registrant Survey. ***, **, and * indicate that the coefficient is statistically significantly different from zero at the 1, 5 and 10 percent levels, respectively.

4. Conclusion

In this paper we have investigated the link between certain measures of self-confidence and eventual academic and labor market outcomes. We have focused on business professionals, in part because of the wealth of data available through the GMAT Registrant Survey, but also because this group is relatively understudied. To our knowledge, we are the first to investigate the effects of multiple measures of confidence on academic progression and performance at the post-bachelor's level.

We incorporate expectation, bias in expectation and optimism which are commonly used concepts for confidence in psychology, but only beginning to be addressed in the economic literature. We also develop three unique measures of confidence. Our findings indicate that all three confidence measures are influenced by several background and demographic variables, most notably race, gender, managerial status and actual GMAT scores. These confidence measures in turn have some predictive power in eventual academic outcomes and more so for labor market outcomes. Initiative is most strongly associated with earnings and job quality indicators. Confidence in one's verbal skills (beyond actual verbal test scores) negatively impact earnings several years later. Confidence based on average verbal and quantitative bias has little predictive power in both academic and labor market outcomes. Finally, overall confidence is shown to strongly improve almost all labor market outcomes.

Our findings suggest that business schools with MBA programs could consider devoting more effort in helping students develop and build self-confidence in order to achieve greater success in the business environment.

REFERENCES

Abrantes-Metz, R.M., 2012. The contribution of innovation to health care costs: At least 50%? Social Science Research Network. Dec 1, 2012, http://dx.doi.org/10.2139/ssrn2121688

Acemoglu, D., Finkelstein, A., 2008. Input and technology choices in regulated industries: Evidence from the health care sector. Journal of Political Economy 116 (5), 837-880.

Acemoglu, D., Finkelstein, A., Notowidigdo M.J. , 2011. Income and health spending: evidence from oil price shocks. Review of Economics and Statistics, forthcoming.

Andersen, R., Benham, L., 1970. Factors affecting the relationship between family income and medical care consumption. In: Klarman HE(Ed), Empirical Studies in Health Economics. Johns Hopkins, Baltimore.

Aizcorbe, A., Nestoriak, N., 2011. Changing mix of medical care services: stylized facts and implications for price indexes. Journal of Health Economics 30 (3), 568-74.

Akin, J., Guilkey, D., Denton, E., 1995. Quality of services and demand for healthcare in Nigeria: a multinomial Probit estimation. Social Science and Medicine 40, 1527-1537.

Anand, S., Barninghausen, T., 2012. Health workers at the core of the health system: Framework and research issues. Health Policy 105 (2-3), 185-191.

Archibald, R., Gillingham, R., 1981. A decomposition of the price and income elasticities of the consumer demand for gasoline. Southern Economic Journal 47 (4), 1021-1031.

Asoni, A., 2011. Intelligence, self-confidence and entrepreneurship. Research Institute of Industrial Economics Working Paper No. 887.

Ballard, D.W., Price, M., Fun,g V., Brand, R., Reed, M.E., Fireman, B., Newhouse, J.P., Selby, J.V., Hsu, J., 2010. Validation of an algorithm for categorizing the severity of hospital emergency department visits. Medical Care 48 (1), 58-63.

Benoit, J-P., Dubra, J., 2011. Apparent overconfidence. Econometrica 79 (5), 1591-1625.

Bils, M., Klenow, P.J., 2001. Quantifying quality growth. American Economic Review 91 (4), 1006-1030.

Borghans, L., Duckworth, A.L., Heckman, J.J., Weel, B., 2008. The economics and psychology of personality traits. Journal of Human Resources 43 (4), 972-1059.

Braakmann, N., 2009. The role of psychological traits for the gender gap in employment and wages: Evidence from German. DIW Discussions Paper, German Institute of Economic Research (DIW), Berlin.

Bradley, T.B., Kominski, G.F., 1992. Contributions of case mix and intensity change to hospital cost increases. Healthcare Financing Review 14 (2), 151-63.

Bundorf, M.K., Royalty, A., BakerL C., 2009. Healthcare cost growth among the privately insured. Health Affairs 28 (5), 1294-1304.

Chan, Y.L., Liaw, S.J., Chen, J.C., Hu, P.M., Liao, H.C., 2000. Nonurgent use of the emergency department in a Medical Center in Taiwan. Journal of Taiwan Emergency Medicine 2, 1-20.

Chang, C., Mirvis, D., Gnuschke, J., Wallace, J., Walker, J., Smith, S., Stanphill, S., 2012. Impacts of Health Reform in Tennessee: An examination of changes in health insurance coverage, use of health care resources, and the implications on health care manpower. Paper by the Methodist Le Bonheur Center for The Methodist Le Bonheur Center for Healthcare Economics and The Sparks Bureau of Business and Economic Research, University of Memphis. Dec,1,2012, http://www.memphis.edu/mlche/pdfs/other_studies/impactsofhealthreformintennesseejanuary2012.pdf

Chang, C., 2013. Understanding and awareness of non-urgent and primary-care-Sensitive hospital emergency department visits in Memphis and Shelby County, Tennessee. Status Report on Efforts to Advance, report 7.

Chernew, M., Newhouse, J.P., 2012. Healthcare spending growth, In: Pauly MV, McGuire TG, Barros PP (Eds), Handbook of Health Economics, chapter 1. Elsevier B.V.

Cheung, P.T., Wiler, J.L., Lowe, R.A., Ginde, A.A., 2012. National study of barriers to timely primary care and emergency department utilization among medicaid beneficiaries" Annals of Emergency Medicine 60 (1), 4-10.

Chiu, M.M., Klassen, R.M., 2010. Relations of mathematics self-concept and its calibration with mathematics achievement: Cultural differences among fifteen-year-olds in 34 countries, Learning and Instruction 20 (1), 2-17.

Compte, O., Postlewaite, A., 2004. Confidence-enhanced performance. American Economic Review 94 (5), 1536-1557.

Copnell, B., Hagger, V., Wilson, S.G., Evans S.M., Sprivulis P.C., Cameron P.A., 2009. Measuring the quality of hospital care: an inventory of indicators. Internal Medicine Journal 39, 352–360.

Costa, J., Garcia, J., 2003. Demand for private health insurance: How important is the quality gap? Health Economics 12 (7), 587-599.

Costa-Font, J., Gemmill, M., Rubert, G., 2011. Biases in the healthcare luxury good hypothesis: a meta-regression analysis. Journal of the Royal Statistical Society: Series A (Statistics in Society) 174 (1), 95-107.

Cuckler, G., Martin, A., Whittle, L., Heffler, S., Sisko, A., Lassman, D., Benson, J., 2011. Health spending by state of residence, 1991-2009. Medicare Medicaid Research Review 1 (4).

Cunningham, P., 1995. The use of hospital emergency departments for nonurgent health problems: A national Perspective. Medical Care Research and Review 52, 453-474.

Cunningham, P., 2006. What accounts for differences in the use of hospital emergency departments across U.S. communities? Health Affairs 25 (5), w324-w336.

Cunningham, P., Artiga, S., 2009. How does health coverage and access to care for immigrants vary by length of time in the U.S. Kaiser Commission on Medicaid and the Uninsured, Kaiser Commission for Medicaid and the Uninsured Issue Paper, June 2009.

Cunningham, P., 2011. Nonurgent use of hospital emergency departments. Statement before the U.S. Senate Health, Education, Labor and Pensions Committee, Subcommittee on Primary Health and Aging, May 11. Center for Studying Health System Change.

Davis, J.W., Fujimoto, R.Y., Chan, H., Juarez, D.T., 2010. Identifying characteristics of patients with low urgency emergency department visits in a managed care setting. Managed Care 19 (10), 38-44.

Deaton, A., 1988. Quality, quantity, and spatial variation of price. American Economic Review 78 (3), 418-430.

Delia, D., Cantor, J.C., 2009. Emergency department utilization and capacity. Synthesis Project Research Synthesis Report, Jul (17). Robert Wood Johnson Foundation. Dec,1,2012, http://www.rwjf.org/files/research/072109policysynthesis17.emergencyutilization.pdf

Di Matteo, L., 2003.The income elasticity of healthcare spending: A comparison of parametric and nonparametric approaches. European Journal of Health Economics 4 (1), 20-29.

Drago, F., 2011. Self-esteem and earnings. Journal of Economic Psychology 32, 480–488.

Dubois, R.W., Feldman, M., Martin, J., Sanderson-Austin, J., Westrich, K.D., 2012. Role of pharmaceuticals in value-based healthcare: A framework for success. The American Journal of Managed Care 18 (7), c245-c247.

Englmaier, F., 2011. Commitment in R&D tournaments via strategic delegation to overoptimistic managers. Managerial and Decision Economics 32, 63–69.

Esparza, S.J., Zoller, J.S., White, A.W., Highfield, M.E., 2012. Nurse staffing and skill mix patterns: Are there differences in outcomes? Journal of Healthcare Risk Management 31 (3), 14-23.

Finkelstein, E.A., Trogdon, J.G., Cohen, J.W., Dietz, W., 2009. Annual medical spending attributable to obesity: payer- and service-specific estimates. Health Affairs 28 (5), w822-w831.

Freeman, D., 2003. Is health care a necessity or a luxury? Pooled estimates of income elasticity from US state-level data. Applied Economics 35, 495-502.

Fuchs, V., Kramer, M., 1972. Determinants of expenditures for physicians' services in the US, 1948–1968, NCHSRD, NBER pub. a117.

Gale, F., Huang, K., 2007. Demand for Food Quantity and Quality in China. Economic Research Report No. (ERR-32) 40.

Garcia, T.C., Bernstein, A.B., Bush, M.A., 2010. Emergency department visitors and visits: who used the emergency room in 2007? NCHS Data Brief May (38), 1-8.

Gertler, P.J., 1985. A decomposition of the elasticity of medicaid nursing home expenditures into price, quality, and quantity effects. NBER Working Paper No. 1751.

Getzen, T.E., 2000. Healthcare is an individual necessity and a national luxury: applying multilevel decision models to the analysis of healthcare expenditures. Journal of Health Economics 19 (2), 259-270.

Gindi, R.M., Cohen, R.A., Kirzinger, W.K., 2012. Emergency room use among adults aged 18-64: Early release of estimates from the National Health Interview Survey, January-June 2011. National Center for Health statistics.

Grabowski, D., 2001. Does an increase in the medicaid reimbursement rate improve bursing home quality? Journal of Gerontology: Social Sciences 56B (2), S84-S93.

Greene, W.H., 2008. Econometric Analysis. Prentice Hall, New York.

Groves, M.O., 2011. How important is your personality? Labor market returns to personality for women in the US and UK. Journal of Economic Psychology 26 (6), 827-841.

Hicks, W.W., Johnson, S.R., 1968. Quantity and quality components for income elasticities of demand for food. American Journal of Agricultural Economics 50 (5), 1512-1517.

Holahan, J., Headen, I., 2010. Medicaid coverage and spending in health reform: National and state-by-state results for adults at or below 133% FPL. Kaiser Commission on Medicaid and the Uninsured.

Jappelli, T., Pistaferri, L., Weber, G., 2007. Healthcare quality, economic inequality, and precautionary saving. Health Economics 16 (4), 327-346.

Jia, H., Zack, M.M., Thompson, W.W., 2011. State quality-adjusted life expectancy for U.S. adults from 1993 to 2008. Quality of Life Research 20 (6), 853-863.

Kaiser Family Foundation. Kaiser State Health Facts: Tennessee. May 12, 2012, http://www.statehealthfacts.org/profileind.jsp?ind=125&cat=3&rgn=44

Kalachek, E., Raines, F., 1976. The structure of wage differences among mature male workers. Journal of Human Resources 11 (4), 484-506.

Kaniel, R., Massey, C., Robinson, D.T., 2010. The importance of being an optimist: Evidence from labor markets, NBER Working paper 16328.

Kieschnick, R., McCullough, B.D., 2003. Regression analysis of variates observed on (0, 1): percentages, proportions and fractions. Statistical Modelling 3,193-213.

Koellinger, P., Minniti, M., Schade, C., 2007. “I think I can, I think I can”: Overconfidence and entrepreneurial behavior. Journal of Economic Psychology 28 (4), 502–527.

Koh, H.C., 1996. Testing hypotheses of entrepreneurial characteristics: a study of Hong Kong MBA students. Journal of Managerial Psychology 11 (3), 12-25.

Koszegi, B., 2006. Ego utility, overconfidence, and task choice. Journal of the European Economic Association 4 (4), 673-707.

LaCalle, E., Rabin, E., 2010. Frequent users of emergency departments: The myths, the data, and the policy implications. Annals of Emergency Medicine 56 (1), 42-8.

Lent, R.W., Brown, S.D., Larkin, K.C., 1986. Self-efficacy in the prediction of academic performance and perceived career options. Journal of Counseling Psychology 33 (3), 265-269.

Lichtenberg, F.R., 2011. The quality of medical care, behavioral risk factors, and longevity growth. International Journal of Healthcare Finance and Economics 11, 1-34.

Liu, T., Sayre, M.R., Carleton, S.C., 1999. Emergency medical care: types, trends, and factors related to nonurgent visits. Academic Emergency Medicine 6 (11),1147-1152.

Long, J.E., 1995. The effects of tastes and motivation on individual income. Industrial and Labor Relations Review 48 (2), 338-351.

Malmendier, U., Tate, G., 2008. Who makes acquisitions? CEO overconfidence and the market's reaction. Journal of Financial Economics 89 (1), 20–43.

Mobius, M.M., Niederle, M., Niehaus P., Rosenblat, T.S., 2011. Managing self-confidence: Theory and experimental evidence. NBER Working Paper No. 17014

Montgomery, M., Powell, I., 2003. Does an advanced degree reduce the gender wage gap? Evidence from MBAs. Industrial Relations 42 (3), 396-418.

Moore, D.A., Healy, P.J., 2008. The trouble with overconfidence. Psychological Review 115 (2), 502-517.

Mueller, G., Plug, E., 2006. Estimating the effect of personality on male and female earnings. Industrial & Labor Relations Review 60 (1), 3-22.

Newhouse, J.P., 1970. Toward a theory of nonprofit institutions: An economic model of a hospital. American Economic Review 60 (1), 64-74.

Newhouse, J., Phelps, C.E., 1976. New Estimates of Price and Income Elasticities of Medical Care Services. In: Rosett RN (Ed), The Role of Health Insurance in the Health Services Sector. National Bureau of Economic Research, Inc; 1976. p. 261-320.

Newhouse, J.P., 1977. Medical care expenditure: a cross-national survey. Journal of Human Resources 12, 115-125.

Newhouse, J.P., 1992. Medical care costs: how much welfare loss? Journal of Economic Perspectives 6 (3), 3-21.

Newton, M.F., Keirns C.C., Cunningham R., Hayward, R.A., Stanley, R., 2009. Uninsured adults presenting to U.S. emergency departments: Assumptions vs. data. Journal of the American Medical Association 300 (16), 1914-1924.

Okunade, A.A., Murthy, V.N.R., 2002. Technology as a "major driver" of healthcare costs: a cointegration analysis of the Newhouse conjecture. Journal of Health Economics 21 (1), 147-159.

Ozcan, Y.A., Luke, R.D., Haksever, C., 1992. Ownership and organizational performance. A comparison of technical efficiency across hospital types. Medical Care 30 (9), 781-94.

Paluch, M., Kneip, A., Hildenbrand, W., 2012. Individual versus aggregate income elasticities for heterogeneous populations. Journal of Applied Econometrics 27 (5), 847-869.

Papke, L.E., Wooldridge, J.M., 1996. Econometric methods for fractional response variables with an application to 401(k) plan participation rates, Journal of Applied Econometrics 11, 619-632.

Paradise, J., Dark, C., 2009. Emergency departments under growing pressures, Policy Brief, Kaiser commission on Medicaid and the uninsured.

Peden, E.A., Freeland, M.S., 1998. Insurance effects on US medical spending. Health Economics 7, 671-687.

Phelps, C.E., 1976. The demand for reimbursement insurance. In The Role of Health Insurance in the Health Services Sector, Rosett R (ed). National Bureau of Economic Research, Cambridge, MA.

Potgieter, M., Ackermann, M., Fletcher, L., 2010. Inaccuracy of self-evaluation as additional variable for prediction of students at risk of failing first-year chemistry. Chemistry Education Research and Practice 11 (1), 17-24.

Riba, M., Ehrlich, N., Udow-Phillips, M., Clark, K., 2011. Cover Michigan Survey 2011. Center for Healthcare Research & Transformation.

Ringel, J.S., Hosek, S.D., Vollaard B.A., Mahnovski S., 2002. The elasticity of demand for healthcare. RAND report MR-1355-OSD.

Santos-Pinto, L., Sobel, J., 2005. A model of positive self-image in subjective assessments. The American Economic Review 95 (5), 1386-1402.

Sarver, J.H., Cydulka, R.K., Baker, D.W., 2002. Usual source of care and nonurgent emergency department use. Academic Emergency Medicine 9 (9), 916-923.

Schneider, H., 2008. Incorporating healthcare quality into health antitrust law. BMC Health Services Research 8, 89.

Schwartz, W.B., 1987. The inevitable failure of current cost-containment strategies. Journal of the American Medical Association 257 (2), 220-224.

Shah, N.M., Shah, M.A., Behbehani, J., 1996. Predictors of non-urgent utilization of hospital emergency services in Kuwait. Social Science & Medicine 42, 1313-1323.

Shang, B., Goldman, D., 2008. Does age or life expectancy better predict health care expenditures? Health Economics 17, 487-501.

Sharma, A., Srivastava, P., 2011. Does disaggregation affect the relationship between health care expenditure and GDP?: an analysis using regime shifts. Australian Economic Papers 50 (1), 27-39.

Silver, M., 1970. An economic analysis of variations in medical expenses and work loss rates. In: Klarman HE (Ed), Empirical Studies in Health Economics. Johns Hopkins, Baltimore.

Sloan, F.A., Hsieh, C.R., 2012. Quality of care and medical malpractice. In: Health Economics. MIT Press; p. 275-317.

Sloan, F., Picone, G., Taylor, D., Chou, S.-Y., 2001. Hospital ownership and cost and quality of care: Is there a dime's worth of difference? Journal of Health Economics, 20, 1-21.

Smith, P. C., Balzer, W. K., Brannick, M., Chia, W., Eggleston, S., Gibson, W., Johnson, B., Josephson, H., Paul, K., Reilly, C., Whalen, M., 1987. The revised JDI: A facelift for an old friend. The Industrial-Organizational Psychologist 24, 31–33.

Smith, S., Newhouse, J.P., Freeland, M.S., 2009. Income, Insurance, And Technology: Why Does Health Spending Outpace Economic Growth? Health Affairs 28 (5), 1276-1284.

Ter Weel, B., 2008. The noncognitive determinants of labor market and behavioral outcomes: Introduction to the symposium. Journal of Human Resources 43 (4), 729–737.

Thiel, H. , Thomsen, S.L., 2009. Noncognitive skills in economics: models, measuresment, and empirical evidence. Centre for European Economic Research, Discussion Paper No. 09-076.

Tosetti, E., Moscone, F., 2010. Health expenditure and income in the United States. Health Economics 19 (12), 1385-1403.

Tsai, J.C., Chen, W., Liang, Y., 2011. Nonemergent emergency department visits under the National Health Insurance in Taiwan. Health Policy 100, 189-195.

Tsui, L., 1998. The effects of gender, education, and personal skills self-confidence on income in business management. Sex Roles 38 (5-6), 363-373.

U. S. Congressional Budget Office. 2008. Technological change and the growth of health spending. Congress of the United States Congressional Budget Office Paper. Publication number 2764. December 1, 2012, http://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/89xx/doc8947/01-31-techhealth.pdf

Uscher-Pines, L., Pines, J., Kellermann, A., Gillen, E., Mehrotra, A., 2013. Emergency department visits for nonurgent conditions: systematic literature review. American Journal of Managed Care 19 (1), 47-59.

Utah Office of Health Care Statistics, 2004. Primary care sensitive emergency department visits in Utah, 2001. Utah Department of Health. Dec,2,2012, http://health.utah.gov/hda/Reports/Primary_Care_ERvisits_Utah2001.pdf

Van den Steen, E., 2004. Rational over-optimism (and other biases). American Economic Review 94 (4), 1141-1151.

Weber, E.J., Showstack, J.A., Hunt, K.A., Colby, D.C., Callaham, M.L., 2005. Does lack of a usual source of care or health insurance increase the likelihood of an emergency department visit? Results of a national population-based study. Annals of Emergency Medicine 45 (1), 4-12.

Weinick, R., Billings, J., Burstin, H., 2007. What is the role of primary care in emergency department overcrowding? Conference paper.

Yang, M.-L., Chuang, H.-H., Chiou, W.-B., 2009. Long-term costs of inflated self-estimate on academic performance among adolescent students: a case of second-language achievements.Psychological Reports 105 (3 Pt 1), 727-37.

Zabojnik, J., 2004. A model of rational bias in self-assessments. Economic Theory 23 (2), 259-282.

Zaman, O.S., Cummings L.C., Spieler S.S., 2010. America's public hospitals and health systems, 2009: Results of the Annual NAPH Hospital Characteristics Survey. National Association of Public Hospitals and Health Systems Report.

Zellner, A., 1962. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. Journal of the American Statistical Association 57, 348-368.

Zuckerman, S., Shen, Y.C., 2004. Characteristics of occasional and frequent emergency department users: do insurance coverage and access to care matter? Medical Care 42 (2), 176-82.

APPENDIX

CHAPTER 5

THE LIFE ORIENTATION TEST-REVISED AND 40 SURVEY QUESTIONS SELECTED FOR THE OVERALL CONFIDENCE INDICATOR

The Life Orientation Test-Revised

Please be as honest and accurate as you can throughout. Try not to let your response to one statement influence your responses to other statements. There are no "correct" or "incorrect" answers. Answer according to your own feelings, rather than how you think "most people" would answer.

A = I agree a lot

B = I agree a little

C = I neither agree nor disagree

D = I Disagree a little

E = I Disagree a lot

1. In uncertain times, I usually expect the best.

[2. It is easy for me to relax.]

3. If something can go wrong for me, it will.

4. I'm always optimistic about my future.

[5. I enjoy my friends a lot.]

[6. It is important for me to keep busy.]

7. I hardly ever expect things to go my way.

[8. I don't get upset too easily.]

9. I rarely count on good things happening to me.

10. Overall, I expect more good things to happen to me than bad.

Scoring:

Ignore your answers to questions 2, 5, 6 and 8. These are fillers!

• For questions 1, 4 and 10 : A gets 4 points, B gets 3, C gets 2, D 1, E 0. Subtotal: ____

• For questions 3, 7 and 9: A gets 0 points, B gets 1, C gets 2, D 3, E 4. Subtotal: ____

Add the two subtotals above: ______. This is your optimism score. On a scale of 0 to 24, 0 is extreme pessimism, 24 is extreme optimism. On average, most people score 15 – slightly optimistic.

40 Selected Questions from Wave 1 Survey for Overall Confidence Indicator

Question 1-9:

Please indicate how difficult you expect each of the admission steps will be for you.

How difficult? 1: very; 2: somewhat; 3: not very; 4: not at all; 5: not applicable

1. Prior work experience

2. Undergraduate grades

3. Letters of recommendation

4. Preparing for the GMAT

5. Doing well on the GMAT

6. Knowing the right people

7. Visiting graduate schools

8. Making the right impression on the application form

9. Paying application fees

If the answer is 3 (not very) or 4 (not at all) for one question, it will count as 1 point for that question, meaning it's a confident answer.

Question 10-11:

Overall, how well do you expect to do on the verbal and quantitative (mathematics) sections of the GMAT?

How well? Excellent: 1; Above average: 2; average: 3; below average: 4; poor: 5

10. Verbal

11. Quantitative

If the answer is 1 or 2 for one question, it will count as 1 point for that question, meaning it's a confident answer.

Question 12-27:

Please indicate the extent to which you think you have each of these characteristics or skills.

Have characteristic? 1: very much; 2: somewhat; 3: not very; 4: not at all

12. Initiative

13. High ethical standards

14. Communication skills

15. Ability to work with people from diverse backgrounds

16. Shrewdness

17. Ability to organize

18. Physical attractiveness

19. Assertiveness

20. Ability to capitalize on change

21. Ability to delegate tasks

22. Ability to adapt theory to practical situations

23. Understanding business in other cultures

24. Good intuition

25. Ability to motivate others

26. Being a team player

27. Knowing the right people

If the answer is 1 or 2 for one question, it will count as 1 point for that question, meaning it's a confident answer.

Question 28-34:

A graduate management education will:

28. Give me opportunities for changing jobs or moving up in my career

29. Lead others to expect too much of me and force me into positions of too much responsibility

30. Provide the right connections to getting a good job

31. Damage my self-esteem if I cannot meet my personal standards in required class work

32. Prove too intimidating if I am unable to compete with other students

33. Be looked upon favorably by people who are important to me

34. Lead to new and interesting friendships and valuable contacts for the future

Circle one number between +3 to -3. : +3 is complete true, 0 is neither true nor false, -3 is completely false for you.

For question 28, 30, 33, 34: one point for each question if the answer is 1 or above for that question. For question 29, 31, 32: one point for each question if the answer is -1 or below for that question.

Question 35-40:

If I do not pursue a graduate management education:

35. There are other avenues to career advancement, such as work experience, that will allow me to be successful.

36. There are other advanced educational programs that I can pursue that will help me accomplish my career goals.

37. There are other ways to enhance my business skills that will be just as valuable.

38. I have other career aspirations that I can pursue instead of management.

39. I will miss an opportunity that is vitally important for career advancement in my field.

40. I will be just as satisfied pursuing other career or educational opportunities.

Circle one number between +3 to -3. : +3 is complete true, 0 is neither true nor false, -3 is completely false for you.

For question 35-38, 40: one point for each question if the answer is 1 or above for that question. For question 39: one point for each question if the answer is -1 or below.

Scoring:

There are totally 40 points. If someone gets 70% of the points (=28 points), he or she is confident. And, our confidence indicator equals to 1.