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Essays in Health Economics and Health Information Systems

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Contents

List of Tables

List of Figures

Abstract

The accelerating cost of healthcare in the United States has prompted increased policy debate. Although it is estimated that prescription drug spending accounts for only eleven percent of total healthcare expenditures, there is evidence that this rate of spending is increasing faster than spending on other types of healthcare. A proven method of decreasing prescription drug spending is by using less expensive generic medications when available. We estimate the price elasticities of switching from branded to generic drugs in three dominant drug classes: antidepressants, statins, and central nervous system agents. We find the price elasticities of switching varies by drug and is between 0.01 and 0.09.

Despite long-standing use of mandatory generic substitution laws, their exact effect on generic fill-rate and prescription drug spending has not been identified. We use the Tennessee Affordable Drug Act of 2005 to identify the effect of implementing the mandatory generic substitution of drugs by pharmacists. Using a differences-in-differences framework, we estimate the effect of this policy on the percentage of generic drugs dispensed in the state of Tennessee. We find the effect to vary across drug classes and health insurance types, with the greatest effect occurring within Point of Service insurance plans among non-chronic prescription drug users.

We propose extensions to the technology acceptance model (TAM) for the adoption of integrated electronic health records that are shared by multiple healthcare providers. In particular, we propose a conceptual model in which we incorporate two new factors—trust and access to shared information—into the TAM. We find a statistically significant effect of shared information on perceived usefulness. We also find a significant effect of trust on both perceived usefulness and behavioral intent to use integrated electronic health records. Our analysis provides insights into the effects of these factors on intent to use integrated

electronic health records for both clinical and non-clinical staff.

Chapter 1

Identifying the Price Elasticity of Switching Between Branded and Generic Drugs

1.1 Introduction

Understanding the consumer response to generic introductions of prescription drugs is critically important to policy makers and insurance plan managers because healthcare costs can be reduced significantly through the use of less expensive generic medications. The absence of studies that analyze consumer purchasing behavior of prescription drugs immediately following the loss of patent exclusivity warrants attention. Current studies focus on the influence of insurance plan design, copayment structure, and formulary structure on prescription drug choice and subsequent costs. We expand upon this research by identifying the sensitivity of consumer adoption of generic drugs to differences between the cost of the generic and branded drugs. Additionally, we determine the impact of the

branded average wholesale price (AWP) on switching. We analyze the switching behavior in three large drug classes that experienced generic introductions during our sample period. These prescription drug classes include the introduction of: the first generic Selective Serotonin Reuptake Inhibitors (SSRIs), Fluoxetine; one of the first large generic introductions in the statin class, Simvastatin; and the first generic gamma-aminobutyric acid, Gabapentin.

We analyze these prescription drugs because of their widespread use and high branded costs that promise a substantial cost-savings from significant generic uptake. The use of antidepressants increased by 74 percent in the first five years of the 1990s, with much of this increase attributed to the addition of SSRIs to the antidepressant drug class [Sleath and Shih, 2002]. In 2000, the year before the introduction of Fluoxetine, Prozac accounted for the fourth-highest level of prescription drug expenditures in the United States. At that time, there existed over 3.4 million individual prescriptions for Prozac, accounting for approximately $2 billion in expenditures [AHRQ, 2000]. Similarly, the use of statins has increased dramatically during this time period. In 2005, Lipitor and Zocor ranked first and second in prescribed drugs by total expenditures, accounting for $9.3 billion and $5.7 billion in sales, respectively. Both drugs ranked in the top ten for total purchases that year, and Zocor was the largest drug (by sales volume) to lose patent protection in 2006 [Smith, 2005]. In 2005, immediately following the introduction of Gabapentin, the generic form of Neurontin, central nervous system agents ranked second-highest in individual prescriptions, with 76.9 million users. When considering expenditures by therapeutic drug class, this class ranked third with $24.5 billion in spending [AHRQ, 2005].

A principle incentive for switching to a generic drug is to reduce one's out-of-pocket (OOP) drug expenditures. We construct a variable that measures the difference in OOP cost between the branded and generic drug to assess how price-sensitive individuals are

to OOP cost changes. Additionally, an individual may switch to a generic drug based on a physician's recommendation or inducements from insurance plans or pharmacists [Coscelli, 2000]. In order to determine the potential impact of these pathways, we use the third-party-payer (TPP) cost differential (CD) between the branded and generic drug, and the AWP of the branded drug when the generic becomes available. Using these metrics, we estimate three sets of price elasticities for each drug class. These estimates can be used to adjust tiered cost sharing schedules in order to induce consumers to switch to generic drugs, thereby reducing prescription drug costs for both private and public payers.

Our study extends the literature by specifically identifying the price elasticity of switching within the antidepressant, statin, and anticonvulsant therapeutic drug classes. Further, we incorporate fixed effects to limit potential omitted variable bias caused by patient selection. This paper proceeds in the following manner: Section 1.2 reviews the previous literature focusing on the pathways influencing switching behavior; Section 1.3 identifies our empirical approach; Section 1.4 follows with details of the data used in the analysis; Section 1.5 provides the results of our study; and Section 1.6 concludes our paper.

1.2 Background and Literature Review

In order to analyze the switching behavior between drug choices, one must understand the factors that influence a patient's prescription drug decision. Prescription decisions are a combination of patient and physician preferences. Pharmacists may also influence the prescription drug a patient receives because of state laws governing how generic drugs are dispensed. We are interested in determining the effect of a change in price on a patients' switching decision; therefore, we must control for these non-price mechanisms that contribute to switching.

Price sensitivity and quality determine patient drug preference [Dubois et al., 2000]. The price that patients pay for each drug is dependent upon their insurance plan and corresponding prescription drug benefit structure (also known as a drug formulary). In the market for prescription drugs, Pharmacy Benefit Managers (PBMs), rather than health insurance companies per se determine prescription drug benefits; in 1999, approximately 70 percent of insurance companies contracted with PBMs to provide these benefits to enrollees [Frank, 2001]. PBMs negotiate prescription drug prices directly with manufacturers, who charge the PBM a price based on volume discounts, rebates, and formulary structure. The PBM subsequently charges the insurance company, who passes on some portion of those costs to patients through copayments and coinsurance. In copayment drug formularies, a generic drug will usually have the lowest copayment, followed by a higher copayment for a preferred branded drug; the highest copayment is for a non-preferred-branded drug. In coinsurance formularies, the coinsurance rate is often constant for all types of prescription drugs [Frank 2001].

In the early 1970s, the RAND Health Insurance Experience (HIE) was the first study to analyze the effect of cost sharing on prescription drug usage. The RAND analysis concluded that patients who were required to pay a larger percentage of their prescription drug costs spent a lower amount on prescription drugs than did their peers. Further, the authors determined that this decreased expenditure occurred through the fulfillment of fewer prescriptions, not by individuals purchasing lower-cost (generic) prescriptions [Leibowitz et al., 1985].

As analysis continued over the next few decades, the relationship between cost sharing and level of usage became a prominent research topic. These studies varied across populations and insurance plan types, and included the Medicaid population [Reeder and Nelson, 1985; Soumerai et al., 1987], the Medicare population [Maio et al., 2005], and the

privately insured [Joyce et al., 2005; Mager and Cox, 2007; Huskamp et al., 2003; Druss et al., 2004]; all confirmed the original finding from the RAND HIE that increased cost sharing decreases spending.

Despite consistent findings that prescription drug demand is sensitive to price increases, disagreement emerges in regard to how the decreased spending occurs. Gibson et al. (2006) find results consistent with the RAND study that higher copayments are associated with decreased drug adherence, not the use of less-costly drugs. In contrast, Mager and Cox (2007) find that a larger generic-to-branded copayment differential decreases costs by increasing the probability of generic prescription-fills. Huskamp et al. (2003) find that changes in cost structure cause some patients to use cheaper drug therapies, while other patients discontinue their use.

Due to endogeneity concerns regarding patient selection into insurance plans, identifying an unbiased price elasticity estimate for prescription drugs remains a difficult empirical task. There are very few studies that identify the impact of price changes on drug demand while accounting for patient selection into drug insurance. Recent examples include Meyerhoefer and Zuvekas (2010), who use panel data methods for this purpose, and Contoyannis et al. (2005), who use a natural experiment. Contoyannis et al. (2005) identify the price elasticity for prescription drug expenditure to be between 0.12 and 0.16, while estimates from Meyerhoefer and Zuvekas (2010) are 0.61 for mental health drugs and 0.31 for drugs used to treat all other conditions.

Quality is another factor that influences patient preference for prescription drugs [Rizzo and Zeckhauser, 2009], and patients may consider branded drugs to be of higher quality than their generic equivalents. Dubois et al. (2000) find that older patients prefer branded drugs citing increased quality and safety. They also find that this concern increases with

the severity of the condition that the drug treats.

In addition to patient preference, physician preference has an important role in determining prescription drug choice. Efficacy of treatment, patient cost, advertising and detailing, and insurance contracts could influence physicians' prescribing behavior. While Gonul et al. (2001) find that physicians consider efficacy of treatment above patients' cost concerns, Lundin (2000) determines that patients with higher cost sharing are generally prescribed lower-cost drugs, supporting the idea that patient cost influences physicians' prescribing behavior. Gonul et al. (2001) find that the effects of advertising, detailing, and sampling have diminishing returns in their influence of physician prescribing behavior.

Insurance plan contracts may have the most influential effect on physician prescribing behavior. For example, Health Maintenance Organizations (HMOs) contract selectively with doctors who provide certain services or agree to provide lower-cost treatment alternatives [Glied, 2000]. This is also common in Point of Service (POS) insurance plans when capitation exists. In these instances, providers are penalized for excessively costly procedures or treatments provided to patients [Glied, 2000], and physicians may be more inclined to prescribe generic drugs under these circumstances. Hellerstein (1997) finds that physicians are more likely to prescribe generic drugs across patients when the majority of their patients are in HMOs. Additionally, the drugs approved or preferred by HMOs are likely to be the drugs prescribed to all the physicians' patients, even those in non-HMO plans [Hellerstien, 1997].

The third important participant in the prescription drug decision is the pharmacist. In 2001, when Prozac lost patent exclusivity, eleven states required pharmacists to dispense the generic form of the prescribed drug, should it exist: Florida, Kentucky, Massachusetts, Minnesota, Missouri, New Jersey, New York, Pennsylvania, Rhode Island, Washington,

and West Virginia. All other states, except Oklahoma, had permissive substitution laws that gave the pharmacist the ability to dispense an equivalent generic drug in place of the branded drug prescribed by the physician. In 2004, when Neurontin lost patent exclusivity, mandatory generic drug dispensation law expanded to Hawaii, and in 2006, when Zocor lost patent exclusivity, Nevada and Tennessee were also bound by this law. Further, a physician or a patient can indicate (on the prescription form) a branded or generic preference; these are referred to as Dispense as Written (DAW) indicators. The pharmacist must honor these requests regardless of the state's law.

Prescription drug choice is a combination of patient, physician, and pharmacist preference and influence. Past studies have focused on these pathways individually. We aim to strengthen the literature by controlling for all of these pathways in our estimates of price elasticities across three distinct drug classes.

1.3 Empirical Approach

We attempt to control for the factors that influence patient preference, physician preference, and pharmacist laws as they impact prescription drug choice. Our sample is subdivided by insurance plan type to account for differences in patient selection, prescription cost-structures, and physician prescribing behavior. We also include state-specific Drug Product Selection (DPS) laws and DAW indicators. These covariates help control for varying patient price-sensitivity and preferences for quality.

As in other health economics studies, we must address the potential for endogeneity from patient selection. Individuals know their health status, and can foresee healthcare needs to a certain extent; therefore, sicker individuals might select into more generous insurance plans because they know they will use the services. Additionally, patients may

select insurance plans based on the generosity of prescription drug coverage that is related to their expected usage of prescription drugs. Ignoring these patient selection issues during empirical analyses can lead to biased estimates. Instead of pure price effects, our estimates could be confounded by patient preference for prescription services and other unobservable characteristics, such as health status.

Because of the potential for endogeneity bias and difficulty in finding valid instruments for prescription drug prices, we include time fixed effects (FEs) to control for aggregate level factors that may influence prescription drug choice. Additionally, we include employer and employer-health insurance plan FEs to control for time-invariant unobservable, but potentially confounding, characteristics of employers and insurance plans. In sensitivity analyses, we assess the extent of patient selection into employer by analyzing different sub-samples of our data.

We identify the impact of branded-to-generic cost differentials (CDs) on the probability of switching between branded and generic drugs using a FE Linear Probability Model (LPM). Our specification is

$$Y_{ijp} = \alpha OOP\_CD_{ijp} + \beta TPP\_CD_{ijp} + \gamma AWP_{ijp} + \omega' \mathbf{X_i} + \delta' \mathbf{E_j} + \mu' \mathbf{S_{ij}} + \rho' \mathbf{I_{ip}} + \lambda_{jp} + \varepsilon_{jp}, \tag{1.1}$$

where the subscripts i, j, and p represent individual, employer, and plan, respectively. The outcome variable, Y, indicates whether or not an individual switches from Prozac to Fluoxetine, from Zocor to Simvastatin, or from Neurontin to Gabapentin. OOP_CD and TPP_CD identify the respective CDs between the generic and branded drugs, while AWP represents the average branded wholesale price of Prozac, Zocor, or Neurontin, dependent upon the specification. $\mathbf{X_i}$ is a vector of patient characteristics, $\mathbf{E_j}$ is a vector of employer

characteristics, $\mathbf{S_{ij}}$ is a vector of state characteristics, $\mathbf{I_{ip}}$ is a vector of insurance plan characteristics, λ_{jp} are employer-plan FEs, and ε_{jp} is a white noise error term.

We consider two outcome variables based on different switching times dependent upon whether or not an individual has switched to the generic drug within one month or within three months of its availability. When using the outcome variable of switching within one month, we include only individuals with 30-day prescriptions. Using three months as our secondary outcome variable allows all individuals in the sample, regardless of prescription fill-rate, the opportunity for at least one prescription-fill after the generic drug becomes available.

We also identify the instantaneous probability of switching using a discrete time hazard function. Pharmaceutical companies that manufacture branded drugs often respond to generic introductions by changing the price of branded drug. Using a discrete time hazard function allows us to use these time varying prices in our model. With this specification, we can also include individual behavior that may change up until the time period in which an individual switches.

We define the discrete time hazard as the conditional probability that switching occurs at time t, given switching has not occurred by t: $h_t \equiv Pr(T = t|T > t-1) = Pr(T = t|T \geq t)$. By including the covariates identified in equation 1.1 with dummy variables to estimate the hazard in each time period we can estimate the effects of the cost differentials and other variable of interest on the hazard (probability that switching occurs). Our discrete time hazard function is specified as

$$
\begin{aligned}
logit\{h_{it}\} = & \\
& logit\{Pr(T_i = t | T_i \geq t, \mathbf{d_t}, \mathbf{x_{ijp}})\} = \\
& logit\{Pr(y_{it} = 1 | \mathbf{d_t}, \mathbf{x_{ijp}})\} = \\
& \tau_1 + \tau_2 d_{2,it} + \cdots + \tau_{16} d_{16,it} + \alpha OOP\_CD_{ijpt} + \beta TPP\_CD_{ijpt} + \\
& \gamma AWP_{ijpt} + \omega' \mathbf{X_{it}} + \delta' \mathbf{E_{jt}} + \mu' \mathbf{S_{ijt}} + \rho' \mathbf{I_{ipt}} + \lambda_{jpt} + \varepsilon_{jpt},
\end{aligned}
\tag{1.2}
$$

where the outcome variable, y_{it}, is a binary variable denoting whether or not individual i switched to the generic drug in period t. The vector $\mathbf{d_t}$ represents dummy variables for each time period in our study, while the vector $\mathbf{x_{ijp}}$ contains all of the covariates described in equation 1.1.

Using equations 1.1 and 1.2, we identify various price elasticities of switching. We identify these elasticities based upon variation within cost differentials (CDs) across employers and plans. Table 1.1 shows the source of variation for our FE regressions, as measured by the coefficient of variation of the CDs and branded AWPs. The coefficient of variation is calculated as the standard deviation of the CD (or branded AWP) divided by its mean. Without any FEs, we have the largest coefficients of variation because these values vary within employers, insurance plans, prescription-fills, and dosages. The coefficient of variation on the CDs and AWPs decreases within employers and employer-plans because the source of variation is limited to the insurance plans, prescription-fills, and dosages in the former case, but only prescription-fills and dosages in the latter. The similarity in variation across these final two specifications indicates that much of the initial variation is across employers. The majority of employers in each drug sample offer more than one type of insurance plan: All but one employer in the Prozac sample, 85% of the employers in the Zocor sample, and 84% of the employers in the Nuerontin sample.

1.4 Data

The principal sources of data for this study are the *Thomson Reuters MarketScan* ® *Research Databases*. We use the *Commercial* database for prescription drug claims and the *Enrollment* database for information detailing insurance plan enrollment. These data sources provide demographic characteristics, geography, employment characteristics, insurance coverage, and payments by prescription claim. Additionally, we use the US Census for detailed population characteristics at the metropolitan statistical area (MSA) level, including per-capita income and population data.

1.4.1 Cost Differential and Average Wholesale Price Calculations

Our main variable of interest in determining the elasticity of switching is the CD between the branded drug and the generic drug. We compute CDs for each individual's out-of-pocket (OOP) payment and their insurance company's third-party-payer (TPP) payment, as detailed by their insurance claim data. Because we cannot observe an individual's generic and branded costs in the same time period, the CDs must be imputed. During the imputation process, we take care to match branded and generic prices based on employer, health insurance plan type, and dosage. For ease of imputation, we calculate all CDs at the unit level determined by dividing the OOP or TPP cost by the number of days of drug therapy covered by the prescription. For each prescription claim made for a branded drug, the CD is calculated using that individual's branded cost minus an imputed generic cost. The imputed generic cost is the average generic cost paid by individuals with the same employer, health insurance plan, and dosage, during that specific month. Similarly, for each generic prescription claim, we subtract that individual's generic cost from an imputed branded cost, which is the average branded cost paid by individuals with the same employer, health insurance plan, and dosage, during that specific month. In the cases when we cannot match observations based on employer, health insurance plan, and

dosage, we attempt to match first on only dosage and second on employer and health insurance plan. Using these methods, we are able to calculate CDs for over 99% of each drug sample.

Another variable of interest for its influencing effect on switching behavior is the AWP of the branded drug. The AWP is the average price charged by wholesalers for the specific drug. We use the listed AWP for branded prescription claims, but impute an average branded AWP for generic prescription claims. Using a similar process as the CD imputation for individuals choosing the generic drug, we match an average branded AWP from individuals who purchase the branded drug during that specific month and who have the same employer, health insurance plan, and dosage. There are more missing values for the AWP variable than for our CD variables, but we still match over 98% of our Prozac sample, 94% of our Zocor sample, and 93% of our Neurontin sample using this imputation method.

1.4.2 Sample Creation

Our most inclusive drug samples are comprised of individuals with at least one prescription claim (for the respective drug) during the 90-day interval before generic introduction, and at least one claim for that drug (or its generic equivalent) during the 16 months after its generic introduction. We consider the 90-day period prior to patent expiration, to ensure we include individuals with 90-day, 60-day, and 30-day prescriptions. We limit our analysis to the 16-month period following generic introduction to decrease the likelihood that switching is due to reasons other than the lowered price caused by the generic introduction. We detail the Prozac sample creation process below, and subsequently summarize the sample creation processes for Zocor and Neurontin.

Prozac lost patent exclusivity on August 2, 2001 [Druss et al., 2004], and the generic form of the drug, Fluoxetine, became available in pharmacies the next day. For our sample, we consider all individuals with at least one prescription-fill for Prozac between May 1, 2001 and July 31, 2001 thus limiting the observations to the time-period immediately before the generic prescription became available. We subsequently match these individuals to their prescription-fills for Prozac or Fluoxetine between August 1, 2001 and December 31, 2002; we keep any individual with at least one of these prescription-fills during this time period. Upon completion of this process, we have 34,810 unique individual claims for Prozac or Fluoxetine. Of the 34,810 individual observations, we can compute CDs for 99.75% of them and AWP prices for 98% of them, yielding a data set containing 34,163 observations.

We conduct the same sample selection process for individuals using Zocor during the three months prior to the availability of its generic drug, Simvastatin, which entered the market on June 23, 2006 [Smith, 2006]. We subsequently identify whether or not those individuals maintained their use of Zocor or switched to Simvastatin at some point during the first 16 months of its availability (through December 2007); this process yields 114,215 observations. Although we are able to calculate CDs for the entire sample, we can only construct AWPs for approximately 94% of this sample, resulting in 107,749 usable observations.

Gabapentin, the generic form of Neurontin, appeared on the market in October of 2004 [Kaplan Fox, 2009]. We identify 38,014 individuals who had a prescription claim for Neurontin between July of 2004 and October of 2004, with a subsequent prescription for Neurontin or Gabapentin before February, 2006. As with Zocor, we create CDs for the entire sample, but we are only able to construct AWPs for approximately 93% of this sample, which yields 35,404 usable observations.

1.4.3 Sample Characteristics

We subset each drug sample by insurance plan type and additionally by prescription-fill rates (30-day, 60-day, or 90-day). Tables 1.2 through 1.7 contain the means and standard deviations of the demographic, geographic, employment, insurance, and prescription control variables for each sub-sample by drug. The regression samples are slightly smaller than original data sets due to missing insurance plan characteristics, employer characteristics, or geographic indication.

The final Prozac sample includes 33,747 individual observations, of which 26,565 are individuals with 30-day prescriptions. The final Zocor sample contains 105,178 observations, of which less than half (48,681) are 30-day prescriptions. The final Neurontin sample is similar in size to the Prozac sample; there are 34,994 individual observations, of which 26,564 are 30-day prescriptions. All three samples have similar geographic, employment, and insurance plan characteristics, but they differ across demographic and prescription characteristics. The underlying illnesses these drugs treat vary, therefore, it is unsurprising that each sample varies across age, gender, and prescription-specific preferences. The Prozac and Neurontin samples are comprised primarily of females (77% and 64%, respectively), while the Zocor sample is comprised mostly of males (58%). The Zocor sample contains the highest average age of prescription claimants, with 90% of the sample over the age of 45, and almost 60% over the age of 55. Seventy-six percent of the Neurontin sample claimants are over the age of 45, while 61% of the Prozac are in this age group.

The individual-prescription characteristics also vary slightly between insurance and drug sub-samples. In the Prozac and Neurontin samples, new prescriptions are slightly higher within the Comprehensive and PPO sub-sample at approximately 50%, and in all three samples the mail-order prescription fill rate is slightly higher in the Comprehensive and PPO insurance sub-sample. For some observations, the prescription order fulfillment

method is unknown; because this data is often missing (especially in the Prozac sample), we construct a dummy variable, Mail Order Unknown, note the missing information, and keep these observations in our sample. In all drug samples, DAW indicators are more common within the HMO and POS sub-samples, but are least common within the Zocor sample, followed by the Neurontin sample, then the Prozac sample. This indicator may demonstrate patient and physician preferences for the branded drug, and indicates that there is a stronger desire to continue use of the branded drug in the antidepressant class and the anticonvulsant class than in the statin class. Mandatory drug substitution laws were unchanged across all drug samples and apply to approximately 15%–25% of the observations based on patient state of residence.

Additionally, there are some differences in characteristics across insurance group sub-samples. The HMO and POS sub-samples are slightly younger, with a larger percentage of enrollees in the 35–44 year-old age group and fewer in the over-55 year-old age group. This is consistent with the literature that details selection of younger, healthier individuals into more restrictive plans like HMOs [Luft and Miller, 1988], and shows some evidence of selection into insurance plan types. There are large differences between the insurance plan sub-samples in terms of geographic location, further supporting the hypothesis that these two insurance sub-samples represent different populations: The Comprehensive and Preferred Provider Organization (PPO) sub-samples have a greater presence in the North-Central and Southern United States and a lower presence in the Northeast and West. The Comprehensive and PPO sub-samples have a greater percentage of union members and retirees; they also have a much greater number of enrollees who are employed in the services sectors. The HMO and POS sub-samples have a greater percentage of enrollees from the transportation, communication, and utilities sectors.

The Comprehensive and PPO insurance sub-sample within the Prozac data set contains 58% PPO members and 42% Comprehensive plan members. The corresponding Zocor and Neurontin sub-samples also have a majority of their individuals enrolled in PPO plans, but at an even greater 81%. This distinction may represent a trend away from comprehensive insurance plans between 2001 and 2006. In the Prozac sample, only 13% of the HMO and POS sub-sample contains HMO members, which is substantially lower than the 56% of the Neurontin sample and the 60% of the Zocor sample. This may be indicative of a trend away from POS plans and towards HMO plans between 2001-2006 for the sub-population represented by this data.

1.4.4 Outcome Variables

Summary statistics for our outcome variables are listed in Table 1.8. Prozac has the largest initial increase in generic prescriptions within the first month of introduction, with 27% of individuals switching immediately. Approximately 10% of individuals in the Neurontin sub-sample switch during this time period, and Zocor has the fewest immediate switchers at 6%. Within three months, between 40% and 60% of individuals switch to the generic for all drugs. The largest switching percentage occurs between Prozac and Fluoxetine, while the smallest occurs between Neurontin and Gabapentin. In the case of Prozac there is no significant difference in switching behavior across insurance sub-samples. However, within the Zocor sample, more individuals from Comprehensive and PPO insurance plans switch than the HMO and POS insurance plans, while the opposite is true in the Neurontin sub-sample.

1.4.5 Cost Differential Variables

As shown in Tables 1.9 and 1.10, we see similar CDs across insurance plan sub-samples. In the cases of Prozac and Neurontin, the CDs within the Comprehensive and PPO sub-sample are slightly larger than the HMO and POS sub-sample, but the opposite is true for Zocor. These differences in CDs could be the result of varying composition of coinsurance and copayment policies across sub-samples. Zocor has the largest average OOP CD across all plans and prescription-fill rates. As shown in Table 1.10, the average individual would pay approimately \$0.40 more per unit[1] of Zocor than Simvastatin. The average Prozac user would pay approximately \$0.35 more for a unit of Prozac than Fluoxetine, while the average Neurontin user would pay approximately \$0.23 more per unit of Neurontin than Gabapentin.

We find more variation across drugs in the TPP CDs, which is due in part to the varying competitive structures across pharmaceutical drug markets upon generic introduction. When introduced to the market, Fluoxetine was only produced by one company, and that company had market exclusivity (among generic competition) for six months. During this time period, the price of Fluoxetine remained high because of the initial lack of competition; upon generic introduction, the average TPP unit cost of Fluoxetine was actually \$0.27 more than the average unit cost of Prozac. Because the price of Fluoxetine was high immediately upon its introduction, we conduct sensitivity analyses in which we compute the CDs as the difference between each branded drug and a generic antidepressant drug that has been available for over thirty years, Amitriptyline. We expect that insurance companies (especially ones using a copayment structure) base their prescription formularies on the expected low price of generic drugs. We note that the TPP CD changes

[1]The unit costs are calculated by dividing the total cost by the number of days of drug therapy covered by the prescription.

substantially when comparing Prozac to Amitriptyline, an established generic antidepressant; the average per unit cost of Amitriptlyine is $3.09 less than the average per unit cost of Prozac. We would expect the TPP CD between Prozac and Fluoxetine to approach that of Prozac and Amitriplyline over time, as more generic competition occurs.

Upon generic entry of Simvastatin, no single manufacturer was given exclusive production rights [Smith, 2006]. Two manufacturers, Teva Pharmaceuticals and Ranbaxy Labs, were granted immediate entrance into the market creating a more competitive environment than the introduction of Fluoxetine. Additionally, when Simvastatin entered the market, Merck chose to lower the price of Zocor in order to compete with the generic entrants on the basis of price. This is evident by the smaller TPP CD between Zocor and Simvastatin than any other pair analyzed in this study; an insurance company would pay an average of $0.53 more per unit of Zocor than Simvastatin during this time period.

When Gabapentin was introduced to the market, it was manufactured by three companies, Teva Pharmaceuticals, Ivax, and Alphaparm [Decker and Petypiece, 2007]. In this instance, Pfizer did not decrease the price of Neurontin and even continued its advertising campaign throughout the generic introduction period [Saul, 2008]. This resulted in a larger TPP CD; an insurance company would pay an average of $1.87 more for a unit of Neurontin than Gabapentin during this time period.

In table 1.11 we have extrapolated the unit CDs and AWPs to 30-day prescription prices by quartile. The median OOP CDs for a 30-day prescriptions of Prozac, Zocor, and Neurontin are $18.41, $19.81, and $11.18, respectively. The median TTP CD is -$38.57 for a 30-day prescription of Prozac, increases to $39.07 for a 30-day Zocor prescription, and $73.14 for a 30-day Neurontin prescription. Prozac and Zocor have relatively similar AWP prices, around $160, for a 30-day prescription, while Neurontin is slightly higher at

$177.

1.5 Results

1.5.1 Primary Results

Our principal analysis uses the employer FE model described in Section 1.3. The complete regression results for these models using the 30-day prescription samples are listed in Appendix A. All other regression results are available from the authors, by request. We detail the elasticity estimates for switching within one month in Table 1.12, and the estimates for switching within three months in Table 1.13. Each table contains the results for all insurance sub-samples: Comprehensive and POS, HMO and PPO, and all plans combined. The first three columns contain the price elasticities from the specification with no FEs, the middle three columns contain the price elasticities from the specification including employer FEs, and the final three columns contain employer health insurance plan FEs. All specifications include time fixed effects, and standard errors clustered by employer and health insurance plan

If we assume patients select plans based on unobservable health status, patients in poorer health would select plans with lower branded drug costs, resulting in smaller cost differentials that would cause over-estimation of the price elasticities due to omitted variable bias. As shown in Tables 1.12 and 1.13, without including any FEs we find slightly higher estimated elasticities than with employer or employer-plan FEs. For example, within the Comprehensive and PPO sub-sample of the full Prozac sample, the OOP CD price elasticity is 0.056 without any FEs and 0.052 with both employer and employer-plan FEs. Similar (and often smaller) changes occur in the other sub-sample regressions, and in TTP CD and AWP price elasticity estimates across all drug samples. Our results across

FE specifications suggest limited selection into employer plans because our elasticities remain relatively unchanged across both employer and employer-plan FE specifications. We include employer FEs in all subsequent specifications.

Our price elasticity estimates detailed in Tables 1.12 and 1.13 indicate the effect of a one-percent change in the CD on the probability of switching between the branded and the generic drug. These results vary across insurance sub-samples and drugs. In the case of Prozac, we find that a one-percent change in the OOP CD results in an increased probability of switching from Prozac to Fluoxetine of between 0.05% and 0.08% depending upon health insurance plan type. The larger effects within the HMO and POS sub-sample indicate increased price sensitivity for individuals who select into these more restrictive forms of insurance in exchange for lower premiums. We find the effects to be smaller in the case of switching between Zocor and Simvastatin, where a one-percent change in the OOP CD results in an increased probability of switching of approximately 0.03%. We find no significant effects of OOP CDs on switching behavior within the Neurontin to Gabapentin sample.

Table 1.13 displays the estimated price elasticities for switching between the branded and generic drug within three months of the generic introduction, and considers prescription-fills of all lengths. In the case of Prozac, we find that the price elasticity falls in significance and magnitude to 0.02. The effects decrease in significance and magnitude when comparing switching within one month to switching within three months. This implies that individuals with the highest CDs are switching to the generic drug before individuals with lower CDs, or that individuals with the 60-day and 90-day prescription-fills are less likely to switch. In addition, it may be the case that non-price factors, such as safety, are stronger determinants of the switching decision for late adopters of the generic drug. We see the opposite trend when reviewing the price elasticities for Zocor using the full

sample. A one-percent increase in OOP CD increases the likelihood of switching between 0.03% and 0.05%. The elasticities estimated for Zocor using the full sample are more indicative of the average price elasticities of this sample because more than 50% of our full sample has 90-day prescriptions. Again, we find stronger OOP CD results in the HMO and POS sub-sample, providing additional evidence of the increased price sensitivity of individuals who choose this type of insurance plan. The lower price sensitivity of Prozac over time, as compared to Zocor, may result from greater concern about the side effects of antidepressants, or because the efficacy of antidepressants tends to vary to a larger extent across patients than it does for statins.

The TPP price elasticities have varying levels of significance across the Prozac and Zocor drug samples, as well. The magnitudes are larger for the 30-day model than the full model for Prozac, implying that they may better capture short-term inducements. The effects are consistent in magnitude across most specifications (between 0.02 and 0.09), except for the AWP branded price in the HMO and POS sub-sample. The large impact of 0.84 indicates the significant influence of the branded wholesale price on switching behavior for this sub-sample. The TPP CD is only significant in the full sample analysis of Zocor; the elasticities are estimated to be between 0.01 and 0.02 in this case. For Prozac these third-party metrics have similar magnitudes when compared to the OOP metrics, but in the case of Zocor the TPP metrics have a decreased effect in comparison. Again, this may be a result of the pricing strategy used by Merck when Simvastatin was introduced into the market.

In the case of Neurontin, our price elasticity estimates increase in significance and become negative when considering all prescriptions and switching within three months. Initially, this seems to be a puzzling result; an increase in the OOP CD between the branded and the generic drug decreases the probability of switching to the generic by between

0.02% and 0.03%. However, we also find that the TPPs and AWPs effects are negative, and have a much larger magnitude in the Neurontin sample than in the other drug samples. This highlights the importance of the role of insurance companies, physicians, and pharmacists in the prescription decision. The negative TPP and AWP effects could be the result of rebates, physician detailing, or other inducements not captured elsewhere in our model. Some of this effect may have spilled over to the consumer, who may associate higher branded costs with increased quality [Dubois et al., 2000], and have an especially high preference for quality in this class of drugs. Additionally, Pfizer continued to advertise for Neurontin after Gabapentin entered the market and continued to advocate for off-label use [Saul, 2008]. These practices could have induced consumers and physicians to continue using the branded drug even with the availability of lower-priced generics.

We use Logit and LPM specifications to estimate the hazard function using equation 1.2 and provide the resulting price elasticities in Table 1.14. In these models, we include multiple observations for each individual during the 16 months after the generic drug becomes available. Our dependent variable is a binary variable set to one during the first time period an individual switches. Many of the covariates remain fixed during each time period, but the CDs and AWPs vary with time. As in our original specification, we include time and employer fixed effects, and cluster the standard errors by employer and health insurance plan. These results represent the price elasticity associated with the instantaneous probability of switching at any point in time.

We do not find any statistically significant effects of the OOP CD on the instantaneous probability of switching in the case of Prozac. This contrasts from our initial findings indicating a positive and significant effect of OOP CD on switching within one month. The TPP CD and AWP price continue to have a more significant effect on switching from Prozac to Fluoxetine than the OOP CD, and this is consistent across specifications.

As in the previous estimation, we find the OOP CD to be more important when switching between Zocor and Simvastatin than any of our other measures of price. The price elasticities we estimate from the hazard function using the LPM are similar in magnitude to the price elasticities found using the original LPM.

In the case of Neurontin, we find more significant effects than in our discrete time hazard model than our original LPM specification. The TPP CD and AWP continue to have a negative impact on switching, but we find the OOP CD to have a positive and significant effect in the case of the Comprehensive and PPO insurance plan types. This is in contrast to our previous specification in which the OOP CD has a negative effect on switching to Neurontin within three months. There are several possible explanations for these varying results. First, when Gabapentin was introduced into the market, there was a significant amount of off-label use of Nuerontin, and individuals who use the branded drug for off-label use may be more skeptical about switching to a generic drug. This is something our model cannot capture, therefore it could be confounding our results. Second, we base our hazard model on the individual's first switch to the generic drug; we do not consider cases where individuals switch back to the branded drug after having a negative experience with the branded drug. These individual effects could be amplified within the neurological class and represent another potentially confounding pathway.

1.5.2 Sensitivity Analysis

We estimated four additional specifications to gain more insight into the robustness of our empirical results. First, we specify another set of regressions in which we do not include DAW indicators in order to validate their effects on the price elasticity estimates. We omit the DAW indicators from our regression specification to determine whether they are capturing some of the effect of price. Including these variables may be decreasing the true estimation of the price elasticity because those patients with the least price sensitivity

are the most likely to avoid generic prescriptions through physician overrides. Second, we remove the TPP CD from our specification to understand its relationship with the OOP CD and the branded AWP prices. Third, we assess the extent of patient selection into employer by analyzing two sub-samples of our data in which one contains employers that only offer one insurance plan, and the other contains employers offering multiple plans. Fourth, we compute CDs associated with switching from Prozac to Amitriptyline rather than Fluoxetine. The former is a generic antidepressant that has been available for a number of years and has reached its equilibrium price. In contrast, the price of Fluoxetine decreased steadily over the two years following its introduction. If insurance plans establish cost sharing levels based on the expected steady-state price of generic drugs, the CD between Prozac and Amitriptyline may be a better proxy for the future branded-to-generic CD than the initial CD between Prozac and Fluoxetine (during which Fluoxetine did not experience any competition from other generic manufacturers). We therefore determine price elasticities using Amitriptyline, which has settled at its expected, much-lower-than-branded price.

As shown in the middle columns of Tables 1.15 and 1.16, removing the DAW indicators increases the price elasticity estimates in all specifications across sub-samples and drugs. This suggests the inclusion of the DAW indicators may capture a small portion of the impact that price has on switching. However, we prefer the specifications that include these indicators because they are less likely to be confounded by differences in prescribing norms and pharmacy behavior.

The final three columns of Tables 1.15 and 1.16 contain the price elasticities from the specification without the TPP CDs. The TPP CDs represent a physician inducement pathway, and these results provide insight into the varying effects of TPP and AWP pricing on switching behavior across drugs. In the case of Prozac, removing the TPP CDs

from the specifications increases the effects of the OOP CDs and decreases the effects of the AWP prices. This implies that the TPP CD has a significant impact on switching behavior that could be mistakenly attributed to consumer price sensitivity if these variables are not included in the model. We see a similar trend in the Neurontin elasticities, although the AWP effects also capture some of the TPP CD effect when it is removed. In the case of the Zocor samples, the full sample is robust to removal of the TPP CD, which implies there is no correlation between these variables in this drug sub-sample.

We conduct another sensitivity test to infer the extent to which individuals select into employers based on health insurance offerings. Specifically, we consider those individuals with a choice of health insurance plan type versus those whose employer offers only one option. We compare the estimated coefficients on OOP CDs across these two sub-samples and the entire pooled sample to determine whether or not there is a systematic difference between the samples. If the coefficients are consistent across these samples, we believe this shows some evidence of a lack of selection into employer based on health insurance offerings. If there were such selection, we would expect to see higher OOP CD price elasticities in the sample containing employers with multiple plan options, as sicker individuals would select employers offering more than one insurance plan. In the case of Prozac, about 6% of its observations have only one health insurance plan choice (all of which have a POS health insurance plan), while approximately 8.5% of the Zocor sample has only one health insurance plan choice. In the Neurontin sample 14%, of the observations are in the sub-sample with only one plan type offered.

Table 1.17 contains the elasticities across the two sub-samples by the number of plan types offered; the first three columns in Table 1.15 contain the elasticities of the pooled sample. Across all sub-samples and drugs, we find higher estimated effects within the sub-sample of the population with only one health insurance plan type available. This

implies that individuals who are employed by companies with only one insurance plan type are more price sensitive than those with more insurance plan options. If selection into employer existed, we would expect to see the opposite result. We believe these results show a lack of selection at the employer level, indicating that this source of endogeneity does not counfound our estimates.

Table 1.18 shows the results from our analysis using the Amitriptyline costs; in general, the TPP CD and the AWP of the branded drug are positive and statistically significant. The TPP CD results in a 0.07% to 0.22% increased probability of switching, with the smaller effect occurring over the longer switching time of three months. These effects are larger in magnitude than those estimated using the Prozac to Fluoxetine CDs, which implies that price sensitivity increases as the price of the generic drug decreases.

1.6 Conclusions

This is the first analysis to identify the price elasticities of switching from branded to generic drugs during the time period of generic entry. We accomplish this using empirical approaches that account for potential issues of endogeneity associated with patient selection into insurance plan while also considering changes in prescription drug prices and patient preferences over time. The OOP CDs provide a direct analysis of consumer behavior, while the TPP CDs provide additional information about the extent to which physicians and insurance plans influence switching behavior.

Our results show that the estimated effect of the OOP CD varies by insurance subsample and class of drug, which implies that prescription payment plans and heterogeneous preferences across disease treatment influence patient behavior differently. For example, in the case of Zocor, we find that the OOP CDs have a greater influence on switching

behavior than the corresponding TPP CDs, and the influence is greatest among those individuals who participate in an HMO or a POS insurance plan. Alternatively, in the case of Prozac and Neurontin, the TPP CDs and branded AWPs have a larger impact than the OOP CDs. These effects are negative when considering switching within three months from Gabapentin to Neurontin. We believe external factors that are outside our ability to control could be causing these results. Some of these external factors could include increased sensitivity among Neurontin users to side effects of Gabapentin, and the promotion of off-label use by the manufacturers of Neurontin.

Based on our OOP CDs, we estimate the elasticity of switching between Prozac and Fluoxetine to be between 0.02 and 0.08; similarly, we find the TPP CDs to have an elasticity between 0.01 and 0.09. We estimate the OOP CD elasticity of switching between Zocor and Simvastatin to be between 0.03 and 0.05, and the TPP CD to be between 0.01 and 0.02. In the case of Neurontin, we highlight the importance of insurance companies, physicians, and pharmacists in the prescription drug choice as the TPP variables are much more significant than the consumer variables and even discourage generic use.

These price elasticity estimates offer insight into the mechanisms influencing patient switching behavior from generic to branded drugs. The variation across insurance plans and class of prescription drug can be used to tailor prescription plans to induce increased levels of switching, thereby reducing prescription costs for both public and private payers. For example in the case of Zocor, each one percent increase in OOP CD ($1.20 decrease in generic payment per 30-day script) increases an individual's probability of switching to Simvastatin by approximately 0.03 percentage points (6%). With these additional individuals choosing the generic drug, the TPP cost savings amounts to $14.73 per prescription (with the change of cost sharing from patient to third-party-payer the unit TPP CD decreases by $0.04 to $0.491). In 2005, there were 37.5 million prescription claims for Zocor.

If 51.6% of users switched within three months instead of 48.6%, this would correspond to 1.135 million additional generic prescription claims and a TPP savings of $16.72 million. Despite seemingly small elasticity estimates, real cost savings can be achieved by adjusting cost-sharing plans in accordance with patient behavior.

Our study is limited to drugs that become generic during our sample period. Future research could improve upon our results by identifying price elasticities in more drug classes in addition to cross-price elasticities within individual drug classes. As demonstrated in our Neurontin results, we also face some limitations due to data availability. There are some external factors that could influence switching behavior that are beyond our ability to model, and these factors could vary across drug class (e.g. off-label use). Despite these limitations, our robustness analyses indicate consistent results across various specifications.

1.7 Tables

Table 1.1: Sources of Variation

	Coefficient of Variation†					
	30-day Scripts			All Scripts		
	Across all Individuals	Within Employer	Within Employer-Plan	Across all Individuals	Within Employer	Within Employer-Plan
Prozac to Fluoxetine:						
OOP CD	1.024	0.100	0.112	1.103	0.157	0.162
TPP CD	2.632	0.360	0.386	5.314	1.123	1.164
AWP Prozac	0.941	0.108	0.136	0.880	0.097	0.129
Zocor to Simvastatin:						
OOP CD	0.981	0.071	0.095	1.858	0.478	0.508
TPP CD	0.998	0.092	0.115	2.318	0.386	0.416
AWP Zocor	1.198	0.182	0.212	0.907	0.094	0.127
Neurontin to Gabapentin:						
OOP CD	1.568	0.203	0.229	2.249	0.385	0.418
TPP CD	1.839	0.235	0.261	1.932	0.211	0.237
AWP Neurontin	0.415	0.113	0.130	0.445	0.094	0.107

† Variation calculated as the standard deviation divided by the mean.

Table 1.2: Summary Statistics of Control Variables Prozac for 30-day Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:						
Age Under 18	0.037	0.188	0.042	0.201	0.039	0.194
Age 18-34	0.119	0.323	0.167	0.373	0.139	0.346
Age 35-44	0.204	0.403	0.298	0.457	0.243	0.429
Age 45-54	0.374	0.484	0.332	0.471	0.356	0.479
Age Over 55	0.267	0.443	0.161	0.368	0.223	0.416
Male	0.234	0.424	0.244	0.430	0.238	0.426
Female	0.766	0.424	0.756	0.430	0.762	0.426
Geographic Variables:						
Northeast	0.085	0.278	0.240	0.427	0.149	0.357
North Central	0.388	0.487	0.177	0.381	0.300	0.458
South	0.486	0.500	0.471	0.499	0.480	0.500
West	0.041	0.198	0.112	0.316	0.071	0.257
Urban Indicator	0.704	0.457	0.854	0.353	0.767	0.423
Employment Variables:						
Non-Union	0.217	0.412	0.640	0.480	0.394	0.489
Union	0.278	0.448	0.118	0.322	0.211	0.408
Union Unknown	0.505	0.500	0.243	0.429	0.396	0.489
Active FT	0.778	0.416	0.812	0.391	0.792	0.406
Active PT	0.003	0.053	0.028	0.164	0.013	0.114
Retiree	0.192	0.394	0.129	0.335	0.165	0.371
Other Status	0.028	0.164	0.032	0.176	0.029	0.169
Manuf., Durable Goods	0.066	0.249	0.194	0.395	0.119	0.324
Manuf., Nondurable Goods	0.094	0.291	0.034	0.180	0.069	0.253
Transp., Comm., Utilities	0.074	0.261	0.356	0.479	0.191	0.393
Services	0.236	0.425	0.048	0.214	0.158	0.364
Other Industry	0.029	0.166	0.087	0.281	0.053	0.224
Employee Size (10,000s)	17.698	14.329	8.068	0.204	16.121	12.257
Number of Observations	15,472		11,093		26,565	

Table 1.2: Summary Statistics of Control Variables Prozac for 30-day Scripts (continued)

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:						
Per Cap. Income ($1000s)	22.747	3.177	23.517	3.695	14.695	11.427
Population (100,000s)	2159	2060	2157	1972	2158	2019
MSA Info Unknown	0.296	0.457	0.296	0.457	0.233	0.423
Insurance Variables:						
Comprehensive	0.406	0.491	0.000	0.000	0.236	0.425
PPO	0.594	0.491	0.000	0.000	0.346	0.476
HMO	0.000	0.000	0.159	0.366	0.066	0.249
POS	0.000	0.000	0.384	0.486	0.160	0.367
POS w/ Capitation	0.000	0.000	0.457	0.498	0.191	0.393
Prescription Variables:						
New Prescription	0.431	0.495	0.407	0.491	0.421	0.494
No DAW	0.747	0.435	0.756	0.429	0.751	0.432
Physician DAW	0.051	0.220	0.088	0.283	0.066	0.249
Patient DAW	0.095	0.294	0.136	0.343	0.112	0.316
Retail Prescription	0.603	0.489	0.782	0.413	0.677	0.467
Mail Order	0.014	0.118	0.006	0.080	0.011	0.104
Mail Status Unknown	0.383	0.486	0.212	0.409	0.312	0.463
Mandatory Drug Subs.	0.121	0.326	0.467	0.499	0.265	0.442
Number of Observations	15,472		11,093		26,565	

Table 1.3: Summary Statistics of Control Variables Prozac for All Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:						
Age Under 18	0.033	0.179	0.037	0.190	0.035	0.184
Age 18-34	0.109	0.312	0.141	0.348	0.123	0.329
Age 35-44	0.193	0.395	0.270	0.444	0.228	0.419
Age 45-54	0.375	0.484	0.344	0.475	0.361	0.480
Age Over 55	0.289	0.453	0.208	0.406	0.253	0.435
Male	0.238	0.426	0.247	0.431	0.242	0.428
Female	0.762	0.426	0.753	0.431	0.758	0.428
Geographic Variables:						
Northeast	0.093	0.291	0.231	0.421	0.155	0.362
North Central	0.416	0.493	0.199	0.399	0.319	0.466
South	0.446	0.497	0.456	0.498	0.450	0.498
West	0.045	0.207	0.115	0.319	0.076	0.265
Urban Indicator	0.703	0.457	0.854	0.353	0.771	0.420
Employment Variables:						
Non-Union	0.243	0.429	0.604	0.489	0.404	0.491
Union	0.296	0.456	0.123	0.329	0.219	0.413
Union Unknown	0.462	0.499	0.272	0.445	0.377	0.485
Active FT	0.761	0.427	0.777	0.416	0.768	0.422
Active PT	0.003	0.051	0.022	0.147	0.011	0.106
Retiree	0.204	0.403	0.166	0.372	0.187	0.390
Other Status	0.033	0.178	0.035	0.183	0.034	0.180
Manuf., Durable Goods	0.073	0.261	0.274	0.446	0.163	0.369
Manuf., Nondurable Goods	0.116	0.321	0.038	0.191	0.081	0.273
Transp., Comm., Utilities	0.074	0.262	0.318	0.466	0.183	0.387
Services	0.250	0.433	0.042	0.202	0.157	0.364
Other Industry	0.032	0.176	0.095	0.293	0.060	0.238
Employee Size (10,000s)	16.607	13.837	14.787	8.362	15.794	11.745
Number of Observations	18,663		15,084		33,747	

Table 1.3: Summary Statistics of Control Variables Prozac for All Scripts (continued)

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:						
Per Cap. Income ($1000s)	22.711	3.200	23.361	3.606	23.033	3.421
Population (100,000s)	2099	2052	2096	1957	2098	2005
MSA Info Unknown	0.297	0.457	0.146	0.353	0.229	0.420
Insurance Variables:						
Comprehensive	0.417	0.493	0.000	0.000	0.231	0.421
PPO	0.583	0.493	0.000	0.000	0.322	0.467
HMO	0.000	0.000	0.129	0.335	0.058	0.233
POS	0.000	0.000	0.393	0.488	0.176	0.381
POS w/ Capitation	0.000	0.000	0.478	0.500	0.214	0.410
Prescription Variables:						
New Prescription	0.467	0.499	0.384	0.486	0.430	0.495
No DAW	0.763	0.425	0.787	0.410	0.774	0.418
Physician DAW	0.058	0.233	0.088	0.284	0.071	0.257
Patient DAW	0.087	0.282	0.106	0.308	0.096	0.294
Retail Prescription	0.547	0.498	0.591	0.492	0.567	0.496
Mail Order	0.118	0.323	0.111	0.314	0.115	0.319
Mail Status Unknown	0.335	0.472	0.297	0.457	0.318	0.466
Mandatory Drug Subs.	0.134	0.341	0.438	0.496	0.270	0.444
Number of Observations	18,663		15,084		33,747	

Table 1.4: Summary Statistics of Control Variables Zocor for 30-day Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:						
Age Under 18	0.000	0.021	0.001	0.029	0.001	0.025
Age 18-34	0.016	0.124	0.019	0.137	0.017	0.130
Age 35-44	0.100	0.300	0.124	0.330	0.111	0.314
Age 45-54	0.333	0.471	0.367	0.482	0.348	0.476
Age Over 55	0.551	0.497	0.489	0.500	0.523	0.499
Male	0.561	0.496	0.577	0.494	0.568	0.495
Female	0.439	0.496	0.423	0.494	0.432	0.495
Geographic Variables:						
Northeast	0.075	0.263	0.107	0.309	0.089	0.285
North Central	0.254	0.435	0.179	0.383	0.222	0.416
South	0.576	0.494	0.451	0.498	0.520	0.500
West	0.095	0.294	0.263	0.440	0.169	0.375
Urban Indicator	0.769	0.422	0.891	0.312	0.823	0.382
Employment Variables:						
Non-Union	0.467	0.499	0.515	0.500	0.489	0.500
Union	0.175	0.380	0.159	0.366	0.169	0.374
Union Unknown	0.358	0.480	0.325	0.468	0.342	0.474
Active FT	0.534	0.499	0.727	0.446	0.619	0.486
Active PT	0.005	0.072	0.013	0.114	0.009	0.092
Retiree	0.203	0.402	0.150	0.358	0.180	0.384
Other Status	0.258	0.437	0.110	0.313	0.192	0.394
Manuf., Durable Goods	0.225	0.418	0.252	0.434	0.236	0.425
Manuf., Nondurable Goods	0.101	0.302	0.021	0.145	0.067	0.251
Transp., Comm., Utilities	0.034	0.182	0.136	0.342	0.079	0.270
Services	0.082	0.274	0.020	0.139	0.054	0.227
Other Industry	0.076	0.265	0.075	0.264	0.078	0.269
Employer Enrollment (10,000s)	43.530	61.924	29.401	28.861	37.116	50.642
Number of Observations	27,244		21,102		48,681	

Table 1.4: Summary Statistics of Control Variables Zocor for 30-day Scripts (continued)

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:						
Per Cap. Income ($1000s)	25.297	4.218	26.220	4.633	25.748	4.444
Population (100,000s)	1907	2128	2228	2165	2061	2180
MSA Info Unknown	0.232	0.422	0.109	0.312	0.177	0.382
Insurance Variables:						
Comprehensive	0.083	0.276	0.000	0.000	0.046	0.210
PPO	0.917	0.276	0.000	0.000	0.513	0.500
HMO	0.000	0.000	0.693	0.461	0.301	0.459
POS	0.000	0.000	0.291	0.454	0.126	0.332
POS w/ Capitation	0.000	0.000	0.016	0.126	0.007	0.083
Prescription Variables:						
New Prescription	0.426	0.495	0.407	0.491	0.419	0.493
No DAW	0.834	0.372	0.717	0.450	0.783	0.412
Physician DAW	0.028	0.166	0.038	0.190	0.032	0.177
Patient DAW	0.076	0.265	0.192	0.394	0.127	0.333
Retail Prescription	0.981	0.138	0.917	0.276	0.953	0.212
Mail Order	0.008	0.091	0.006	0.076	0.007	0.085
Mail Order Unknown	0.011	0.104	0.078	0.267	0.040	0.195
Mandatory Drug Subs.	0.205	0.404	0.275	0.446	0.236	0.424
Number of Observations	27,244		21,102		48,681	

Table 1.5: Summary Statistics of Control Variables Zocor All Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:						
Age Under 18	0.000	0.016	0.000	0.020	0.000	0.018
Age 18-34	0.010	0.099	0.013	0.114	0.011	0.106
Age 35-44	0.072	0.258	0.094	0.292	0.082	0.274
Age 45-54	0.291	0.454	0.322	0.467	0.305	0.460
Age Over 55	0.628	0.483	0.571	0.495	0.602	0.489
Male	0.575	0.494	0.593	0.491	0.583	0.493
Female	0.425	0.494	0.407	0.491	0.417	0.493
Geographic Variables:						
Northeast	0.078	0.269	0.131	0.337	0.102	0.303
North Central	0.346	0.476	0.228	0.419	0.294	0.456
South	0.478	0.500	0.400	0.490	0.443	0.497
West	0.097	0.296	0.241	0.428	0.160	0.367
Urban Indicator	0.788	0.409	0.893	0.309	0.834	0.372
Employment Variables:						
Non-Union	0.431	0.495	0.542	0.498	0.481	0.500
Union	0.285	0.452	0.181	0.385	0.240	0.427
Union Unknown	0.284	0.451	0.276	0.447	0.280	0.449
Active FT	0.503	0.500	0.666	0.472	0.576	0.494
Active PT	0.005	0.069	0.011	0.103	0.007	0.085
Retiree	0.304	0.460	0.222	0.416	0.267	0.443
Other Status	0.189	0.392	0.101	0.301	0.150	0.357
Manuf., Durable Goods	0.359	0.480	0.323	0.468	0.343	0.475
Manuf., Nondurable Goods	0.125	0.331	0.024	0.152	0.081	0.273
Transp., Comm., Utilities	0.040	0.195	0.170	0.375	0.097	0.296
Services	0.080	0.271	0.023	0.151	0.055	0.228
Other Industry	0.067	0.250	0.061	0.239	0.066	0.249
Employer Enrollment (10,000s)	32.353	53.692	27.972	28.107	30.250	44.328
Number of Observations	58,803		45,694		105,178	

Table 1.5: Summary Statistics of Control Variables Zocor All Scripts (continued)

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:						
Per Cap. Income ($1000s)	25.444	4.293	26.316	4.598	25.863	4.456
Population (100,000s)	1854	2067	2128	2092	1984	2084
MSA Info Unknown	0.212	0.409	0.107	0.309	0.166	0.372
Insurance Variables:						
Comprehensive	0.183	0.387	0.000	0.000	0.103	0.303
PPO	0.817	0.387	0.000	0.000	0.457	0.498
HMO	0.000	0.000	0.605	0.489	0.263	0.440
POS	0.000	0.000	0.359	0.480	0.156	0.363
POS w/ Capitation	0.000	0.000	0.036	0.185	0.015	0.123
Prescription Variables:						
New Prescription	0.591	0.492	0.526	0.499	0.563	0.496
No DAW	0.674	0.469	0.544	0.498	0.616	0.486
Physician DAW	0.035	0.184	0.034	0.181	0.035	0.183
Patient DAW	0.048	0.214	0.114	0.318	0.077	0.266
Retail Prescription	0.549	0.498	0.530	0.499	0.540	0.498
Mail Order	0.423	0.494	0.362	0.481	0.397	0.489
Mail Status Unknown	0.028	0.165	0.108	0.310	0.063	0.242
Mandatory Drug Subs.	0.217	0.412	0.299	0.458	0.253	0.435
Number of Observations	58,803		45,694		105,178	

Table 1.6: Summary Statistics of Control Variables Neurontin for 30-day Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:						
Age Under 18	0.011	0.104	0.018	0.134	0.013	0.114
Age 18-34	0.059	0.236	0.066	0.248	0.061	0.240
Age 35-44	0.146	0.353	0.178	0.382	0.156	0.363
Age 45-54	0.342	0.474	0.369	0.483	0.351	0.477
Age Over 55	0.442	0.497	0.369	0.482	0.419	0.493
Male	0.360	0.480	0.357	0.479	0.359	0.480
Female	0.640	0.480	0.643	0.479	0.641	0.480
Geographic Variables:						
Northeast	0.041	0.198	0.075	0.264	0.051	0.221
North Central	0.285	0.451	0.241	0.427	0.271	0.445
South	0.541	0.498	0.426	0.495	0.506	0.500
West	0.134	0.340	0.258	0.437	0.172	0.377
Urban Indicator	0.685	0.464	0.790	0.408	0.717	0.450
Employment Variables:						
Non-Union	0.305	0.461	0.391	0.488	0.332	0.471
Union	0.194	0.396	0.158	0.364	0.183	0.387
Union Unknown	0.500	0.500	0.451	0.498	0.484	0.500
Active FT	0.479	0.500	0.631	0.483	0.526	0.499
Active PT	0.001	0.031	0.008	0.089	0.003	0.056
Retiree	0.195	0.396	0.146	0.353	0.180	0.384
Other Status	0.324	0.468	0.215	0.411	0.291	0.454
Manuf., Durable Goods	0.175	0.380	0.156	0.363	0.169	0.375
Manuf., Nondurable Goods	0.069	0.253	0.026	0.159	0.056	0.230
Transp., Comm., Utilities	0.042	0.201	0.161	0.368	0.078	0.269
Services	0.084	0.277	0.014	0.118	0.062	0.242
Other Industry	0.154	0.361	0.076	0.266	0.132	0.338
Employer Enrollment (10,000s)	51.110	58.941	27.936	29.894	43.931	52.876
Number of Observations	18,393		8,122		26,564	

Table 1.6: Summary Statistics of Control Variables Neurontin for 30-day Scripts (continued)

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:						
Per Cap. Income ($1000s)	23.23	2.593	22.93	2.639	23.14	2.611
Population (100,000s)	1258	1280	1215	1137	1245	1237
MSA Info Unknown	0.315	0.464	0.210	0.408	0.283	0.450
Insurance Variables:						
Comprehensive	0.162	0.369	0.000	0.000	0.112	0.316
PPO	0.838	0.369	0.000	0.000	0.580	0.494
HMO	0.000	0.000	0.600	0.490	0.184	0.387
POS	0.000	0.000	0.355	0.479	0.109	0.311
POS w/ Capitation	0.000	0.000	0.045	0.206	0.014	0.116
Prescription Variables:						
New Prescription	0.406	0.491	0.359	0.480	0.392	0.488
No DAW	0.818	0.386	0.807	0.395	0.815	0.388
Physician DAW	0.041	0.198	0.046	0.210	0.042	0.202
Patient DAW	0.098	0.298	0.105	0.307	0.101	0.301
Retail Prescription	0.982	0.133	0.945	0.227	0.970	0.170
Mail Order	0.014	0.119	0.011	0.106	0.013	0.115
Mail Status Unknown	0.004	0.060	0.043	0.203	0.016	0.127
Mandatory Drug Subs.	0.130	0.336	0.230	0.421	0.160	0.367
Number of Observations	18,393		8,122		26,564	

Table 1.7: Summary Statistics of Control Variables Neurontin All Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:						
Age Under 18	0.010	0.098	0.016	0.125	0.012	0.108
Age 18-34	0.051	0.219	0.058	0.234	0.053	0.224
Age 35-44	0.130	0.336	0.157	0.364	0.139	0.346
Age 45-54	0.331	0.471	0.358	0.479	0.340	0.474
Age Over 55	0.478	0.500	0.411	0.492	0.457	0.498
Male	0.359	0.480	0.365	0.481	0.361	0.480
Female	0.641	0.480	0.635	0.481	0.639	0.480
Geographic Variables:						
Northeast	0.043	0.202	0.087	0.282	0.057	0.231
North Central	0.298	0.457	0.232	0.422	0.277	0.447
South	0.518	0.500	0.411	0.492	0.484	0.500
West	0.141	0.348	0.270	0.444	0.182	0.386
Urban Indicator	0.694	0.461	0.802	0.398	0.729	0.445
Employment Variables:						
Non-Union	0.311	0.463	0.399	0.490	0.339	0.473
Union	0.225	0.418	0.175	0.380	0.209	0.407
Union Unknown	0.464	0.499	0.426	0.495	0.451	0.498
Active FT	0.457	0.498	0.608	0.488	0.505	0.500
Active PT	0.001	0.029	0.008	0.087	0.003	0.055
Retiree	0.229	0.420	0.183	0.387	0.214	0.410
Other Status	0.314	0.464	0.201	0.401	0.278	0.448
Manuf., Durable Goods	0.225	0.418	0.189	0.391	0.214	0.410
Manuf., Nondurable Goods	0.087	0.281	0.025	0.157	0.067	0.251
Transp., Comm., Utilities	0.045	0.208	0.174	0.379	0.086	0.280
Services	0.074	0.261	0.011	0.106	0.054	0.226
Other Industry	0.131	0.337	0.076	0.265	0.114	0.318
Employer Enrollment (10,000s)	46.676	57.901	29.308	30.093	41.102	51.373
Number of Observations	23,845		11,099		34,994	

Table 1.7: Summary Statistics of Control Variables Neurontin All Scripts (continued)

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:						
Per Cap. Income ($1000s)	23.19	2.603	22.98	2.679	23.13	2.629
Population (100,000s)	1215	1223	1228	1132	1219	1195
MSA Info Unknown	0.306	0.461	0.198	0.398	0.271	0.445
Insurance Variables:						
Comprehensive	0.192	0.394	0.000	0.000	0.131	0.337
PPO	0.808	0.394	0.000	0.000	0.550	0.497
HMO	0.000	0.000	0.563	0.496	0.178	0.383
POS	0.000	0.000	0.386	0.487	0.122	0.328
POS w/ Capitation	0.000	0.000	0.052	0.221	0.016	0.127
Prescription Variables:						
New Prescription	0.442	0.497	0.448	0.497	0.444	0.497
No DAW	0.831	0.375	0.786	0.410	0.817	0.387
Physician DAW	0.050	0.218	0.047	0.212	0.049	0.216
Patient DAW	0.084	0.277	0.084	0.277	0.084	0.277
Retail Prescription	0.782	0.413	0.713	0.452	0.760	0.427
Mail Order	0.214	0.410	0.199	0.399	0.209	0.406
Mail Status Unknown	0.004	0.065	0.088	0.283	0.031	0.173
Mandatory Drug Subs.	0.134	0.341	0.231	0.421	0.165	0.371
Number of Observations	23,845		11,099		34,994	

Table 1.8: Summary Statistics of Time to Switch by Drug

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
Time to Switch	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prozac to Fluoxetine:						
One Month	0.275	0.446	0.261	0.439	0.269	0.444
Three Months	0.595	0.491	0.604	0.489	0.599	0.490
Zocor to Simvastatin:						
One Month	0.066	0.247	0.055	0.227	0.061	0.239
Three Months	0.548	0.498	0.407	0.491	0.486	0.500
Neurontin to Gabapentin:						
One Month	0.094	0.292	0.123	0.328	0.103	0.304
Three Months	0.400	0.490	0.451	0.498	0.417	0.493

Table 1.9: Cost Differentials by Branded Drug for 30-day Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prozac to Fluoxetine:						
OOP CD	0.367	0.375	0.320	0.383	0.346	0.379
TPP CD	-0.340	1.353	-0.191	1.327	-0.273	1.344
AWP Prozac	5.216	6.029	5.147	1.272	5.185	4.563
Prozac to Amitriptyline:						
OOP CD	0.563	0.515	0.406	0.344	0.496	0.457
TPP CD	3.290	1.210	3.024	0.735	3.180	1.046
AWP Prozac	5.272	1.026	5.194	1.017	5.270	4.959
Zocor to Simvastatin:						
OOP CD	0.841	0.826	0.868	0.828	0.854	0.827
TPP CD	0.970	0.934	0.966	0.934	0.968	0.933
AWP Zocor	5.014	0.780	5.770	9.662	5.347	6.404
Neurontin to Gabapentin:						
OOP CD	0.335	0.517	0.305	0.495	0.326	0.511
TPP CD	1.947	3.420	1.776	3.474	1.897	3.436
AWP Neurontin	6.432	2.641	6.739	2.844	6.524	2.709

Cost Differentials are calculated by multiplying the unit level by 30.

Table 1.10: Cost Differentials by Branded Drug for All Scripts

	Comprehensive and PPO Sample		HMO and POS Sample		All Plans Sample	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Prozac to Fluoxetine:						
OOP CD	0.367	0.375	0.320	0.383	0.346	0.379
TPP CD	-0.340	1.353	-0.191	1.327	-0.273	1.344
AWP Prozac	5.216	6.029	5.147	1.272	5.185	4.563
Prozac to Amitriptyline:						
OOP CD	0.543	0.525	0.428	0.339	0.491	0.455
TPP CD	3.232	1.200	2.912	0.786	3.089	3.089
AWP Prozac	5.212	6.024	5.140	1.275	5.180	4.559
Zocor to Simvastatin:						
OOP CD	0.392	0.673	0.401	0.731	0.397	0.727
TPP CD	0.526	1.204	0.538	1.197	0.531	1.201
AWP Zocor	4.930	0.860	5.320	6.939	5.103	4.626
Neurontin to Gabapentin:						
OOP CD	0.242	0.512	0.207	0.490	0.231	0.505
TPP CD	1.932	3.450	1.741	3.456	1.873	3.452
AWP Neurontin	6.375	2.781	6.677	3.069	6.469	2.879

Cost Differentials are calculated at the unit level.

Table 1.11: 30 Day Cost Differentials by Quartile

	Quartile			
	First	Second	Third	Fourth
Prozac to Fluoxetine:				
OOP CD	$4.82	$18.41	$18.41	$34.81
TPP CD	$-38.57	$-38.57	$33.66	$88.68
AWP Prozac	$140.54	$156.09	$167.48	$261.61
Zocor to Simvastatin:				
OOP CD	$9.99	$19.81	$37.41	$64.77
TPP CD	$6.05	$39.07	$46.50	$101.63
AWP Zocor	$82.19	$157.45	$158.12	$258.67
Neurontin to Gabapentin:				
OOP CD	$-4.68	$11.18	$16.85	$48.19
TPP CD	$-51.35	$73.14	$124.25	$343.94
AWP Neurontin	$141.43	$177.22	$256.40	$388.39

Table 1.12: LPM Elasticity Estimates for Switching within One Month For 30-day Scripts

	No FEs			Employer FEs			Employer-Plan FEs		
	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All
Prozac to Fluoxetine									
OOP	0.031	0.086***	0.056**	0.030	0.080***	0.0520**	0.030	0.081***	0.052**
	[0.028]	[0.030]	[0.026]	[0.028]	[0.030]	[0.025]	[0.028]	[0.030]	[0.025]
TPP	0.093***	0.064***	0.070***	0.092***	0.064***	0.070***	0.093***	0.067***	0.071***
	[0.016]	[0.018]	[0.015]	[0.016]	[0.018]	[0.015]	[0.016]	[0.018]	[0.016]
Zocor to Simvastatin									
OOP	0.021	0.001	0.032**	0.018	0.0010	0.032**	0.016	0.0015	0.032**
	[0.015]	[0.022]	[0.013]	[0.015]	[0.023]	[0.013]	[0.014]	[0.023]	[0.014]
TPP	0.015	0.015	0.029	0.008	0.014	0.027	0.008	0.0123	0.027
	[0.019]	[0.035]	[0.019]	[0.019]	[0.035]	[0.020]	[0.019]	[0.035]	[0.020]
Neurontin to Gabapentin									
OOP	-0.001	-0.017	-0.009	0.008	-0.013	0.000	0.009	-0.012	0.0010
	[0.016]	[0.019]	[0.012]	[0.016]	[0.019]	[0.012]	[0.017]	[0.018]	[0.012]
TPP	-0.111***	-0.148***	-0.132***	-0.080**	-0.132***	-0.102***	-0.077**	-0.127***	-0.099***
	[0.029]	[0.027]	[0.025]	[0.031]	[0.029]	[0.028]	[0.031]	[0.030]	[0.028]

OOP represents OOP CD and TPP represents TPP CD.

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1

Table 1.13: LPM Elasticity Estimates for Switching within Three Months For All Scripts

	No FEs			Employer FEs			Employer-Plan FEs		
	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All
Prozac to Fluoxetine									
OOP	-0.016	0.022*	-0.000	-0.014	0.021*	0.000	-0.014	0.022*	0.000
	[0.023]	[0.011]	[0.016]	[0.023]	[0.012]	[0.016]	[0.023]	[0.012]	[0.016]
TPP	0.029***	0.004	0.014***	0.029***	0.005	0.014***	0.029***	0.005	0.014***
	[0.006]	[0.004]	[0.005]	[0.006]	[0.004]	[0.005]	[0.006]	[0.004]	[0.005]
Zocor to Simvastatin									
OOP	0.031***	0.045***	0.037***	0.029***	0.045***	0.034***	0.028***	0.046***	0.035***
	[0.008]	[0.012]	[0.009]	[0.008]	[0.011]	[0.007]	[0.008]	[0.011]	[0.007]
TPP	0.014***	0.021**	0.018***	0.011**	0.020***	0.013***	0.011**	0.021***	0.015***
	[0.005]	[0.009]	[0.005]	[0.004]	[0.008]	[0.004]	[0.004]	[0.008]	[0.004]
Neurontin to Gabapentin									
OOP	-0.027***	-0.038***	-0.033***	-0.023***	-0.037***	-0.030***	-0.023***	-0.036***	-0.029***
	[0.006]	[0.007]	[0.005]	[0.006]	[0.007]	[0.005]	[0.006]	[0.007]	[0.005]
TPP	-0.138***	-0.144***	-0.146***	-0.126***	-0.140***	-0.136***	-0.127***	-0.140***	-0.135***
	[0.015]	[0.023]	[0.014]	[0.016]	[0.023]	[0.015]	[0.016]	[0.023]	[0.015]

OOP represents OOP CD and TPP represents TPP CD.

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1

Table 1.14: Elasticities from Discrete Time Duration Models

	Logit			LPM		
	Comp. & PPO	HMO & POS	All	Comp. & PPO	HMO & POS	All
Prozac to Fluoxetine						
OOP	0.023	-0.030	-0.002	0.014	-0.012	0.002
	[0.074]	[0.025]	[0.041]	[0.036]	[0.010]	[0.020]
TPP	0.045**	0.087**	0.074***	0.032***	0.035***	0.039***
	[0.022]	[0.035]	[0.026]	[0.010]	[0.013]	[0.010]
Obs.	101,941	69,540	171,484	101,944	69,540	171,484
Zocor to Simvastatin						
OOP	0.066***	0.090***	0.075***	0.027***	0.037**	0.031***
	[0.015]	[0.033]	[0.017]	[0.007]	[0.015]	[0.008]
TPP	0.040***	0.096***	0.060***	0.018***	0.042***	0.027***
	[0.011]	[0.024]	[0.012]	[0.005]	[0.010]	[0.005]
Obs.	257,298	239,135	500,726	257,877	239,264	500,825
Neurontin to Gabapentin						
OOP	0.063***	0.023	0.050***	0.014**	0.004	0.011**
	[0.009]	[0.015]	[0.008]	[0.006]	[0.006]	[0.005]
TPP	-0.109***	-0.119***	-0.112***	-0.077***	-0.061***	-0.073***
	[0.025]	[0.022]	[0.019]	[0.016]	[0.013]	[0.013]
Obs.	113,525	49,209	162,982	113,534	49,259	162,982

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer fixed effects.
Dependent variable is first switch.

Table 1.15: LPM Elasticity Estimates for Robustness Specifications for 30-day Scripts

	Original			No DAW			No TPP CD		
	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All
Prozac to Fluoxetine									
OOP	0.030	0.080***	0.052**	0.034	0.097***	0.061**	0.135***	0.156***	0.135***
	[0.028]	[0.030]	[0.025]	[0.030]	[0.032]	[0.027]	[0.025]	[0.031]	[0.017]
TPP	0.092***	0.064***	0.070***	0.088***	0.052***	0.064***			
	[0.016]	[0.018]	[0.015]	[0.017]	[0.017]	[0.016]			
Zocor to Simvastatin									
OOP	0.018	0.001	0.032**	0.021	0.002	0.034**	0.013	-0.006	0.018**
	[0.015]	[0.023]	[0.013]	[0.015]	[0.023]	[0.014]	[0.012]	[0.013]	[0.008]
TPP	0.008	0.014	0.027	0.013	0.014	0.029			
	[0.019]	[0.035]	[0.020]	[0.019]	[0.035]	[0.020]			
Neurontin to Gabapentin									
OOP	0.008	-0.013	0.0000	0.020	-0.008	0.010	-0.003	-0.044**	-0.017
	[0.016]	[0.019]	[0.012]	[0.016]	[0.018]	[0.011]	[0.017]	[0.021]	[0.014]
TPP	-0.080**	-0.132***	-0.102***	-0.059**	-0.108***	-0.079***			
	[0.031]	[0.029]	[0.028]	[0.029]	[0.028]	[0.025]			

OOP represents OOP CD and TPP represents TPP CD.
Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer fixed effects.

Table 1.16: LPM Elasticity Estimates for Robustness Specifications for All Scripts

	Original			No DAW			No TPP CD		
	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All	Comp. &PPO	HMO &POS	All
Prozac to Fluoxetine									
OOP	-0.016	0.021*	0.000	-0.011	0.027**	0.006	0.033*	0.034***	0.029***
	[0.023]	[0.012]	[0.016]	[0.025]	[0.011]	[0.017]	[0.020]	[0.007]	[0.010]
TPP	0.029***	0.005	0.014***	0.027***	0.003	0.013**			
	[0.006]	[0.004]	[0.005]	[0.006]	[0.004]	[0.005]			
Zocor to Simvastatin									
OOP	0.031***	0.045***	0.034***	0.027***	0.048***	0.034***	0.028***	0.045***	0.034***
	[0.008]	[0.011]	[0.007]	[0.009]	[0.015]	[0.009]	[0.008]	[0.012]	[0.007]
TPP	0.014***	0.020***	0.013***	0.011**	0.023**	0.014**			
	[0.005]	[0.008]	[0.004]	[0.005]	[0.010]	[0.006]			
Neurontin to Gabpentin									
OOP	-0.027***	-0.037***	-0.030***	-0.018***	-0.033***	-0.025***	-0.040***	-0.062***	-0.050***
	[0.006]	[0.007]	[0.005]	[0.005]	[0.007]	[0.005]	[0.007]	[0.012]	[0.007]
TPP	-0.137***	-0.140***	-0.136***	-0.118***	-0.128***	-0.125***			
	[0.015]	[0.023]	[0.015]	[0.014]	[0.022]	[0.014]			

OOP represents OOP CD and TPP represents TPP CD.
Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer fixed effects.

Table 1.17: LPM Elasticity Estimates Across Employers by Available Plans

	One Plan Offered			Multiple Plans Offered		
	Comp. & PPO	HMO & POS	All	Comp. & PPO	HMO & POS	All
Prozac to Fluoxetine						
OOP	N/A	0.218**	0.218**	0.030	0.064**	0.046*
		[0.073]	[0.073]	[0.028]	[0.028]	[0.024]
TPP	N/A	0.055	0.055	0.092***	0.066***	0.072***
		[0.037]	[0.037]	[0.016]	[0.018]	[0.015]
Obs.	0	1,689	1,689	15,472	9,404	24,876
Zocor to Simvastatin						
OOP	0.118**	0.013	0.088*	0.008	-0.001	0.027*
	[0.054]	[0.000]	[0.048]	[0.013]	[0.024]	[0.015]
TPP	0.108*	0.027	0.100*	-0.002	0.010	0.022
	[0.061]	[0.000]	[0.057]	[0.019]	[0.036]	[0.020]
Obs.	3,566	629	4,195	23,678	20,473	44,486
Neurontin to Gabapentin						
OOP	-0.043	0.086***	0.014	0.012	-0.028*	-0.003
	[0.035]	[0.015]	[0.050]	[0.018]	[0.016]	[0.013]
TPP	-0.125	-0.054*	-0.119	-0.067**	-0.137***	-0.097***
	[0.186]	[0.027]	[0.138]	[0.030]	[0.031]	[0.028]
Obs.	2,825	923	3,748	15,568	7,199	22,816

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer fixed effects.
Results shown for switching within one month using the 30-day script sample.

Table 1.18: LPM Elasticity Estimates for Switching From Prozac to Fluoxetine Using Amitriptyline CDs

	No FEs			Employer FEs			Employer-Plan FEs		
	Comp. & PPO	HMO & POS	All	Comp. &PPO	HMO & POS	All	Comp. & PPO	HMO & POS	All
Switch Within One Month for 30-day Scripts									
OOP	0.027	0.027	0.030	0.014	-0.014	0.008	0.010	-0.018	0.000
	[0.018]	[0.046]	[0.024]	[0.018]	[0.053]	[0.019]	[0.019]	[0.065]	[0.022]
TPP	0.190***	0.085	0.195***	0.206***	0.162	0.220***	0.204***	0.192	0.220***
	[0.072]	[0.097]	[0.050]	[0.070]	[0.107]	[0.051]	[0.071]	[0.118]	[0.055]
Switch Within Three Months for All Scripts									
OOP	0.006	0.021	0.006	0.000	-0.013	-0.001	-0.002	-0.019	-0.007
	[0.015]	[0.022]	[0.012]	[0.009]	[0.023]	[0.009]	[0.009]	[0.028]	[0.009]
TPP	0.099***	-0.066	0.056*	0.095***	-0.031	0.077***	0.093***	-0.044	0.070***
	[0.032]	[0.045]	[0.029]	[0.028]	[0.034]	[0.019]	[0.029]	[0.037]	[0.022]

OOP represents OOP CD and TPP represents TPP CD.

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1

Chapter 2

Identifying the Effect of the Tennessee Affordable Drug Act of 2005: Do mandatory generic substitution laws matter?

2.1 Introduction

Due to publicly-funded healthcare plans, including Medicare and Medicaid, the government accounts for over one-third of prescription drug spending [Dicken et al., 2011]. With rates of prescription drug spending increasing faster than in other areas of healthcare [Zuvekas et al., 2007], policy-makers continuously strive to decrease these costs. Because public and private spending on prescription drugs can be reduced through the purchase of lower-priced generic drugs [Smithet al., 2005], many states have passed laws mandating that pharmacists substitute branded prescription drugs with their generic equivalents. Despite the relative prevalence of these mandatory substitution laws, their effect has not been

identified. The recent adoption of the Tennessee Affordable Drug Act (TADA) provides a natural experiment in which we can use a differences-in-differences (DID) estimation procedure to compare Tennessee (TN) to similar states to estimate the effect of this law.

Generic substitution laws vary by state within the United States, and they have changed drastically over the course of their history. In the 1940s and 1950s, anti-substitution laws were the norm. Historically, pharmacists would often substitute the physician-prescribed branded drugs with inferior quality (or even counterfeit) drugs, so mandates were passed to end this practice. Laws required pharmacists to provide the exact drug physicians prescribed regardless of the availability of cheaper, equivalent drugs [Abood, 2008]. In the 1960s and 1970s, however, opinions began to change as concerns grew over soaring prescription drug costs. At the same time, there was an influx of Federal Drug Administration (FDA)-approved generic drugs to the market. Anti-substitution laws transformed into permissive substitution laws in almost all states. Permissive substitution laws allow the pharmacist to choose to substitute the generic drug provided the physician did not prohibit that action. In some states, these permissive laws further evolved into mandatory substitution laws, in which a pharmacist must substitute a generic drug for a branded drug, provided: 1) The generic drug is bio-equivalent to the branded drug. 2) The generic drug represents a cost savings. 3) The physician has not expressly prohibited the substitution [Abood, 2008].

During the time period of this study, pharmacists in eleven states were required to substitute a generic prescription drug for a branded drug: Florida, Kentucky, Massachusetts, Minnesota, Michigan, New Jersey, New York, Pennsylvania, Rhode Island, Washington, and West Virginia [Survey of Pharmacy Law, 2001-2006]. All other states had permissive substitution laws. During this same time period, six states changed their drug product substitution (DPS) laws: Alaska, Hawaii, Maine, Nevada, Vermont, and Tennessee. These

states all switched to mandatory substitution laws between 2002 and 2005. We analyze the change of law in TN because we have a large sample of prescription-level data from TN and comparable control states during 2005.

This mandate could decrease prescription drug expenditures through increased generic fill rates, or it could have the opposite effect if physicians and patients use DAW indicators to avoid compliance with the mandate. We use the *Thomson Reuters MarketScan® Research Databases* to analyze the prescription drug-fills during the six-month periods before and after the TADA legislation, which enables us to determine the short-term effect of this legislation. The *Commercial* database, detailing prescription drug claims, consists of approximately four million prescription claims in the state of TN in 2005. Additionally, we consider three control states in our analysis: Georgia (GA), Alabama (AL), and Arkansas (AR), providing a control group with approximately six million prescription claims. We include a complete set of demographic, employment-specific, prescription-specific, and insurance-specific regressors in our model in addition to time trends, state dummy variables, and interaction terms for state and time variables. We do this to capture any pre- or post-treatment trend or other state-specific unobservables that could bias our estimation. Our results provide insight into the limited effect of mandatory generic substitution laws. However, we find that the law discourages patient-directed requests for branded prescriptions.

2.2 Literature Review

Prescription decisions are affected by both patient and physician preferences. Because of state laws governing the dispensation of generic drugs, pharmacists also have a role in determining which prescription drug a patient receives. In this essay, we focus on this role of the pharmacist and on DPS laws. For a complete review of the influence of the

patient and physician in the prescription drug decision, please reference the Background and Literature Review section of the previous essay.

DPS laws exist in every state. When substitution occurs, all DPS laws (regardless of permissive versus mandatory status) require that pharmacists substitute an equivalent drug, as identified by the FDA. Additional substitution requirements vary by state. The TADA of 2005 mandates that the pharmacist dispense a generic drug equivalent to the branded drug unless prohibited from doing so by the prescribing physician. In order to prevent generic substitution, the prescribing physician must clearly communicate that the branded drug should be dispensed by using one of the following annotations on the written prescription: 'brand name medically necessary'; 'dispense as written'; 'medically necessary'; 'brand name'; or 'no generic'. A pharmacist must heed the directive of the prescribing physician. Additionally, pharmacists are permitted to dispense the branded drug if they believe the generic drug will not result in a cost-savings for the patient.

In addition to DPS laws, there are several other factors influencing the pharmacists' substitution behavior. These include actions prescribers take to prohibit substitution, requirements for additional record keeping in the case of substitutions, requirements for cost-savings, pharmacists' liability, patient consent requirements, and formats of prescription forms [Carroll et al., 1987]. Carroll et al. (1987) find that additional record keeping requirements decrease generic substitution, but patient consent requirements increase generic substitution. Furthermore, they find generic substitution rates vary across states, depending on the format of the prescription pads doctors use. For example, in some states physicians use a two-line format, which requires a signature for 'Drug Product Selection Permitted'. Carroll et al. (1987) find a lower drug substitution rate when this line appears at the bottom left-hand-side of the prescription pad versus the bottom right-hand-side. Regardless of the placement of this signature line, the two-line format results in a lower

generic substitution rate when compared to a single-line format prescription pad [Carroll et al., 1987]. However, a major limitation of this study is that it only represents an association of generic fill rates with these contributing factors.

A few studies attempt to identify the specific effect of the generic substitution laws on pharmacists' dispensing behavior. Shrank et al. (2010) estimate the effect of DPS laws on generic fill rates for generic Simvastatin after the patent expiration of Zocor. Using a time series analysis, the authors find increased generic prescription-fills among Medicaid patients in states where the law requiring patient consent for generic substitution was removed during the study period. Similarly, Anis (1994) uses panel data methods to identify the effect of varying drug substitution laws across provinces in Canada, and finds that mandatory drug substitution laws contribute to generic drug use.

Unfortunately, these existing studies have limitations preventing them from being generalizable or interpreted across various contexts. The results from Carroll et al. (1987) identify associations, which cannot be interpreted as causal effects. Shrank et al. (2010) conduct a limited study of the Medicaid population using one specific drug, which limits generalizability. The study conducted by Anis (1994) provides meaningful insight, but cannot be generalized to the United States because of differing laws and healthcare systems. We expand the current literature by determining if mandatory substitution laws are effective for the privately insured population.

2.3 Empirical Analysis

We use a trend-break DID approach to isolate the effect of the TADA of 2005. We accomplish this by comparing the TN prescription drug claims to those in three control states (GA, AR, and AL) before and after the passage of the TADA of 2005. Our control

states satisfy two important requirements: prescription drug substitution was permissible (but not mandatory) and none of these states experienced a pharmacy law change in 2005 [Survey of Pharmacy Law, 2001-2006].

In defining our empirical specification, we consider additional factors that influence prescription drug choice to limit the potential of omitted variable bias. First, we segment our analysis by type of health insurance plan. The four insurance plan types we consider are Comprehensive, Preferred Provider Organizations (PPOs), Health Maintenance Organizations (HMOs), and Point of Service (POS) plans. Healthier, more price-sensitive patients tend to choose HMOs versus other insurance plan types [Glied, 2000]. Additionally, drug formularies, which could influence physician and patient prescription decisions are likely to vary by health insurance plan type [Frank, 2001]. These factors may contribute to a finding by Weiner et al. (1994) that patients participating in HMOs have a three to thirty-three percentage point higher generic fill rate than those participating in fee-for-service insurance plans. By sub-setting our sample into insurance plan type, we can identify the effect of the DPS laws on each type of plan, thus limiting unobserved heterogeneity across plans.

Despite the cost-savings associated with generic drug use [Shrank et al., 2010; Frank, 2001; Leibowitzet al., 1985], patients could potentially prefer branded drugs based on quality concerns [Suh, 1999; Dubois et al., 2000; Rizzo and Zeckhauser, 2009]. We account for quality preference through two methods. First, we subset our sample into chronic and non-chronic prescription drug users. We define chronic prescription drug users as those individuals who average more than one prescription drug fill per month (within a therapeutic drug class) during our sample period. We expect that these individuals would be more concerned with quality than individuals who do not use the prescription drugs on a regular basis. Our second method of accounting for quality preference is inclusion

of the dispense as written (DAW) indicators as covariates in our models. Individuals who specifically request (or have the physician request) the branded drug are choosing the branded drug regardless of cost or DPS law. We conduct specifications with and without these indicators because the law could also affect DAW requests.

Of additional concern when conducting DID analyses is omitted variable bias resulting from other state and time specific policy changes. For example, any Tennessee-specific shock occurring at the same time as TADA has the potential to bias our estimates. Additionally, differences in baseline trends across states or shocks in the control states in 2005 could result in biased estimates. We address these concerns in two ways. First, we use a trend-break DID analysis. In addition to capturing time and state-specific effects, we include an interaction term for each state and the pre-treatment period. These additions allow for different baseline trends across states. Second, we conduct falsification tests in which we arbitrarily change the date of the implementation of the law. A significant effect of this placebo law on our dependent variable could imply biased estimates arising from unobservable state- and time-specific factors.

Our empirical approach is

$$Y_{ist} = \alpha Policy_{st} + \beta State_s + \delta Pre_t + \mu State * Pre_{st} + \lambda X_{it} + \gamma_m + \rho_j + \epsilon_j. \quad (2.1)$$

In equation 2.1, i represents individual presciption-fills, s represents states, t represents time (before or after the law), and m represents month. $Policy_{st}$ is a binary variable identifying observations in TN after the passage of TADA. The $State_s$ variables are binary values that indicate each of the control states, and Pre_t is a binary variable set to one if the observation occurred before TADA and zero if it occurred afterwards. The $State * Pre_{st}$ variables are interaction terms between the control state indicators and the pre-treatment

indicators, which allow for differences in baseline trends across states. Vector X_{it} includes individual control variables related to demographics, geographic location, employment status, and prescription-specific preferences. In addition to these covariates, we include month and employer fixed effects (γ_m and ρ_j) and a white noise error term (ϵ_j). The principle outcome variable of interest is a generic indicator, which identifies whether or not a prescription was filled with a generic drug or a branded drug.

2.4 Data

2.4.1 Sample Creation

We use the *Thomson Reuters MarketScan ® Research Databases* as our main data source. Specifically, the *Commercial* database provides prescription drug claims by state, and the *Enrollment* database provides information detailing insurance plan enrollment. Together, these data sources provide information regarding demographic characteristics, geography, employment status, insurance coverage, and payments by prescription claim. Additionally, we use the 2000 US Census for certain population characteristics at the Metropolitan Statistical Area (MSA) level, including per-capita income and population.

The TADA of 2005 went into effect on June 5, 2005. We include prescription claims from January 1, 2005 to June 4, 2005 in the pre-law period, and claims from June 5, 2005 to December 31, 2005 in the post-law period. We consider the six months before and after the law for two reasons. First, we want to ensure our panel is long enough to allow for prescription-fills after the law, regardless of prescription-fill rate. Second, we want to limit the potential for biased estimates resulting from the use of too many time periods. In their review of the accuracy of DID estimates, Bertrand, Duflo, and Mullainathan (2008) argue that over-rejection rates increase with increasing time periods. Limiting our time frame to one year is an attempt to reduce this risk.

We further decrease our sample size by limiting the sample to only those drugs for which a generic drug is available. This yields approximately 1.5 million pre-period observations and 2.1 million post-period observations in TN. The pre-law period contains approximately 2.4 million observations in the state of GA, 320,000 in AL, and 240,000 in AR. The post-law period includes approximately 3.2 million observations in the state of GA, 400,000 in AL, and 300,000 in AR[1].

As noted in Section 2.3, we subset our analysis by insurance plan type and chronic versus non-chronic prescription-fill behavior. We consider four health insurance plan types: Comprehensive, Preferred Provider Organization (PPO), Health Maintenance Organization (HMO), and Point of Service (POS). We do not consider POS plans with capitation because we do not have enough observations from TN identify our model. In order to determine the relative frequency with which individuals purchase prescription drugs, we construct a per-month average by therapeutic drug class. Individuals are labeled chronic users by therapeutic drug class if this average is greater than or equal to one and non-chronic users (by therapeutic drug class) if this average is less than one.

2.4.2 Sample Characteristics

Tables 2.1 and 2.2 show our outcome and control variables by time period and treatment status for the chronic and non-chronic samples, respectively. Across all samples, approximately 45% of prescriptions are in the pre-period and 55% are in the post-period. We notice that the demographic and prescription characteristics do not vary widely across comparison groups or treatment periods. On the contrary, we find variation across the geographic and employment characteristics. This is expected because these individuals

[1]The varying sample sizes by state are a product of the data. This data represents contains claims from large employers only, and there are many more large employers in GA and TN than in AL and AR

reside in different areas, with varying industries and standards of living. Our control sample is comprised mostly of observations from GA (80%), which appears to have a larger concentration of observations from big cities. The control states have a higher average per capita income and population than TN. Although these characteristics vary across comparison groups, they do not appear to vary within groups across treatment status. This provides some assurance that no underlying trend is changing the composition of our data across time periods.

Summary statistics for the chronic and non-chronic sub-samples are shown in Tables 2.3 and 2.4. The chronic sub-sample is larger than the non-chronic sub-sample across all insurance plan types. The largest insurance plan sub-sample is PPO; it contains almost six million observations in the chronic sample and approximately 720,000 observations in the non-chronic sub-sample. The chronic sub-sample contains an older population with a higher percentage of females, compared to the non-chronic sub-sample. The geographic and employment variables are similar across these two sub-samples, but there are differences within some prescription-specific variables. In particular, the non-chronic sub-sample has a higher percentage of new prescriptions and fewer physician-initiated DAW indicators. These summary statistics indicate sufficient differences between samples that could influence the effectiveness of the DPS law.

Within each sub-sample we find both similarities and differences across insurance plan type. The HMO plans contain the youngest individuals, while the Comprehensive plans contain the oldest. However, there does not appear to be selection by gender into various types of health insurance plans. On the contrary, we see many differences across employment variables. The Comprehensive plans have a larger number of unionized workers than the other plans, and also contain the highest number of retirees. Most individuals working in the manufacturing of durable goods have a Comprehensive plan, while those working in

transportation, communications, and utilities services most likely have a POS insurance plan. These differences provide some evidence that insurance plan selection varies across employer and individual characteristics. We attempt to control for similar differences that may be unobservable by conducting separate analyses by insurance plan type.

As part of our sensitivity analyses, we identify the effect of the TADA on individual drugs within the antidepressant class, specifically Prozac and its generic equivalent, Fluoxetine. In order to ensure our results are not affected by changes in demand for different drugs over time, we compare our results from the chronic sub-sample analysis to the Prozac analysis because Prozac is used to treat depression, which is a chronic condition. Summary statistics for the Prozac-Fluoxetine sub-sample are shown in Table 2.5. There are similar trends across insurance plans in this sub-sample as in the chronic and non-chronic sub-samples. This sub-sample has a greater percentage of females than the chronic sub-sample and most of the individuals are over the age of 45. Less than half of these observations are for new prescriptions and the majority are filled via retail pharmacy, not through the mail.

2.4.3 Key Variables

We detail the summary statistics of key variables by sub-sample in Table 2.6. Our outcome variable, the generic indicator, varies by sub-sample from 87.5% in the non-chronic Comprehensive sub-sample to 97.2% in the Prozac-Fluoxetine HMO sub-sample. In general, we see the highest generic usage within the prozac-fluoxetine sub-sample and lower, but similar generic usage levels, in the chronic and non-chronic sub-samples. When comparing across insurance plan types, we find the highest generic script usage within the HMO sub-sample and the lowest within the Comprehensive sub-sample. This is consistent with HMOs having the most restrictive insurance plans and Comprehensive plans being the least-restrictive [Glied, 2000].

Our main variable of interest is the TN*POST variable, which is an interaction term identifying an observation as being treated by the policy. We find the largest percentage of our treated observations within the POS sub-samples and the fewest in the Comprehensive sub-samples. This results from the fact that the employers whose data was collected by *Thomson Reuters MarketScan*® vary across geographic region and insurance plan offerings. Of the employers in our sample, those based in TN offered more POS plans and fewer Comprehensive plans.

2.5 Results

2.5.1 Primary Results

We use the DID approach identified in equation (2.1) to determine the effect of the mandatory generic drug substitution law on the probability of individuals filling their prescription with a generic drug. The coefficients from the LPM regressions for the chronic and non-chronic samples by insurance plan are listed in Tables 2.7 and 2.8. In the chronic sub-sample, we find the DPS law increases the probability of a generic prescription by 0.006 percentage points among individuals with the HMO insurance plan, which corresponds to a 0.62% increase. We do not find the law to have a significant effect on generic prescription-fills within any other insurance sub-sample. Within the non-chronic sub-sample, we find statistically significant and positive effects of the law on the PPO and POS sub-samples. Those individuals in a PPO are 0.005 percentage points more likely to receive the generic prescription as a results of the law, while those in the POS plans are 0.014 percentage points more likely. This corresponds to an increase of 0.54% and 1.5%, respectively. We find the largest effect within the non-chronic subsample in part because these individuals use the drugs less frequently and may have fewer concerns about potential side-effect

differences between the branded and generic drug[2].

Because we do not find a relatively large or consistent effect of this law change across insurance plan types, we assess the effect of this law on DAW indicators[3]. Patients may be avoiding this mandate by requesting the branded drug from their physician. Physicians can override the DPS law by noting that the brand is medically necessary. Table A.3 shows the effect of the TADA of 2005 on the physician DAW indicator and the patient DAW indicator. The outcome variable in the first panel is an indicator detailing whether or not the physician required the branded drug be dispensed. We find no significant effects within the chronic or non-chronic sub-samples. However, in the second panel we find statistically significant negative effects of the law on patient's request for the branded drug. As a result of the law, patients may believe that they are not capable of overriding the generic substitution, therefore patient-initiated requests decrease.

To further understand how the DAW indicators are affecting the generic prescription-fills when the mandatory DPS law takes effect, we remove the DAW indicators from our original regression. Tables 2.10 contain the estimates on our variable of interest, TN*POST, for the chronic and non-chronic sample. For ease of comparison, the first and third panels in this table contain the results from our initial specification (for each sub-sample). We notice larger effects in most cases of the specification without the DAW indicators. This implies that the DAW indicators have a negative effect on generic substitution, which is smaller in magnitude than the positive effect of the law.

[2]We also conduct specifications using only observations from GA in the control group. We estimate similar effects in this specification, but the statistical precision of the estimates varies across insurance categories.

[3]We have a large sample, which mitigates concerns that there is limited statistical power.

We also note that compliance with DAW directives is not 100%. Within our sample, approximately 18% of prescriptions with physician DAW indications and 23% of prescriptions with patient DAW indications are filled with generic drugs. These proportions remain relatively stable during the pre and post time periods. Before the law 19% of prescriptions with physician DAW indications were filled with generics and after the law this also dropped slightly to 17%. Similarly, 23.8% of prescriptions with patient DAW indications were filled with generic drugs before the law and this dropped slightly to 22.4% after the law. If there were more regulation over compliance with DAW directives, the effect of the TADA would be muted.

2.5.2 Sensitivity Results

In addition to the separate analyses by insurance plan type, we conduct an analysis using only Prozac and Fluoxetine. Past research indicates that consumers have varying concerns over drug efficacy, side-effect, and quality depending on the severity of the condition the drug treats [Dubois et al., 2000]. For this reason, consumers may have different branded or generic drug preferences across drug classifications. Additionally, we want to ensure our positive results are not confounded by individuals increasing their volume of generic drug use for other reasons, as opposed to switching between branded and generic equivalents. We compare these results with our results from the chronic sample, as individuals using Prozac or Fluoxetine are likely to use these drugs consistently for a certain period of time. The first panel in Table 2.11 displays the results from our initial regression using the chronic sub-sample, and the second panel shows our results from the Prozac-Fluoxetine sub-sample. We continue to find positive and statistically significant effects of the law on the generic prescription-fills within the HMO insurance plan type. The law increases the probability of receiving Fluoxetine by 0.006 percentage points, which corresponds to an increase of 0.59%. This is consistent with our results from the chronic sub-sample in

which the law increased the probability of generic prescription-fills by 0.62%.

We conduct two additional sensitivity analyses to determine the robustness of our results to issues of omitted variable bias and serial correlation. In order to assure that our results are not capturing the effect of potential unobservables that occur simultaneously, we conduct falsification tests by introducing a placebo law six months prior to and six months after the actual DPS law was implemented. If we find an effect of this placebo, it could indicate an error in our specification. Lastly, we use a method suggested by Bertrand et al. (2008) to determine if our standard errors are underestimated due to serial correlation. Bertrand et al. (2008) highlight and identify the three factors contributing to serial correlation in DID models: long time series data, highly positively serially correlated dependent variables, and low variation in the treatment variable over time [Bertrand et al., 2008]. We test our model by aggregating our data into two time periods, thus removing serial correlation from the data.

The results of our falsification tests are detailed in panels three and four of Tables 2.12 and 2.13. We do not find any statistically significant effects of our placebo laws on the probability of a generic prescription-fill. This provides some supportive evidence to the robustness of our specification.

In order to address the potential issue of serial correlation, we aggregate our data into pre- and post-treatment time periods. We collapse our key variables (TN*POST, indicators for each state, and indicators for pre-treatment trends for these states) by state, treatment period, and chronic script status; this yields a sample size of 8 for each subsample and 16 for the entire group. The marginal effects from our LPM regression on these averaged variables are listed in Table 2.14. We find a positive, but insignificant, effect of the law on the generic prescription-fill. This indicates that there may be some

serial correlation biasing our standard errors downward. However, because of our small number of groups (i.e. four groups–one treated and three controls) these results should be interpreted with caution [Bertrand et al., 2008].

2.6 Conclusions

In general, we find a very limited effect of the mandatory generic drug substitution law on generic prescription-fills in TN. The law results in a 0.54%—1.5% increase in the probability of generic prescription-fill; this effect is largest for non-chronic prescription drug users with POS insurance plans. It is important to note that all of the control states allow pharmacists to dispense generic drugs under permissive drug produce substitution laws. The lack of consistent and large effects of this law could imply that much of the substitution happened under the permissive law. Therefore, mandating the substitution produces only limited increases in generic prescription-fills. There is no evidence that patients or physicians are seeking to avoid this mandate by increasing their use of dispense as written directives. On the contrary, we find patient-intitiated requests for the branded drug decrease with the passage of this law.

Our results have implications for policy makers. In the transition from permissive to mandatory DPS laws, we do not find large effects, hence, mandatory DPS laws should not be implemented as a means of reducing drug expenditures. Other methods of reducing drug expenditures (i.e. cost-sharing changes suggested in the first essay) will likely have a larger influence and should be considered above changes in DPS laws.

Our study is limited to the mandatory drug substitution law passed in Tennessee in 2005, and our results are not necessarily generalizable to other populations or regions. Further research could extend this analysis to other DPS laws to determine the robustness

of these findings; however, we expect more recent law changes to have an even smaller influence on generic prescription fills. Due to the recent consolidation of large Pharmacy Benefit Managers (PBMs), pharmacists have an increased incentive to promote generic drug substitution whenever available, as generic drugs represent a higher profit-margin. This further suggests that initial permissive substitution laws will continue to have a larger influence on drug substitution in contrast to mandatory DPS laws. One additional limitation of our data is that only considers individuals with private insurance who are employed at large corporations, which could further limit the generalizability of our results.

2.7 Tables

Table 2.1: Summary Statistics of Control Variables for Chronic Sub-sample by Time Period

	Tennessee				Control States			
	Pre Law		Post Law		Pre Law		Post Law	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:								
Age Under 18	0.057	0.233	0.052	0.222	0.070	0.255	0.064	0.245
Age 18-34	0.139	0.346	0.135	0.342	0.140	0.347	0.134	0.341
Age 35-44	0.170	0.376	0.169	0.375	0.169	0.374	0.167	0.373
Age 45-54	0.302	0.459	0.303	0.460	0.284	0.451	0.285	0.452
Age Over 55	0.331	0.471	0.340	0.474	0.337	0.473	0.349	0.477
Male	0.342	0.474	0.342	0.474	0.333	0.471	0.334	0.472
Female	0.658	0.474	0.658	0.474	0.667	0.471	0.666	0.472
Geographic Variables:								
AL	0.000	0.000	0.000	0.000	0.108	0.311	0.104	0.305
AK	0.000	0.000	0.000	0.000	0.079	0.270	0.077	0.266
GA	0.000	0.000	0.000	0.000	0.813	0.390	0.819	0.385
TN	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
Urban	0.681	0.466	0.683	0.465	0.715	0.452	0.716	0.451
Employment Variables:								
Union	0.086	0.280	0.089	0.285	0.082	0.275	0.080	0.271
Non-Union	0.831	0.375	0.827	0.379	0.211	0.408	0.213	0.410
Union Unknown	0.083	0.276	0.084	0.278	0.707	0.455	0.707	0.455
Active FT	0.765	0.424	0.763	0.425	0.715	0.452	0.710	0.454
Active PT	0.015	0.123	0.016	0.125	0.003	0.051	0.002	0.049
Retiree	0.071	0.257	0.070	0.255	0.171	0.377	0.177	0.382
Other Status	0.149	0.356	0.150	0.357	0.112	0.315	0.111	0.314
Manuf., Durable	0.117	0.322	0.121	0.326	0.097	0.296	0.095	0.294
Manuf., Nondurable	0.084	0.278	0.081	0.273	0.052	0.223	0.051	0.220
Transp., Comm., Utilities	0.083	0.276	0.084	0.278	0.039	0.194	0.039	0.193
Services	0.031	0.173	0.033	0.179	0.019	0.136	0.020	0.140
Other Industry	0.072	0.259	0.075	0.263	0.103	0.303	0.105	0.306
Number of Observations	1,449,562		1,921,513		2,598,052		3,443,929	

Table 2.1: Summary Statistics of Control Variables for Chronic Sub-sample by Time Period (continued)

	Tennessee				Control States			
	Pre Law		Post Law		Pre Law		Post Law	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:								
Per Cap. Income ($1000s)	23.173	2.423	23.185	2.418	24.423	3.622	24.432	3.625
Population (100,000s)	8.742	4.883	8.768	4.895	24.910	22.672	25.189	22.688
MSA Info Unknown	0.319	0.466	0.317	0.465	0.285	0.452	0.284	0.451
Prescription Variables:								
Generic Indicator	0.904	0.294	0.918	0.275	0.895	0.307	0.912	0.283
New Prescription	0.560	0.496	0.547	0.498	0.603	0.489	0.592	0.492
No DAW	0.912	0.283	0.922	0.267	0.920	0.271	0.931	0.253
Physician DAW	0.039	0.194	0.039	0.193	0.014	0.119	0.015	0.121
Patient DAW	0.037	0.188	0.029	0.168	0.024	0.154	0.023	0.149
Retail Prescription	0.936	0.245	0.935	0.246	0.841	0.366	0.840	0.366
Mail Order	0.064	0.244	0.064	0.245	0.037	0.190	0.038	0.191
Mail Unknown	0.000	0.021	0.001	0.025	0.122	0.327	0.122	0.327
Number of Observations	1,449,562		1,921,513		2,598,052		3,443,929	

Table 2.2: Summary Statistics of Control Variables for Non-chronic Sub-sample by Time Period

	Tennessee				Control States			
	Pre Law		Post Law		Pre Law		Post Law	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:								
Age Under 18	0.238	0.426	0.200	0.400	0.260	0.438	0.220	0.414
Age 18-34	0.154	0.361	0.157	0.364	0.169	0.375	0.165	0.371
Age 35-44	0.157	0.363	0.157	0.363	0.167	0.373	0.167	0.373
Age 45-54	0.236	0.425	0.247	0.431	0.210	0.407	0.223	0.416
Age Over 55	0.215	0.411	0.240	0.427	0.194	0.395	0.224	0.417
Male	0.442	0.497	0.433	0.495	0.415	0.493	0.411	0.492
Female	0.558	0.497	0.567	0.495	0.585	0.493	0.589	0.492
Geographic Variables:								
AL	0.000	0.000	0.000	0.000	0.096	0.295	0.099	0.298
AK	0.000	0.000	0.000	0.000	0.089	0.285	0.099	0.299
GA	0.000	0.000	0.000	0.000	0.815	0.389	0.802	0.398
TN	1.000	0.000	1.000	0.000	0.000	0.000	0.000	0.000
Urban	0.681	0.466	0.683	0.465	0.715	0.452	0.716	0.451
Employment Variables:								
Union	0.085	0.279	0.084	0.277	0.056	0.229	0.056	0.230
Non-Union	0.825	0.380	0.827	0.378	0.241	0.428	0.258	0.438
Union Unknown	0.089	0.285	0.089	0.285	0.703	0.457	0.686	0.464
Active FT	0.821	0.383	0.814	0.389	0.804	0.397	0.790	0.407
Active PT	0.019	0.138	0.018	0.135	0.003	0.056	0.003	0.057
Retiree	0.053	0.225	0.055	0.228	0.084	0.277	0.097	0.296
Other Status	0.106	0.308	0.113	0.316	0.109	0.312	0.110	0.313
Manuf., Durable	0.123	0.328	0.119	0.324	0.084	0.278	0.080	0.272
Manuf., Nondurable	0.113	0.316	0.097	0.296	0.053	0.224	0.051	0.219
Transp., Comm., Utilities	0.090	0.286	0.093	0.291	0.043	0.204	0.044	0.206
Services	0.037	0.188	0.033	0.179	0.022	0.146	0.019	0.137
Other Industry	0.092	0.289	0.105	0.307	0.113	0.317	0.139	0.346
Number of Observations	181,470		204,636		364,519		411,053	

Table 2.2: Summary Statistics of Control Variables for Non-chronic Sub-sample by Time Period (continued)

	Tennessee				Control States			
	Pre Law		Post Law		Pre Law		Post Law	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:								
Per Cap. Income ($1000s)	23.047	2.472	23.098	2.434	24.647	3.558	24.501	3.582
Population (100,000s)	8.637	4.935	8.699	4.908	26.177	22.641	25.398	22.634
MSA Info Unknown	0.307	0.461	0.311	0.463	0.266	0.442	0.272	0.445
Prescription Variables:								
Generic Indicator	0.905	0.293	0.917	0.275	0.901	0.299	0.915	0.279
New Prescription	0.673	0.469	0.631	0.483	0.737	0.440	0.689	0.463
No DAW	0.924	0.265	0.931	0.253	0.937	0.242	0.941	0.235
Physician DAW	0.035	0.184	0.036	0.187	0.010	0.100	0.011	0.107
Patient DAW	0.027	0.163	0.022	0.146	0.019	0.137	0.018	0.135
Retail Prescription	0.941	0.235	0.932	0.251	0.797	0.402	0.829	0.376
Mail Order	0.058	0.234	0.067	0.250	0.028	0.166	0.034	0.180
Mail Unknown	0.000	0.022	0.001	0.024	0.175	0.380	0.344	0.000
Number of Observations	181,470		204,636		364,519		411,053	

Table 2.3: Summary Statistics of Control Variables for Chronic Sub-sample

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:								
Age Under 18	0.026	0.158	0.056	0.229	0.086	0.280	0.072	0.258
Age 18-34	0.047	0.213	0.123	0.328	0.183	0.387	0.174	0.379
Age 35-44	0.064	0.245	0.156	0.363	0.214	0.410	0.204	0.403
Age 45-54	0.229	0.420	0.297	0.457	0.290	0.454	0.295	0.456
Age Over 55	0.634	0.482	0.369	0.483	0.227	0.419	0.255	0.436
Male	0.324	0.468	0.340	0.474	0.321	0.467	0.348	0.476
Female	0.676	0.468	0.660	0.474	0.679	0.467	0.652	0.476
Geographic Variables:								
AL	0.103	0.304	0.089	0.285	0.005	0.073	0.048	0.213
AK	0.064	0.244	0.069	0.254	0.003	0.057	0.020	0.142
GA	0.654	0.476	0.519	0.500	0.731	0.443	0.133	0.340
TN	0.179	0.383	0.323	0.468	0.260	0.439	0.798	0.401
Urban	0.712	0.453	0.659	0.474	0.824	0.381	0.723	0.447
Employment Variables:								
Union	0.346	0.476	0.089	0.285	0.000	0.022	0.073	0.260
Non-Union	0.193	0.394	0.409	0.492	0.274	0.446	0.914	0.280
Union Unknown	0.462	0.499	0.502	0.500	0.725	0.446	0.013	0.114
Active FT	0.368	0.482	0.681	0.466	0.927	0.260	0.820	0.384
Active PT	0.002	0.046	0.001	0.035	0.000	0.016	0.054	0.227
Retiree	0.539	0.499	0.143	0.350	0.042	0.201	0.084	0.278
Other Status	0.091	0.288	0.174	0.379	0.031	0.172	0.041	0.199
Manuf., Durable	0.396	0.489	0.109	0.312	0.014	0.118	0.083	0.275
Manuf., Nondurable	0.053	0.224	0.093	0.290	0.001	0.032	0.012	0.110
Trans., Comm., Utilities	0.074	0.262	0.006	0.077	0.018	0.133	0.364	0.481
Services	0.004	0.064	0.034	0.180	0.005	0.072	0.013	0.115
Other Industry	0.022	0.146	0.131	0.337	0.025	0.157	0.020	0.140
Emp. Enroll. (10,000s)	8.909	10.196	45.330	50.655	24.267	11.040	14.290	7.718
Number of Observations	509,150		5,935,537		1,870,612		1,097,757	

Table 2.3: Summary Statistics of Control Variables for Chronic Sub-sample (continued)

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:								
Per Cap. Income ($1000s)	24.193	3.547	23.496	3.385	25.246	3.061	23.837	2.541
Population (100,000s)	22.595	21.975	16.379	19.281	27.901	21.324	15.605	14.728
MSA Info Unknown	0.288	0.453	0.341	0.474	0.176	0.381	0.277	0.447
Prescription Variables:								
New Prescription	0.523	0.499	0.521	0.500	0.751	0.432	0.640	0.480
No DAW	0.098	0.297	0.084	0.277	0.049	0.215	0.074	0.261
Physician DAW	0.024	0.153	0.024	0.154	0.014	0.119	0.032	0.176
Patient DAW	0.022	0.145	0.027	0.162	0.023	0.151	0.033	0.178
Retail Prescription	0.827	0.378	0.955	0.208	0.595	0.491	0.940	0.238
Mail Order	0.170	0.375	0.045	0.206	0.011	0.105	0.060	0.238
Mail Unknown	0.003	0.054	0.001	0.029	0.394	0.489	0.000	0.008
Number of Observations	509,150		5,935,537		1,870,612		1,097,757	

Table 2.4: Summary Statistics of Control Variables for Non-chronic Sub-sample

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:								
Age Under 18	0.121	0.326	0.210	0.407	0.289	0.453	0.265	0.441
Age 18-34	0.079	0.269	0.154	0.361	0.194	0.395	0.180	0.384
Age 35-44	0.079	0.269	0.159	0.366	0.182	0.386	0.176	0.381
Age 45-54	0.209	0.407	0.239	0.426	0.199	0.400	0.213	0.409
Age Over 55	0.512	0.500	0.238	0.426	0.135	0.342	0.167	0.373
Male	0.418	0.493	0.419	0.493	0.407	0.491	0.456	0.498
Female	0.582	0.493	0.581	0.493	0.593	0.491	0.544	0.498
Geographic Variables:								
AL	0.101	0.302	0.088	0.283	0.005	0.070	0.052	0.223
AK	0.064	0.245	0.094	0.291	0.004	0.061	0.022	0.148
GA	0.664	0.473	0.504	0.500	0.815	0.388	0.158	0.365
TN	0.171	0.377	0.314	0.464	0.176	0.381	0.767	0.423
Urban	0.750	0.433	0.668	0.471	0.833	0.373	0.732	0.443
Employment Variables:								
Union	0.268	0.443	0.077	0.266	0.000	0.016	0.064	0.245
Non-Union	0.224	0.417	0.443	0.497	0.193	0.395	0.922	0.269
Union Status Unknown	0.508	0.500	0.480	0.500	0.807	0.395	0.014	0.118
Active FT	0.519	0.500	0.753	0.431	0.955	0.206	0.856	0.351
Active PT	0.006	0.074	0.001	0.038	0.000	0.019	0.060	0.238
Retiree	0.408	0.492	0.080	0.272	0.028	0.164	0.063	0.243
Other Status	0.067	0.250	0.165	0.371	0.016	0.127	0.021	0.143
Manuf., Durable	0.342	0.474	0.110	0.313	0.007	0.084	0.087	0.282
Manuf., Nondurable	0.050	0.217	0.106	0.308	0.000	0.008	0.018	0.134
Trans., Comm., Utilities	0.084	0.277	0.008	0.087	0.023	0.150	0.370	0.483
Services	0.005	0.067	0.034	0.180	0.007	0.083	0.021	0.143
Other Industry	0.022	0.147	0.172	0.377	0.025	0.155	0.025	0.156
Emp. Enroll. (10,000s)	8.072	9.667	50.731	53.680	26.141	10.140	14.213	7.953
Number of Observations	43,341		718,427		260,667		139,243	

Table 2.4: Summary Statistics of Control Variables for Non-chronic Sub-sample (continued)

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:								
Per Cap. Income ($1000s)	24.066	3.554	23.424	3.366	25.528	3.044	23.991	2.587
Population (100,000s)	21.860	21.899	15.963	19.114	30.631	21.249	16.785	15.659
MSA Info Unknown	0.250	0.433	0.332	0.471	0.167	0.373	0.268	0.443
Prescription Variables:								
New Prescription	0.591	0.492	0.626	0.484	0.857	0.350	0.748	0.434
No DAW	0.902	0.297	0.916	0.278	0.951	0.215	0.926	0.261
Physician DAW	0.018	0.133	0.021	0.143	0.010	0.099	0.027	0.161
Patient DAW	0.018	0.133	0.022	0.146	0.015	0.122	0.025	0.157
Retail Prescription	0.848	0.359	0.956	0.206	0.528	0.499	0.945	0.227
Mail Order	0.151	0.358	0.043	0.204	0.008	0.087	0.055	0.227
Mail Unknown	0.001	0.038	0.001	0.028	0.464	0.499	0.000	0.005
Number of Observations	43,341		718,427		260,667		139,243	

Table 2.5: Summary Statistics of Control Variables for Prozac-Fluoxetine Sub-sample

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
Demographic Variables:								
Age Under 18	0.032	0.177	0.034	0.182	0.046	0.210	0.052	0.223
Age 18-34	0.053	0.224	0.115	0.319	0.165	0.371	0.155	0.362
Age 35-44	0.090	0.286	0.196	0.397	0.272	0.445	0.251	0.433
Age 45-54	0.273	0.446	0.343	0.475	0.324	0.468	0.320	0.466
Age Over 55	0.552	0.497	0.312	0.463	0.193	0.395	0.222	0.416
Male	0.221	0.415	0.212	0.409	0.201	0.401	0.228	0.420
Female	0.779	0.415	0.788	0.409	0.799	0.401	0.772	0.420
Geographic Variables:								
AL	0.072	0.259	0.066	0.248	0.004	0.063	0.048	0.215
AK	0.052	0.223	0.062	0.242	0.002	0.047	0.020	0.142
GA	0.720	0.449	0.547	0.498	0.706	0.456	0.148	0.355
TN	0.155	0.362	0.325	0.468	0.288	0.453	0.783	0.412
Urban Indicator	0.729	0.444	0.686	0.464	0.830	0.375	0.744	0.436
Employment Variables:								
Union	0.223	0.416	0.056	0.230	0.000	0.012	0.047	0.212
Non-Union	0.183	0.387	0.397	0.489	0.302	0.459	0.940	0.237
Union Unknown	0.594	0.491	0.547	0.498	0.698	0.459	0.013	0.112
Active FT	0.461	0.499	0.704	0.456	0.936	0.244	0.851	0.356
Active PT	0.002	0.041	0.002	0.039	0.000	0.011	0.027	0.161
Retiree	0.450	0.498	0.126	0.332	0.035	0.185	0.076	0.265
Other Status	0.086	0.281	0.168	0.374	0.028	0.166	0.046	0.209
Manuf., Durable	0.277	0.448	0.081	0.273	0.012	0.110	0.053	0.223
Manuf., Nondurable	0.044	0.205	0.083	0.276	0.002	0.044	0.020	0.138
Trans., Comm., Utilities	0.069	0.254	0.006	0.077	0.018	0.132	0.309	0.462
Services	0.004	0.064	0.035	0.184	0.003	0.055	0.018	0.135
Other Industry	0.022	0.147	0.124	0.330	0.022	0.146	0.018	0.131
Emp. Enroll. (10,000s)	7.307	9.442	45.753	49.897	23.669	11.145	13.239	7.035
Number of Observations	7,888		96,366		33,136		17,380	

Table 2.5: Summary Statistics of Control Variables for Prozac-Fluoxetine Sub-sample (continued)

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
MSA Variables:								
Per Cap. Income ($1000s)	24.319	3.556	23.753	3.416	25.255	3.075	23.737	2.720
Population (100,000s)	23.810	22.282	18.059	20.029	27.854	21.436	15.252	15.668
MSA Info Unknown	0.271	0.444	0.314	0.464	0.170	0.375	0.256	0.436
Prescription Variables:								
New Prescription	0.357	0.479	0.327	0.469	0.618	0.486	0.416	0.493
No DAW	0.898	0.302	0.927	0.259	0.967	0.187	0.938	0.241
Physician DAW	0.040	0.196	0.031	0.173	0.017	0.128	0.024	0.153
Patient DAW	0.024	0.152	0.016	0.125	0.007	0.085	0.020	0.140
Retail Prescription	0.803	0.398	0.941	0.236	0.594	0.491	0.914	0.280
Mail Order	0.195	0.396	0.059	0.235	0.015	0.123	0.086	0.280
Mail Unknown	0.002	0.039	0.000	0.022	0.391	0.488	0.000	0.000
Number of Observations	7,888		96,366		33,136		17,380	

Table 2.6: Summary Statistics of Key Variables by Sample

	Comp.		PPO		HMO		POS	
	Mean	S.D	Mean	S.D.	Mean	S.D.	Mean	S.D.
Chronic Sub-sample:								
Generic Indicator	0.884	0.321	0.905	0.293	0.918	0.274	0.914	0.281
TN*POST	0.100	0.300	0.183	0.387	0.147	0.354	0.447	0.497
Pre Law	0.443	0.497	0.433	0.495	0.414	0.493	0.438	0.496
AL Pre Law	0.044	0.204	0.039	0.194	0.002	0.047	0.021	0.142
GA Pre Law	0.293	0.455	0.224	0.417	0.298	0.457	0.057	0.232
AK Pre Law	0.028	0.164	0.030	0.171	0.001	0.037	0.009	0.094
Number of Observations	509,150		5,935,537		1,870,612		1,097,757	
Non-chronic Sub-sample:								
Generic Indicator	0.875	0.331	0.908	0.290	0.918	0.274	0.915	0.279
TN*POST	0.094	0.292	0.167	0.373	0.093	0.291	0.405	0.491
Pre Law	0.447	0.497	0.464	0.499	0.484	0.500	0.473	0.499
AL Pre Law	0.045	0.208	0.041	0.197	0.002	0.049	0.025	0.155
GA Pre Law	0.294	0.456	0.234	0.424	0.397	0.489	0.076	0.264
AK Pre Law	0.030	0.171	0.041	0.199	0.002	0.043	0.010	0.102
Number of Observations	43,341		718,427		260,667		139,243	
Prozac-Fluoxetine Sub-sample:								
Generic Indicator	0.940	0.237	0.960	0.196	0.972	0.165	0.966	0.180
TN*POST	0.085	0.279	0.180	0.384	0.163	0.369	0.437	0.496
Pre Law	0.451	0.498	0.427	0.495	0.416	0.493	0.438	0.496
AL Pre Law	0.031	0.175	0.028	0.166	0.001	0.036	0.019	0.136
GA Pre Law	0.325	0.468	0.227	0.419	0.288	0.453	0.063	0.243
AK Pre Law	0.024	0.153	0.026	0.161	0.001	0.032	0.010	0.099
Number of Observations	7,888		96,366		33,136		17,380	

Table 2.7: LPM Regression Estimates for Chronic Sub-sample

	Comp.	PPO	HMO	POS
TN*Post	-0.003	-0.000	0.006**	-0.000
	[0.004]	[0.002]	[0.003]	[0.003]
Pre Law	0.004	0.007	0.007**	0.000
	[0.005]	[0.005]	[0.003]	[0.003]
AL Pre	0.000	-0.004	-0.004	-0.003
	[0.005]	[0.005]	[0.005]	[0.004]
GA Pre	-0.006	-0.013**	-0.011***	0.002
	[0.005]	[0.005]	[0.003]	[0.003]
AL	-0.002	-0.008***	0.006	-0.000
	[0.004]	[0.003]	[0.005]	[0.005]
AK	-0.006***	-0.011***	-0.007	-0.004
	[0.003]	[0.003]	[0.010]	[0.004]
GA	-0.004	-0.004	0.005	0.008
	[0.005]	[0.003]	[0.004]	[0.008]
Age Between 18-34	0.011***	0.010**	0.003***	0.014***
	[0.002]	[0.004]	[0.001]	[0.002]
Age Between 35-44	0.008***	0.012***	0.005	0.010***
	[0.002]	[0.002]	[0.003]	[0.002]
Age Begween 45-54	0.012***	0.010***	0.002	0.012***
	[0.003]	[0.002]	[0.006]	[0.003]
Age Over 55	0.011***	0.013***	0.003	0.016***
	[0.003]	[0.003]	[0.005]	[0.003]
Male	0.035***	0.027***	0.024***	0.015***
	[0.004]	[0.005]	[0.003]	[0.001]
MSA Population (100,000s)	-0.000*	-0.000*	-0.000	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
Employer Enrollment	-0.002***	-0.000***	-0.000***	0.007***
	[0.000]	[0.000]	[0.000]	[0.000]
MSA Per Capita Income (1000s)	0.001*	0.001	-0.000	0.003***
	[0.001]	[0.001]	[0.001]	[0.000]
Urban	-0.036**	-0.019	0.008	-0.067***
	[0.017]	[0.015]	[0.035]	[0.009]
Union	0.010***	0.002	-0.021	0.010**
	[0.002]	[0.003]	[0.018]	[0.004]
Union Status Unknown	-0.009	0.011	0.012	-0.005
	[0.027]	[0.008]	[0.010]	[0.004]

Standard errors shown in brackets clustered by employer: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer and time fixed effects.

Table 2.7: LPM Regression Estimates for Chronic Sub-sample (continued)

	Comp.	PPO	HMO	POS
Active Full Time	-0.019***	-0.005***	-0.010***	-0.007***
	[0.005]	[0.001]	[0.001]	[0.001]
Active Part Time or Seasonal	0.018***	-0.009***	-0.009*	0.006**
	[0.004]	[0.003]	[0.004]	[0.002]
Retiree	-0.006	-0.003***	-0.006**	-0.007**
	[0.008]	[0.001]	[0.003]	[0.003]
Manufacturing, Durable Goods	-0.079***	-0.031***	-0.250***	-0.027***
	[0.005]	[0.004]	[0.046]	[0.003]
Manufacturing, Nondurable Goods	-0.093***	-0.021***		0.219***
	[0.008]	[0.007]		[0.015]
Transportation, Communiation, Utilities	-0.112***	-0.073***	0.010	-0.030***
	[0.007]	[0.015]	[0.010]	[0.004]
Other Industry	-0.085***	-0.023***	-0.060***	-0.030***
	[0.005]	[0.003]	[0.011]	[0.005]
New Prescription	0.034**	0.032***	0.014***	0.012***
	[0.013]	[0.009]	[0.000]	[0.002]
Physician DAW	-0.781***	-0.763***	-0.783***	-0.760***
	[0.023]	[0.014]	[0.041]	[0.025]
Patient DAW	-0.660***	-0.696***	-0.778***	-0.771***
	[0.128]	[0.076]	[0.035]	[0.052]
Mail Order	-0.074***	-0.025	-0.029***	-0.030
	[0.009]	[0.015]	[0.008]	[0.024]
Mail Order Status Unknown	-0.087***	-0.005	-0.050***	-0.009
	[0.014]	[0.005]	[0.003]	[0.007]
Observations	509,150	5,935,537	1,870,612	1,097,757

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer and time fixed effects.

Table 2.8: LPM Regression Estimates for Non-chronic Sub-sample

	Comp.	PPO	HMO	POS
TN*Post	-0.007	0.005***	-0.005	0.014***
	[0.006]	[0.002]	[0.005]	[0.003]
Pre Law	-0.010	0.009**	0.005	0.011*
	[0.009]	[0.003]	[0.006]	[0.006]
AL Pre	-0.013	-0.012**	-0.017	-0.006
	[0.009]	[0.006]	[0.014]	[0.008]
GA Pre	0.001	-0.014***	0.004	-0.010**
	[0.006]	[0.004]	[0.005]	[0.004]
AL	0.005	-0.003	0.008	0.018
	[0.010]	[0.005]	[0.015]	[0.014]
AK	-0.021*	-0.006*	-0.043**	0.011
	[0.010]	[0.003]	[0.017]	[0.009]
GA	-0.007	0.001	-0.019***	0.018**
	[0.008]	[0.004]	[0.007]	[0.008]
Age Between 18-34	0.016	0.005**	-0.015***	-0.002
	[0.011]	[0.002]	[0.003]	[0.007]
Age Between 35-44	0.019**	0.006***	-0.009*	0.000
	[0.009]	[0.002]	[0.005]	[0.006]
Age Begween 45-54	0.001	0.002	-0.014***	0.000
	[0.009]	[0.002]	[0.005]	[0.008]
Age Over 55	-0.004	0.009***	-0.012	0.006
	[0.013]	[0.003]	[0.009]	[0.005]
Male	0.052***	0.029***	0.021***	0.018***
	[0.011]	[0.005]	[0.002]	[0.004]
MSA Population (100,000s)	-0.000	-0.000	0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]
Employer Enrollment	-0.002	0.000***	0.001***	-0.003***
	[0.002]	[0.000]	[0.000]	[0.000]
MSA Per Capita Income (1000s)	0.001	0.001	-0.001	0.003***
	[0.002]	[0.001]	[0.001]	[0.001]
Urban	-0.053	-0.015	0.024	
	[0.037]	[0.025]	[0.035]	
Union	0.022***	0.007	0.159***	0.011
	[0.007]	[0.005]	[0.051]	[0.006]
Union Status Unknown	-0.090**	0.042***	0.075***	0.015*
	[0.043]	[0.009]	[0.016]	[0.008]

Standard errors shown in brackets clustered by employer: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer and time fixed effects.

Table 2.8: LPM Regression Estimates for Non-chronic Sub-sample (continued)

	Comp.	PPO	HMO	POS
Active Full Time	-0.015	0.001	-0.007	-0.023***
	[0.021]	[0.004]	[0.010]	[0.004]
Active Part Time or Seasonal	-0.004	-0.009	-0.010	-0.014***
	[0.026]	[0.008]	[0.008]	[0.004]
Retiree	0.002	-0.009	-0.019	-0.023***
	[0.014]	[0.008]	[0.013]	[0.008]
Manufacturing, Durable Goods	-0.0392**	0.095***	0.127***	0.111***
	[0.016]	[0.006]	[0.020]	[0.008]
Manufacturing, Nondurable Goods	0.059	0.116***		
	[0.063]	[0.010]		
Transportation, Communiation, Utilities	-0.004	0.115***	0.197***	0.087***
	[0.012]	[0.010]	[0.013]	[0.010]
Other Industry	-0.059***	0.077***	-0.124***	0.119***
	[0.012]	[0.008]	[0.013]	[0.009]
New Prescription	0.059***	0.045***	0.018***	0.019***
	[0.019]	[0.013]	[0.002]	[0.004]
Physician DAW	-0.746***	-0.753***	-0.756***	-0.743***
	[0.030]	[0.018]	[0.044]	[0.015]
Patient DAW	-0.549***	-0.676***	-0.732***	-0.715***
	[0.168]	[0.078]	[0.021]	[0.041]
Mail Order	-0.108***	-0.042**	-0.045**	-0.061*
	[0.014]	[0.017]	[0.018]	[0.030]
Mail Order Status Unknown	0.027	-0.010	-0.045***	-0.260***
	[0.024]	[0.009]	[0.001]	[0.008]
Observations	43,341	718,427	260,667	139,243

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specification includes employer and time fixed effects.

Table 2.9: Effect of Law on Physician and Patient DAW Indicators

	Insurance Plan Type			
	Comp.	PPO	HMO	POS
Effect on Physician DAW Indicators:				
Chronic Sub-sample:				
TN*POST	-0.001	-0.000	0.002	-0.001
	[0.003]	[0.001]	[0.002]	[0.001]
Observations	509,150	5,935,537	1,870,612	1,097,757
Non-chronic Sub-sample:				
TN*POST	0.003	-0.001	0.006	-0.001
	[0.008]	[0.001]	[0.005]	[0.007]
Observations	43,341	718,427	260,667	139,243
Effect on Patient DAW Indicators:				
Chronic Sub-sample:				
TN*POST	-0.002	-0.009***	-0.003	-0.009
	[0.002]	[0.001]	[0.004]	[0.006]
Observations	509,150	5,935,537	1,870,612	1,097,757
Non-chronic Sub-sample:				
TN*POST	0.000	-0.003*	-0.006	-0.007*
	[0.005]	[0.002]	[0.007]	[0.004]
Observations	43,341	718,427	260,667	139,243

Standard errors shown in brackets clustered by employer-plan: *** p<0.01, ** p<0.05, * p<0.1
Specifications include employer and time fixed effects.

Table 2.10: Comparison: With and Without DAW Indicators

	Insurance Plan Type			
	Comp.	PPO	HMO	POS
Chronic Sub-sample:				
Basic Results:				
TN*POST	-0.003	-0.001	0.006**	-0.000
	[0.004]	[0.002]	[0.003]	[0.003]
No DAW Indicators:				
TN*POST	-0.000	0.007***	0.007	0.008*
	[0.004]	[0.002]	[0.004]	[0.004]
Non-chronic Sub-sample:				
Basic Results:				
TN*POST	-0.007	0.005***	-0.005	0.014***
	[0.006]	[0.002]	[0.005]	[0.003]
No DAW Indicators:				
TN*POST	-0.000	0.006***	0.007	0.008*
	[0.004]	[0.002]	[0.004]	[0.004]

Standard errors shown in brackets clustered by employer-plan:
*** p<0.01, ** p<0.05, * p<0.1
Specifications include employer and time fixed effects.

Table 2.11: LPM Estimates for Prozac and Fluoxetine Sub-sample

	Insurance Plan Type			
	Comp.	PPO	HMO	POS
Basic Results Chronic Sub-sample:				
TN*POST	-0.003	-0.001	0.006**	-0.000
	[0.004]	[0.002]	[0.003]	[0.003]
Observations	509,150	5,935,537	1,870,612	1,097,757
Basic Results Prozac and Fluoxetine Sub-sample:				
TN*POST	0.001	-0.000	0.011**	-0.004
	[0.005]	[0.002]	[0.004]	[0.012]
Observations	7,888	96,366	33,136	17,380

Standard errors shown in brackets clustered by employer-plan:
*** p<0.01, ** p<0.05, * p<0.1
Specifications include employer and time fixed effects.

Table 2.12: Sensitivity Analysis: Chronic Sub-sample

	Insurance Plan Type			
	Comp.	PPO	HMO	POS
Basic Results:				
TN*POST	-0.003	-0.001	0.006**	-0.000
	[0.004]	[0.002]	[0.003]	[0.003]
Falsification Test 1: Six Months Before Law:				
TN*POST (Jan. 2005)	0.001	-0.001	-0.011	-0.001
	[0.005]	[0.006]	[0.015]	[0.005]
Falsification Test 2: Six Months After Law:				
TN*POST (Dec. 2005)	-0.002	-0.002	-0.005	-0.007
	[0.004]	[0.005]	[0.005]	[0.004]

Standard errors shown in brackets clustered by employer-plan:
*** p<0.01, ** p<0.05, * p<0.1
Specifications include employer and time fixed effects.

Table 2.13: Sensitivity Analysis: Non-chronic subsample

	Insurance Plan Type			
	Comp.	PPO	HMO	POS
Basic Results:				
TN*POST	-0.007	0.005***	-0.005	0.014***
	[0.006]	[0.002]	[0.005]	[0.003]
Falsification Test 1: Six Months Before Law:				
TN*POST (Jan. 2005)	0.005	0.001	-0.011	0.004
	[0.008]	[0.005]	[0.014]	[0.004]
Falsification Test 2: Six Months After Law:				
TN*POST (Dec. 2005)	-0.009	-0.001	-0.011	-0.000
	[0.009]	[0.003]	[0.010]	[0.004]

Standard errors shown in brackets clustered by employer-plan:
*** p<0.01, ** p<0.05, * p<0.1
Specifications include employer and time fixed effects.

Table 2.14: Sensitivity Analysis: Effect on Average Values

	Sample		
	Chronic	Non-chronic	All
TN*POST	0.004	0.002	0.003
	[0.004]	[0.005]	[0.003]
Pre Law	-0.055***	-0.054***	-0.055***
	[0.004]	[0.005]	[0.003]
AL Pre	0.002	-0.004	-0.001
	[0.005]	[0.006]	[0.003]
AK Pre	0.017*	0.021*	0.019***
	[0.005]	[0.006]	[0.003]
GA Pre	-0.013	-0.010	-0.012***
	[0.005]	[0.006]	[0.003]
Observations	8	8	16

Chapter 3

Extending the Technology Acceptance Model in Healthcare: Identifying the Role of Trust and Shared Information

3.1 Introduction

As the incentives authorized by the American Recovery and Reinvestment Act (P.L. 111-5) accelerate the adoption of electronic health records (EHRs) [Jha, DesRoches, Kralovec and Joshi, 2010], health organizations continue to adopt integrated records shared by multiple care providers. We expect that access to shared information and users' trust of this information will affect adoption and use of these integrated record systems.

Healthcare represents a unique industry, with employees (physicians and other healthcare staff, whom we refer to as 'providers' in the context of this paper) intimately vested

in the outcome (patient health) of their service. Patient health is a complex outcome that is affected by the services administered by multiple care providers, often in different care settings. Integrated EHRs enable healthcare physicians and staff to share information between departments and practices within a health network. Multiple providers have access to each patient's records, which implies that updating and processing patient records is a group responsibility. Because trust is a fundamental aspect of cooperative work [Herzum, 2002], we believe the extent to which employees will use the EHRs is a direct result of their trust in the shared data within these systems. If the providers do not trust the data, we expect they will find ways to work around the system, leading to inefficiencies and unrealized benefits of implementation.

The proposed benefits of EHR implementation include: productivity growth; reduction of medical errors; improvements in quality of care; and the increased ability to measure and pay providers based on performance [Goldschmidt, 2005]. In the absence of interoperability, however, these expected benefits are likely to be stifled. Grimson, Grimson and Hasselbring (2000) argue that the current inability to automatically share information across systems presents a significant barrier to these potential improvements in care and efficiency. We posit that access to information from various care practices within a health network will directly influence the usefulness and degree to which physicians and administrative staff use the interoperable health information technology (HIT) system. Access to, use, maintenance, and availability of a shared EHR are fundamental to the successful implementation of these systems [Grimson et al., 2000].

The Technology Acceptance Model (TAM) is a common research method used to asses the factors that influence the successful adoption of new technology. Researchers using the TAM have found different relationships between its key components, which have often been attributed to cultural differences [Yousafzai, Foxall and Pallister, 2007]. We believe

that the healthcare industry has unique characteristics that influence these relationships. Additionally, the TAM research finds different results in mandatory usage environments versus voluntary adoption situations; the implementation of a shared EHR requires mandatory use of the system to achieve a basic level of effectiveness. This represents a departure from the premise of the standard TAM, which operates differently under varying volitional contexts [Brown, Massey, Montoya-Weiss and Burkman, 2002; Rawstorne, Jayasuriya and Caputi, 2000].

The objective of our research is to extend the TAM in the healthcare environment, particularly for the adoption of integrated health records that require providers to share information. In subsequent sections, we present background on the literature related to the TAM, its use in healthcare, and its application in environments where shared information is critical. We propose an extension to the TAM in the conceptual model section. The data and analyses follow. We offer conclusions and ideas for future research in the final section of the paper.

3.2 Literature Review

3.2.1 Modeling Technology Acceptance

The TAM provides a general theoretical foundation for how users accept and use technology [Davis, 1989], highlighting the role of perceived usefulness (PU) and perceived ease of use (PEOU) on attitude (ATT), behavioral intent (BI), and actual system usage. The basic TAM is displayed in Figure 3.1. Additional factors that influence these variables have been introduced over time in TAM2 [Venkatesh and Davis, 2000] and the UTAUT model [Venkatash, Moffis, Davis and Davis, 2003]. For a complete review of the development of the TAM models, please refer to Appendix B.

In addition to these extended theories, many other studies have conducted expanded analyses. In some instances, these studies validate TAM [Pai and Huang, 2011; Melas, Zampetakis, Dimopoulou and Moustakis, 2010; Bhattacherjee and Hikmet, 2007; Venkatesh and Davis, 2000], but in others the TAM findings are not supported [Yi, Jackson, Park and Probst, 2006; Han, Carcillo, Venkataraman, Clark, Watson and Nguyen, 2005; Barker, Van Schaik, Simpson and Corbett, 2003; Chismar and Wiley-Patton, 2002; Hu, Chau, Sheng and Tam 1999]. In further cases, authors criticize the TAM for simplicity and lack of contextualization [Holden and Karsh, 2010; Bagozzi, 2007].

Researchers using the TAM have found different relationships between PEOU-BI, PU-BI, and PEOU-PU [Yosafzai et al., 2007]. Some research suggests that PEOU has only an indirect effect on BI through PU [Davis, 1989; Adams, Nelson and Todd, 1992; Chau, 1996; Gefen and Straub, 2000]. Other studies find PEOU to have a direct effect on BI, with a magnitude that is equal to the effect of PU on BI [Adams et al., 1992; Agarwal and Prasad, 1997]. Further studies find PEOU to have a direct effect on BI that is larger than the effect of PU on BI [Chau, 1996; Karahanna and Limayen, 2004]. One proposed explanation for differences in the relationships is the voluntariness of adoption. In a mandatory setting, researchers have found an increased effect of PEOU on BI, and a diminished direct effect of PU on BI. Also, in mandatory contexts [Brown et al. 2002, Venkatash and Davis, 2000] PEOU and PU directly affect ATT, which subsequently influences BI [Brown et al., 2002]. A second proposed explanation cites the importance of external factors over PEOU and PU. In these studies, the influence of PEOU and PU on BI diminishes completely when other external factors (e.g., perceived behavioral control and subjective norms) are considered [Brown, et al. 2002; Lucas and Spitler, 1999].

Additionally, culture has been found to be a contributing factor to the applicability of the TAM [Yousafzai et al., 2007]. Table 3.1 provides a brief snapshot of the types

of conflicting results across employee groups and countries. The importance of culture suggests that application in the healthcare industry, which has its own unique culture (even across provider roles), may require specific contextualization.

Another contributing factor to the applicability of the TAM is the stage of technology acceptance. Bhattacherjee (2001) highlights the importance of including the additional factors of satisfaction and confirmation when analyzing cases involving continued systems usage. However, when comparing the effectiveness of three distinct models (Expectation-Confirmation (EC) Model, TAM, and an EC-TAM hybrid) in post-adoption situations, Hong, Thong, and Tam (2006) find the TAM to be the most parsimonious. In post-adoption settings, PU is found to have continued and significant effects on the use of technology [Hong et al., 2006]. Further, Saeed and Abdinnour-Helm (2008) find information quality and system integration to have significant effects on post-adoption usage. Additionally, Al-maghrabi, Dennis, and Halliday (2009) find that PU, enjoyment, and social norms influence post-adoption technology use.

3.2.2 Technology Acceptance in Healthcare

In studies analyzing the TAM in the healthcare industry, the inconsistent results identifying the relationship between PEOU and BI still exist [Holden and Karsh, 2010]. One theory suggests that lack of exposure to IT systems may be consistent with non-significant PEOU-ATT and PEOU-BI relationships [Barker et al., 2003; Van Schaik et al., 2002; Duyck et al., 2008], but another suggests employee role could be the influencing factor [Chau and Hu, 2002; Hu and Chau, 1999; Yi et al. 2006]. Of the seven studies with non-significant relationships, six of them contained only physician samples, suggesting that different factors influence the behavior among physicians as compared to other healthcare workers [Holden and Karsh, 2010]. Some authors attribute the lack of significance of PEOU to physicians' increased intellect and ability to learn to use the EHR [Hu and Chau, 1999;

Yi et al., 2006], while others find that physicians are not interested in usability, provided the EHR is useful [Barker et al., 2003; Chismar and Wile-Patton, 2002].

More recent studies attempt to identify other external factors influencing PEOU and PU in the healthcare industry. Melas et al. (2010) test external factors influencing physicians' and nurses' attitudes towards the use of general computer information systems (CISs) for purposes of "storage, retrieval, sharing, and use of healthcare information, data, and knowledge for communication and decision-making". They determine that self-reported measures related to information and communication technology understanding influence PEOU and PU, but do not influence BI. Additionally, Melas et al. (2010) confirm findings that healthcare professionals are more likely to adopt systems that they perceive to be compatible with their current work processes, and also confirm the predictive pattern of attitude to usage. Walter and Lopez (2008) find that perceived threat to autonomy has a significant negative effect on PU and BI when considering the adoption of both clinical decision support systems (CDSs) and electronic medical records systems (EMRs). Both of these studies validate the use of the TAM in the healthcare industry.

Despite these positive findings and the determination of some external factors applicable in this context, the existing studies have limitations. The findings of Walter and Lopez (2008) consider pre-adopters, so these results cannot be generalized to other phases of IT implementation. Additionally, the analysis considers only office-based practitioners responding to general questions about CISs and EHRs, not specific systems [Walter and Lopez, 2008]; this limitation is also present in Melas et al. (2010). Further, neither of these studies considers the mandatory adoption environment.

Holden and Karsh (2010) identify additional limitations of existing studies in this field. Existing HIT studies capture the systems of telemedicine, picture archiving and communication systems (PACS), and computerized provider order entry (CPOE); there is a lack of findings related to EHRs and collaborative information systems. Further, the existing studies identify PU in a broad context by defining it as follows: leading to the enhancement of gains in job performance. In healthcare, usefulness may also be defined in terms of efficacy, cost reduction, and improved quality and safety of care. Usefulness could also be assessed from the point of view of various people involved in the care process: physicians, specialists, patients, and family members. Current studies are not able to distinguish between these varying aspects of usefulness, but these items may play a particularly important and distinctive role in IT applications in the healthcare field. In general, the existing studies focus on a limited and generic method of considering the constructs of usefulness, perceived ease of use, and social influence. This could result in overlooking constructs or important factors influencing user acceptance, and leaves many opportunities for future research in the field [Holden and Karsh, 2010].

3.2.3 Technology Acceptance, Trust, and Shared Information

Because a shared EHR system involves user reliance on shared information across multiple practices within a hospital, we expect trust will be an important factor influencing BI. Trust has been most commonly analyzed in the technology acceptance of electronic commerce (e-commerce) systems and Electronic Data Interchange (EDI) systems; both cases involve asymmetric information sharing, as would be present in the case of an EHR adoption. In the case of technology acceptance of e-commerce systems, trust is of paramount concern due to the risk that e-vendors might participate in harmful opportunistic behaviors, including: unfair pricing, conveying inaccurate information, or violating privacy laws [Gefen et al., 2003]. During the EDI adoption process, trust increases the probability of

greater EDI use. As more and more information is shared, higher levels of trust must be attained amongst those who share and use the information [Hart and Saunders, 1997].

Trust is a significant factor in the TAM when considering the adoption of e-commerce and in other contexts of sharing information across parties [Benamati, Fuller, Serve and Baroudi, 2010; Gefen, Karahanna and Straub, 2003; Hart and Saunders, 1997]. Tan and Thoen (2001) believe trust to be such an important component of e-commerce adoption that they claim it to be the single factor contributing to e-commerce success. The few studies incorporating trust into the TAM find that it has a statistically significant effect on BI [Benamati et al., 2010], in addition to a significant effect on PU and PEOU [Gefen et al., 2003]. Benemati et al. (2010) and Gefen et al. (2003) both find that the effect of PEOU and PU on BI continues to be significant, even with the addition of trust in the model. Although we do not expect physicians to engage in opportunistic behaviors, as might be a concern in e-commerce or EDI transactions, risk is inherent in any situation involving asymmetric information. In this case, medical staff become vulnerable to others' mistakes or incompetence when relying upon information provided by outside sources; this becomes a risky situation if medical staff then base care decisions on incomplete or inaccurate information. The potential for these information asymmetries represent an underlying factor requiring trust as a predecessor of use.

Analyses identifying access to shared information as a factor in the TAM are scarce. In a review of TAM studies, Yousafzai et al. (2007) note that information quality (of which information availability and accessibility are components) has been proposed to affect PU. When analyzing adoption of online reputation systems, Komiak (2010) find users' perceived information quality to affect BI through PU; when considering the effects of information quality on post adoption behavior, Saeed and Abdinnour-Helm (2008) find significant effects of information quality on perceived usefulness and continuance of

use. We seek to further extend this literature by identifying the influencing effect of the accessibility and availability of shared information on adoption within healthcare systems.

3.3 Conceptual Model

We propose an extension to the TAM for the adoption of mandatory-shared EHRs by introducing two additional factors to the model: trust (T) in the accuracy of the data; and accessibility and availability of shared information (SI) coming from multiple units within the health network. Figure 3.2 depicts our proposed model.

We define trust according to McAllister (1995): "trust is the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another." In order to obtain the proposed benefits from this HIT implementation, physicians and other healthcare workers must use the shared information regarding patient health status to make clinical decisions. We propose that these healthcare providers will use the information only if they trust it; therefore, trust influences the perceived usefulness of the EHR.

Hertzum (2002) argues that trust is a fundamental aspect of cooperative work, and exists whenever people exchange information. Trust is prominent in healthcare because it is a team effort [Berwick, 2003], especially when we consider sharing information across EHRs. Further, Paul and McDaniel (2004) find that physicians place a larger emphasis on trust than on usefulness or ease of use in adoption decisions. We expect to find similar results in the adoption of EHRs, and hypothesize that trust directly influences the perceived usefulness of the system and individuals' intention to use the system.

In order to determine the trustworthiness of shared data, the information must be available and accessible. We define SI as relevant information from other departments

that is maintained in the system in a timely manner, and is easily accessible from within the system. O'Malley, Grossman, Choen, Kemper and Pham (2009) assess the effect of EMRs on the coordination of patient care, and find the following factors necessary for appropriate care across departments: timely exchange of relevant information, timely communication between inpatient and outpatient settings, and ability to access necessary information from the EHR. We expect that with more available, accessible, and timely information, providers and other staff members will be more inclined to use the EHR for patient care. Alternatively, medical and non-medical staff members may resort to working around the system, and accessing patient information through other methods. Specifically, if information is not readily available or current, providers may forgo use of the system entirely, which could result in a negative relationship between SI and BI.

In industries outside of healthcare, the adoption of Enterprise Resource Planning (ERP) systems began in the 1980s and 1990s as a means of gaining efficiency by connecting business processes into one system [Murrell, 2001]. Palaniswamy and Frank (2000) identify improved cross-functional integration as a critical success factor in implementation. Tarn et al. (2002) further attribute the success of ERP systems to integrated flow of information providing an invaluable tool in which all departments can coordinate activities and communicate across a common interface. In healthcare, successful care of patients also depends critically on providers' ability to share information across specialties [Grimson et al., 2000]. We therefore expect the availability of patient information from separate physician or hospital units to enhance the effectiveness and success of EHR implementations. If users feel the EHR system increases their productivity and improves job performance and effectiveness, their perceived usefulness of the system increases. It follows that the availability, timeliness, and accuracy of the information within the system will affect the perceived usefulness of the system.

Building upon the basic TAM, in which PU and PEOU are the two distinct predecessors of BI, we propose that SI will also affect BI and PU. In contexts of mandatory adoption, past research indicates outside factors may have a greater effect on BI than PU and PEOU [Brown et al., 2002]. As discussed in the literature review, prior studies have also found constructs capturing various components of information quality, accessibility, and availability to influence usefulness and usage [Saeed et al., 2008; Komiak et al., 2010].

3.4 Data and Setting

We analyze a Pennsylvania health network currently implementing a shared EHR system. All physician-owned ambulatory practices in this network are implementing the same system, which has shared EHRs for patients receiving care across specialties. We focus specifically on adoption within the four obstetrics (OB) ambulatory practices. These practices share information across care settings within the hospital system, and one location, in particular, sees bi-directional data flow between the ambulatory and the hospital labor and delivery unit. This data includes the triage subunit where patients are evaluated for admission. We survey physicians and office staff to capture details about their attitudes and experiences with the adoption of these systems.

The questions we use to analyze our proposed model are listed in Table 3.2. We use questions validated in past studies of the TAM, information systems, and psychology [Pai and Huang, 2011; Bhattacherjee and Hikmet, 2007; Gefen et al., 2003]. In order to capture the complexities of this industry, we formulate the questions to be specific to healthcare, when appropriate. All responses are scored on a five-point Likert scale: 1–disagree strongly, 2–disagree slightly, 3–neutral, 4–agree slightly, and 5–agree strongly.

We have survey responses for 123 employees during this round of the study. We dropped 21 observations due to missing user identification, which prevented us from gathering demographic information for those responses, 10 observations because of missing clinical indication, and 17 observations due to missing age and experience data; our final sample contains 75 complete records.

Summary statistics regarding our final sample are detailed in Table 3.3. Research indicates that physicians may interact with new technology differently than administrative staff. Hu, Chau, Sheng, and Tam (1999) consistently find that physicians differ from other types of users when accepting technology, specifically in the area of telemedicine. These differences can be attributed to their specialized training, autonomous practices, and professional work environments [Walter and Lopez, 2008]. Because of our limited physician sample size, we conduct our analysis at the clinical vs. non-clinical level. Clinical employees are those actively providing medical treatment to patients, while non-clinical staff would include receptionists, billing specialists, and administrators who do not directly provide medical care. Non-clinical staff often have more experience using IT systems in the office, as they normally conduct billing and scheduling through specialized software systems; Barker et al. (2003) find prior levels of IT usage to influence adoption behavior, so this difference could influence non-clinical providers' acceptance of a new EHR in a different manner than clinical staff members. Additionally, Yi et al. (2006) and Mathieson (1991) posit that medical providers may behave differently in the presence of EHRs because of the availability of support staff to deal with the system on their behalf.

Our clinical sample contains 9 physicians and 19 clinical staff members (i.e., physician's assistants and nursing staff), for a total sample size of 28; our non-clinical sample contains 47 non-clinical staff members (i.e., administrative staff). The average age of our clinical sample is 46, with an average of 18 years of experience. This represents a distinction

compared to our non-clinical sample, which has an average age of 40 and an average of 14 years of experience. Our clinical sample is 85% female, while our non-clinical sample contains all female observations.

3.5 Data Analyses and Discussion

We begin our factor analysis by validating the general fit of the data, which is 0.8246. This corresponds to a Kaiser-Meyer-Olkin (KMO) rating of 'meritorious', which is well-above the 0.6 minimum threshold. Additionally, we review the individual Measures of Sampling Adequacy (MSA) to ensure that specific variables will not compromise the overall fit of the data. Due to a low MSA value (under 0.5), we dropped question T3 from our analysis. Further, we dropped SI5 and T4 due to low alphas; we also removed question PEOU3 from our analysis because it loaded on two factors.

We use the remaining 17 questions to conduct our analysis. Using principal component factor analysis, five factors result with an eigenvalue greater than one. We validate the internal reliability of the factors by calculating each Cronbach's alpha. The SI, PEOU, and BI factors score above 0.80, corresponding to a good internal consistency. The alpha for the PU factor is above 0.9, representing excellent internal consistency. The T factor alpha score is lowest at 0.61; although it meets the minimum required level to remain in the model, we also analyze a second metric, its inter-item correlation, to further verify the factor's internal consistency. According to Briggs and Cheek (1986), the optimal inter-item correlation is between 0.2 and 0.4; Clark and Watson (1995) recommend this value to be between 0.15 and 0.5. The inter-item correlation for our T factor falls precisely within both ranges at 0.33. Based on this additional validation, we feel confident continuing with all five factors in the model; we show the final factor loadings in Table 3.4.

As noted in the literature review and data sections, the importance of cultural differences, social norms, and previous exposure to IT influences technology acceptance [Holden and Karsh, 2010]. In order to account for this distinction in our model, we conduct separate path analyses by clinical and non-clinical designation. Figure 3.3 shows our path analysis results for the clinical sample and Figure 3.4 shows the results for the non-clinical sample.

In the clinical sample, we find PEOU directly affects PU in a positive and statistically significant manner, while SI has a significantly negative effect on PU. Additionally, T has a positive and significant effect on BI, while there is no statistically significant effect of PU or PEOU on BI.

The positive effect of PEOU on PU is consistent with prior research [Benemati and Rajkumar 2002; Lowry 2002; Lucas and Spitler 2000]. The lack of effect of PEOU and PU on BI may initially seem surprising and appear inconsistent with standard TAM research; however, some previous studies find no significant effect of PEOU or PU on BI [Holden and Karsh, 2010; Duyck et al., 2008; Bhattacherjee and Hikmet, 2007; Yi, et al., 2006; Han et al., 2005; Barker, et al. 2003; Brown et al. 2002; Chismar and Wiley 2002; Van Schaik et al., 2002; Dishaw and Strong, 1999; Lucas and Spitler, 1999; Jackson, et al., 1997; Subramanian, 1994]. Brown et al. (2002) do not find either PEOU or PU to be a significant factor leading to adoption in mandatory adoption situations, especially in situations where the system is integrated across users. As interoperability is a principal component of the EHR system we analyze, it is unsurprising to find a lack of significant effects between PEOU and PU on BI. In the studies finding no relationship between PEOU and BI, the authors identify outside factors that have a more significant effect on BI. Bhattacherjee and Hikmet (2007) study physician adoption of a CPOE system and find that resistance to change affects BI; Brown et al. (2002) find that perceived behavioral

control and subject norms influence BI. Our findings are similar in that we also identify an outside factor, trust, to have a significant effect on BI while PU and PEOU are not significant.

Paul and McDaniel (2004) find that physicians place a larger emphasis on trust than on usefulness or ease of use in adoption decisions. Our finding that identifies the positive and significant effect of trust on BI supports this consensus. Similarly, within e-commerce systems, Tan and Thoen (2001) find trust to be the single factor contributing to e-commerce success. Our findings continue to emphasize the importance of trust when information sharing occurs.

An additional significant finding in our model is the negative effect of SI on PU. We believe this result highlights an interesting aspect of technology adoption in healthcare: We interpret the negative coefficient as indicating that decreased amounts of SI increase the perceived usefulness of this EHR. This may imply resistance among users to sharing information and its access across practices and practitioners. This resistance may further limit the timeliness, completeness, and accessibility of the records, reducing the perceived usefulness of the technology. As determined by O'Malley et al. (2009), these factors would be necessary for EMRs to have effective coordination of care.

Evidence of the negative impact of sharing information across practices emerged from interviews with providers. When questioned regarding the problems encountered during EHR implementation, many providers discussed their resistance to relying upon shared data, and lack of trust in the information that exists within the system. As one individual states, "... you can't assume that what's there [in the EHR] is always accurate ... I feel like I have to confirm things more [often]." Other individuals' distrust in the data is so absolute, they display severe reluctance to use it, as evidenced by this statement: " ... you

should never just depend on what somebody six months ago wrote in the computer ... you have to confirm it with the patient."

In addition to capturing potential user resistance, the negative effect of SI may be a result of information overload. According to Schultze and Vandenbosch (1998), information overload is the "state in which the volume and speed of incoming stimuli with which an individual has to cope is beyond his or her processing capacity", or more simply stated, as "receiving too much information" [Eppler and Mengis, 2004]. Information overload can counteract potential gains from IT systems' usage [Edmunds and Morris, 2000] and decrease the likeliness to use a system [Farhoomand and Drury, 2002]. Wild, Laumer and Kroenke (2012) find information overload to lead to confusion, stress, tension, and anxiety, which can cause individuals to protect themselves by avoiding further information. In the presence of information overload, MacDonald et al. (2011) similarly find people avoiding certain information channels and ending searches before gathering all relevant information. If this occurs within the adoption of EHR systems, users may find increasing levels of information to decrease the perceived usefulness of the system due to information overload. This could lead users to work around the system, and prevent the beneficial effects of EHR adoption from being achieved.

Data gleaned from our interviews support this finding, as well; many providers appear overwhelmed by the volume and detail of data within the EHR, and have not developed the necessary skills to sort through it in a timely manner. As one provider explains his or her experience, "It's very frustrating as a clinician to data mine ... it's gotten worse because every single practice in [the hospital network] is on [the EHR]." Some providers become so frustrated trying to access the appropriate data that they find methods to work around the system: "I would like to lean on the system some more, but ... it would take me more time than just asking the patient, so I just ask the patient." Others find "it's

harder with the EHR to get that comprehensive, quick look," and they are "wasting time trying to find data." These anecdotes provide some supporting evidence that information overload could be a factor contributing to the negative effect of SI on BI.

In the non-clinical sample, we continue to see the negative relationship between SI and PU, but we find no additional significant pathways influencing either PU or BI for this sub-sample. We believe information overload could be a significant barrier to PU for non-clinical staff as well as clinical staff, and note similar feelings regarding information overload amongst clinical and non-clinical staff from our in-person interviews. The non-clinical staff has been using electronic record-keeping for administrative purposes prior to the implementation of this EHR; therefore, they may be more comfortable with electronic data flow, and may not be affected on a daily basis by the interoperability of clinical data flowing between departments. For these reasons, it is unsurprising that we do not find factors influencing their behavioral intention to use the system. They may have pre-determined adoption patterns from past usage of administrative systems.

3.6 Conclusions and Future Research

We posit that the unique aspects of the healthcare industry need to be included in the TAM when it is applied to health information systems adoption. We include trust and shared information as important factors in the adoption and use of integrated EHRs. Our work extends the literature by providing a contextualized model of the TAM suitable for application in cases of integrated healthcare systems, specifically concerning systems with shared information. Our model provides improved insight into the specific behaviors and attitudes that influence intention and subsequent adoption of HIT. We conduct our analyses using the introduction of a specific EHR system at a large health network in Pennsylvania, so our analyses provide insight into users' actual perceptions during the adoption

process, as opposed to their hypothetical perception of a to-be-adopted technology. Additionally, we test our contextualized and extended TAM in a mandatory environment, further expanding the literature in the mandatory-adoption situation.

We find evidence for the importance of trust on the behavioral intent associated with HIT adoption. Additionally, we find that shared information negatively influences the perceived usefulness of a system. This brings attention to the importance of different influencing factors in situations of shared electronic data, as is the case with this technology adoption scenario. Our results also highlight differences between adoption perceptions of clinical and non-clinical staff in the healthcare environment.

In the future, we are interested in analyzing adoption perceptions over time to determine how they change at different phases of the adoption process. We believe our contextualized model can provide additional insight into influencing behaviors of technological adoption in the healthcare industry. Management can use this information to improve the implementation process and acceptance of HIT.

Table 3.1: Conflicting TAM Findings

Study	Country	Employee Type	Significant Findings	Non-significant Findings
Lowry (2002)	UK	Professional Engineers	PEOU to BI PEOU to PU	PU to BI
Schaik, Bettany-Saltikov and Warren (2002)	UK	Physiotherapists	PU to BI	PEOU to BI
Spitler (1999)	USA	Brokers and Sales Assistants	PEOU to PU	PEOU to BI PU to BI
Benemati and Rajkumar (2002)	USA	Outsourcing Managers	PU to BI PEOU to BI PEOU to PU	

Figure 3.1: Basic TAM

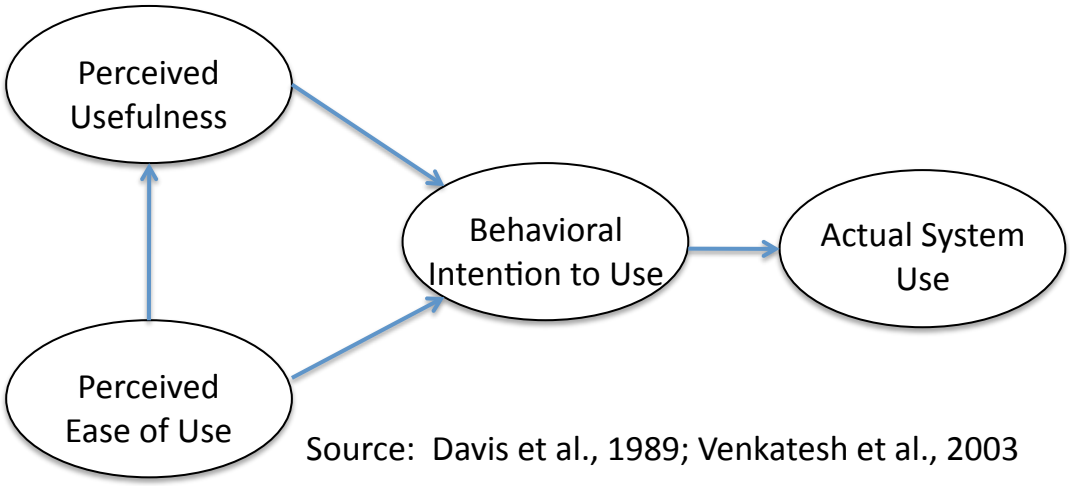


Table 3.2: Survey Questions

Question ID	Question
SI1	The information that I need from visits to triage is complete.
SI2	The information that I need from visits to triage is easily accessible.
SI3	Documentation from visits to triage is incorporated into the office prenatal record.
SI4	Laboratory tests and diagnostic studies performed at triage are recorded in the office prenatal record.
SI5	New diagnoses determined on triage are recorded in the office prenatal problem lists within one week.
T1	I am willing to rely on the information within the EHR system.
T2	I feel comfortable depending on the information within the EHR system if no other source of patient information is available.
T3	If I had my way, I would not permit other providers to update data in patients' records.
T4	If I had my way, I would not permit other providers to add documents to my patients' records.
PU1	Using the EHR system increases my productivity.
PU2	I find the EHR system useful.
PU3	Using the EHR system would improve my job performance.
PU4	Using the EHR system would enhance my effectiveness on the job.
PEOU1	The EHR system is easy to use.
PEOU2	My interaction with the EHR system is clear and understandable.
PEOU3	I find it easy to complete documentation within the EHR system.
PEOU4	I find it easy to find previously documented information in the EHR system.
BI1	In the next year, I intend to use 'Y' as my primary source of historical patient information.
BI2	In the next year, I intend to document more patient information in the EHR system.
BI3	In the next year, I intend to adjust my work practices to better utilize the EHR system.

Table 3.3: Summary Statistics

Variable	Clinical Mean	Std. Dev	Non-Clinical Mean	Std. Dev
Physician	0.321	0.476	0	0
Non-Physician Provider	0.679	0.476	0	0
Non-Physician Staff	0	0	1	0
Location 1	0.571	0.504	0.596	0.496
Location 2	0.357	0.488	0.404	0.496
Age	46.357	10.612	39.872	13.33
Experience	18.089	12.335	13.872	10.533
SI1	3.321	0.983	3.298	0.689
SI2	3.5	1.036	3.34	0.891
SI3	3.393	0.916	3.128	0.824
SI4	3	0.861	2.936	0.791
PEOU1	3.679	0.905	4.106	0.814
PEOU2	3.893	0.832	4.021	0.794
PEOU4	3.5	1.291	3.872	0.947
T1	4.036	0.881	4.404	0.712
T2	4.321	0.548	4.17	0.94
PU1	3.643	1.254	4.021	0.675
PU2	4.107	0.786	4.319	0.594
PU3	3.857	0.97	4.085	0.717
PU4	3.857	1.079	4.149	0.691
BI1	4.179	0.772	4	0.834
BI2	4.107	0.786	3.894	0.84
BI3	4.036	0.838	3.894	0.84
Observations	28		47	

Table 3.4: Factor Loadings

Question ID	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
PU 1	0.8256				
PU 2	0.8241				
PU 3	0.8829				
PU 4	0.8791				
SI 1		0.8249			
SI 2		0.8938			
SI 3		0.9207			
SI 4		0.7186			
PEOU 1			0.8619		
PEOU 2			0.7825		
PEOU 4			0.6925		
BI 1				0.633	
BI 2				0.8801	
BI 3				0.8887	
T 1					0.6183
T 2					0.9128

Figure 3.2: Proposed Model

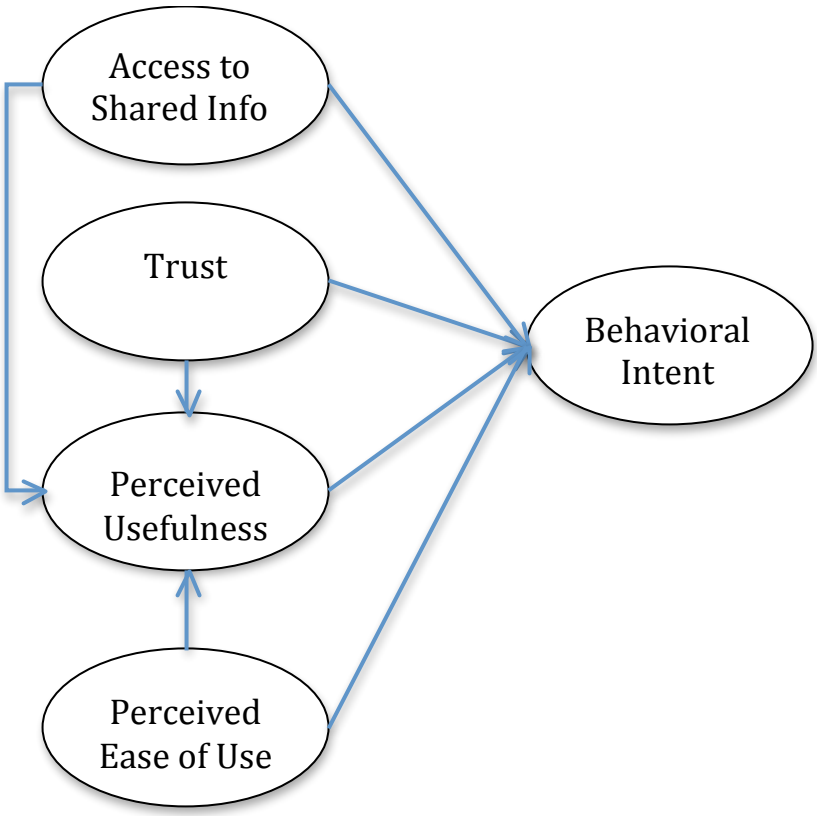


Figure 3.3: Clinical Path Regression Results

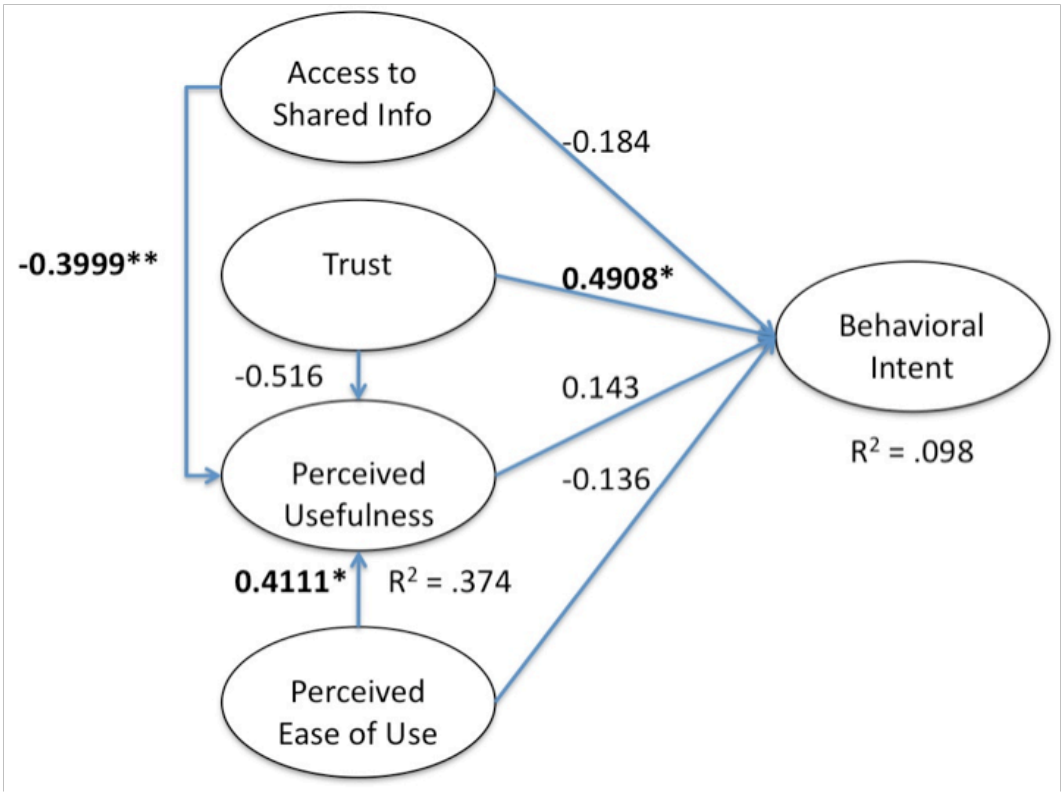
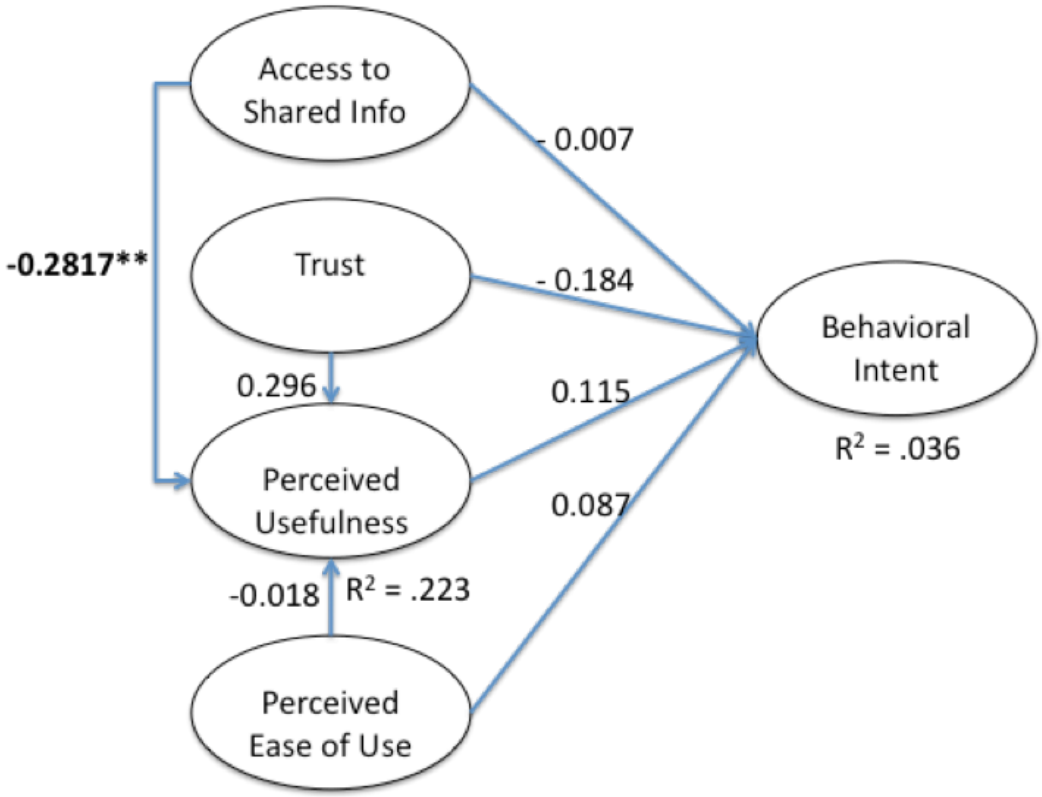


Figure 3.4: Non-clinical Path Regression Results



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Appendix A

LPM Regression Estimates for 30-day Scripts

Table A.1: LPM Regression Estimates for Prozac 30-day Scripts

	Switch Within One Month		
	Comp. and PPO	HMO and POS	All Plans
OOP CD	0.02	0.0578**	0.037**
	[0.019]	[0.022]	[0.018]
TPP CD	-0.047***	-0.035***	-0.037***
	[0.008]	[0.010]	[0.008]
AWP Prozac	0.001***	0.043***	0.002**
	[0.000]	[0.009]	[0.001]
Age Between 18-34	0.069***	0.044**	0.060***
	[0.018]	[0.019]	[0.015]
Age Between 35-44	0.056***	0.051**	0.057***
	[0.015]	[0.021]	[0.013]
Age Between 45-54	0.052***	0.056**	0.056***
	[0.017]	[0.023]	[0.014]
Age Over 55	0.058***	0.054**	0.059***
	[0.015]	[0.022]	[0.014]
Male	0.002	0.012**	0.006
	[0.008]	[0.005]	[0.006]
MSA Population (100,000s)	0.000*	0.000	0.000*
	[0.000]	[0.000]	[0.000]
Employer Enrollment	0.002***	-0.002*	0.002***
	[0.000]	[0.001]	[0.000]
MSA Per Capita Income (1000s)	-0.003	-0.003	-0.003**
	[0.002]	[0.002]	[0.001]
No MSA Indicator	-0.063*	-0.061	-0.062**
	[0.032]	[0.038]	[0.024]
Northeast	-0.025	-0.040***	-0.032***
	[0.021]	[0.013]	[0.011]
North Central	-0.015	0.002	-0.012
	[0.019]	[0.011]	[0.010]
South	0.000	-0.018	-0.012
	[0.013]	[0.011]	[0.008]
Union	0.006	0.002	0.007
	[0.009]	[0.011]	[0.007]
Union Status Unknown	-0.032	-0.010	-0.005
	[0.026]	[0.010]	[0.009]

Table A.1: LPM Regression Estimates for Prozac 30-day Scripts (continued)

	Switch Within One Month		
	Comp. and PPO	HMO and POS	All Plans
Active Full Time	0.008	-0.005	0.003
	[0.014]	[0.019]	[0.012]
Active Part Time or Seasonal	-0.082***	0.021	0.007
	[0.024]	[0.022]	[0.018]
Retiree	-0.012	-0.003	-0.006
	[0.022]	[0.025]	[0.016]
Manufacturing, Durable Goods	0.097**	-0.062***	-0.039**
	[0.036]	[0.015]	[0.018]
Manufacturing, Nondurable Goods	0.095***	-0.057***	-0.031
	[0.031]	[0.018]	[0.025]
Transportation, Communication, Utilities	-0.075*	-0.008	-0.048
	[0.042]	[0.011]	[0.032]
Other Industry	0.072**	-0.044***	-0.030**
	[0.033]	[0.009]	[0.015]
New Prescription	0.241***	0.239***	0.241***
	[0.014]	[0.061]	[0.025]
Physician DAW	-0.304***	-0.289***	-0.292***
	[0.039]	[0.029]	[0.022]
Patient DAW	-0.269***	-0.287***	-0.273***
	[0.023]	[0.025]	[0.016]
Mail Order	0.053***	-0.074**	0.022
	[0.017]	[0.032]	[0.019]
Mail Order Status Unknown	-0.006	-0.043	-0.020
	[0.023]	[0.046]	[0.019]
Mandatory Generic Substitution	0.015	0.021*	0.014*
	[0.015]	[0.011]	[0.008]
Comprehensive	0.035**		0.021*
	[0.013]		[0.011]
HMO		0.021*	0.011
		[0.012]	[0.009]
POS		-0.044**	0.017*
		[0.020]	[0.009]
Pos w/ Capitation		0.009	
		[0.011]	

Table A.2: LPM Regression Estimates for Zocor 30-day Scripts

	Switch Within One Month		
	Comp. and PPO	HMO and POS	All Plans
OOP CD	0.001	0.000	0.002**
	[0.001]	[0.001]	[0.001]
TPP CD	0.001	0.001	0.002
	[0.001]	[0.002]	[0.001]
AWP Zocor	0.004**	0.000	0.000
	[0.002]	[0.000]	[0.000]
Age Between 18-34	-0.017	0.076***	0.043
	[0.067]	[0.025]	[0.031]
Age Between 35-44	-0.003	0.087***	0.055*
	[0.066]	[0.029]	[0.031]
Age Between 45-54	-0.010	0.085***	0.051
	[0.064]	[0.030]	[0.031]
Age Over 55	-0.015	0.087***	0.049
	[0.066]	[0.030]	[0.032]
Male	-0.001	0.000	-0.000
	[0.002]	[0.003]	[0.002]
MSA Population (100,000s)	0.000	0.000	-0.000**
	[0.000]	[0.000]	[0.000]
Employer Enrollment	0.000***	-0.002*	-0.000
	[0.000]	[0.001]	[0.000]
MSA Per Capita Income (1000s)	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]
No MSA Indicator	-0.024**	-0.029	-0.034***
	[0.013]	[0.020]	[0.009]
Northeast	0.007	0.005	0.008
	[0.010]	[0.013]	[0.008]
North Central	0.012	0.010	0.012*
	[0.007]	[0.013]	[0.006]
South	0.012*	0.012	0.012**
	[0.006]	[0.012]	[0.006]
Urban	-0.017**	-0.016	-0.023***
	[0.008]	[0.017]	[0.007]
Union	-0.005	-0.011*	-0.006
	[0.005]	[0.006]	[0.004]

Table A.2: LPM Regression Estimates for Zocor 30-day Scripts (continued)

	Switch Within One Month		
	Comp. and PPO	HMO and POS	All Plans
Active Full Time	-0.002	0.003	0.000
	[0.006]	[0.003]	[0.003]
Active Part Time or Seasonal	0.009	0.014	0.009
	[0.023]	[0.013]	[0.011]
Retiree	0.001	0.009	0.006
	[0.007]	[0.006]	[0.004]
Manufacturing, Durable Goods	-0.055	-0.023	-0.014
	[0.039]	[0.073]	[0.024]
Manufacturing, Nondurable Goods	-0.030***	0.123	-0.025
	[0.008]	[0.088]	[0.018]
Transportation, Communication, Utilities	-0.059	-0.020	-0.008
	[0.038]	[0.065]	[0.023]
Other Industry	0.002	-0.032	-0.004
	[0.021]	[0.064]	[0.019]
New Prescription	0.047***	0.048***	0.047***
	[0.003]	[0.005]	[0.003]
Physician DAW	-0.045***	-0.024	-0.038**
	[0.010]	[0.025]	[0.015]
Patient DAW	-0.035***	-0.002	-0.018
	[0.008]	[0.025]	[0.020]
Mail Order	-0.017	-0.054***	-0.029**
	[0.018]	[0.020]	[0.014]
Mail Order Status Unknown	-0.031**	0.007	-0.011
	[0.013]	[0.013]	[0.008]
Mandatory Generic Substitution	-0.002	-0.006	-0.004
	[0.005]	[0.007]	[0.004]
Comprehensive	-0.006		-0.011*
	[0.007]		[0.006]
HMO		0.041***	-0.012*
		[0.014]	[0.007]
POS		0.050***	-0.001
		[0.015]	[0.006]
POS w/ Capitation		-0.027**	
		[0.010]	

Table A.3: LPM Regression Estimates for Neurontin 30-day Scripts

	Switch Within One Month		
	Comp. and PPO	HMO and POS	All Plans
OOP CD	0.002	-0.005	0.000
	[0.005]	[0.007]	[0.004]
TPP CD	-0.004**	-0.009***	-0.006***
	[0.001]	[0.002]	[0.002]
AWP Prozac	-0.022***	-0.019***	-0.021***
	[0.003]	[0.003]	[0.002]
Age Between 18-34	0.079***	-0.016	0.039**
	[0.017]	[0.033]	[0.018]
Age Between 35-44	0.077***	-0.001	0.043**
	[0.019]	[0.032]	[0.018]
Age Between 45-54	0.082***	-0.008	0.044**
	[0.018]	[0.028]	[0.017]
Age Over 55	0.078***	-0.020	0.038**
	[0.018]	[0.028]	[0.017]
Male	0.007*	0.003	0.006*
	[0.004]	[0.006]	[0.003]
MSA Population (100,000s)	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Employer Enrollment	0.000***	-0.002	0.000
	[0.000]	[0.002]	[0.000]
MSA Per Capita Income (1000s)	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
No MSA Indicator	-0.008*	-0.004	-0.006
	[0.005]	[0.012]	[0.004]
Northeast	-0.014	-0.034	-0.015
	[0.011]	[0.033]	[0.011]
North Central	0.008	-0.000	0.005
	[0.009]	[0.027]	[0.008]
South	0.007	-0.010	0.005
	[0.009]	[0.030]	[0.008]
Union	-0.006	0.016	0.000
	[0.010]	[0.017]	[0.009]
Union Status Unknown	0.056**	-0.044	0.004
	[0.028]	[0.041]	[0.027]

Table A.3: LPM Regression Estimates for Neurontin 30-day Scripts (continued)

	Switch Within One Month		
	Comp. and PPO	HMO and POS	All Plans
Active Full Time	0.008	-0.0008	0.005
	[0.005]	[0.005]	[0.004]
Active Part Time or Seasonal	0.002	-0.054***	-0.038**
	[0.052]	[0.016]	[0.018]
Retiree	0.015*	-0.011	0.006
	[0.008]	[0.007]	[0.006]
Manufacturing, Durable Goods	-0.120*	-0.276***	-0.265***
	[0.072]	[0.096]	[0.094]
Manufacturing, Nondurable Goods	0.108	-0.249**	-0.133
	[0.285]	[0.096]	[0.142]
Transportation, Communication, Utilities	-0.107	-0.303***	-0.273***
	[0.070]	[0.099]	[0.099]
Other Industry	-0.249***	-0.234**	-0.244***
	[0.014]	[0.093]	[0.084]
New Prescription	0.049***	0.054***	0.051***
	[0.006]	[0.008]	[0.005]
Physician DAW	-0.124***	-0.142***	-0.130***
	[0.012]	[0.013]	[0.009]
Patient DAW	-0.137***	-0.156***	-0.142***
	[0.012]	[0.010]	[0.009]
Mail Order	0.043**	0.037	0.045***
	[0.018]	[0.027]	[0.015]
Mail Order Status Unknown	-0.023	0.045*	0.039
	[0.034]	[0.023]	[0.023]
Mandatory Generic Substitution	0.003	0.006	0.001
	[0.006]	[0.012]	[0.006]
Comprehensive	0.027***		0.028***
	[0.007]		[0.008]
HMO		0.004	0.032**
		[0.031]	[0.014]
POS		-0.009	0.009
		[0.032]	[0.010]
POS w/ Capitation		0.035*	
		[0.019]	

Appendix B

History of the Technology Acceptance Model

The TAM is based on two theories from social psychology: the Theory of Reasoned Action (TRA) [Ajzen and Fishbein, 1980] and the Theory of Planned Behavior (TPB) [Ajzen, 1991]. The TRA states that a person's behavior is dependent on her attitude and social norms. It further claims that a person's intention to engage in a particular behavior is a likely predictor of actual future behavior. Ajzen (1991) introduced the TPB as an extension to the TRA in order to analyze behaviors in non-volitional contexts. Ajzen added the component 'perceived behavioral control' to the TRA in order to create a more robust model and account for those situations where intention does not fully predict action. The TPB predicts behavioral intention to be a construct of attitude, social norms, and perceived behavioral control [Ajzen, 1991]. The TRA and TPB provide a theoretical foundation for the TAM.

In 1989, Davis developed the TAM, which provides a theoretical foundation for how users accept and use technology. Davis highlights the two main pathways of perceived

usefulness (PU) and perceived ease of use (PEOU) as those influencing the behavioral intent (BI) to use a new technology. Davis (1989) defines PU as "the degree to which a person believes that using a particular system would enhance his or her job performance," and PEOU as "the degree to which a person believes that using a particular system would be free from effort." The application of the TAM spread to a variety of settings over its history, and during that time two major extensions were introduced: TAM2 and the Unified Theory of Acceptance and Use of Technology (UTAUT). Each of these extensions focus on identifying the influencing factors of PEOU and PU.

Venkatesh and Davis (2000) identify five additional factors influencing PU in the TAM2 model. These factors are subjective norm, image, job relevance, output quality, and result demonstrability. Further, they identify two additional factors of voluntariness and experience as potential influencing pathways on BI. They find that this model explains up to 60%of the variance in PU, but do not offer any suggestions regarding external factors influencing PEOU. Venkatesh and Davis (2000) apply this model to four different industries and find relatively consistent results.

The UTAUT model incorporates ideas from TRA, TPB, TAM, and TAM2, among other theories in psychology and sociology, to identify the influencing factors on actual usage. In this model, three constructs influence BI: performance expectancy, effort expectancy, and social influence. Facilitating conditions influence actual usage directly, and the UTAUT model hypothesizes that gender, age, experience, and voluntariness of use have moderating effects on all other variables in the model. Venkatesh et al. (2003) compare the performance of UTAUT to TAM, TAM2, and other behavioral models, and determine that the UTAUT performs exceedingly well and identifies up to 70% of the variance in BI. However, there are some limitations in the study preventing the generalization of their findings; Venkatesh et al. (2003) do not consider collaborative systems or e-commerce

systems, nor does their analysis include implementation in the healthcare sector. Because UTAUT is based on the TAM and other behavioral models, which do vary in consistency across industries, we cannot expect the same performance of UTAUT in healthcare without empirical support.

Appendix C

Curriculum Vitae

Curriculum Vitae

Sabrina Ann Terrizzi

Contact Information

Department of Economics and Business, Moravian College
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Professional Profile

College professor with teaching and research experience in the fields of economics and information systems. Teaching experience includes: Principles of Economics; Money, Banking, and Financial Markets; Health Economics; Labor Economics; Statistical Methods; and Accounting Information Systems. Research experience includes applied microeconomic analysis of: healthcare system implementations; the quantity-quality tradeoff of family size; and prescription drug usage, costs, and benefits. Leverages past industry experience as an Information and Systems Engineer, and current research interests as an Applied Economist, to provide an enhanced learning environment to students.

Education

2008–2013	Ph.D., Economics, Lehigh University Fields: Health Economics and Management Information Systems Dissertation: *Essays in Health Economics and Health Information Systems* Advisor & Committee Chair: Chad Meyerhoefer Committee Members: Mary E. Deily, James Dearden, Susan Sherer
2004–2005	M.S., Information and Systems Engineering, Lehigh University Thesis: *A Comparison of Inventory Systems in the Face of Obsolescence* Advisor: Larry Snyder
2000–2004	B.S., Integrated Business and Engineering, Lehigh University Major: Information and Systems Engineering Minor: Spanish

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Awards And Honors

2011	Teacher Development Program Completion, Lehigh University
2008–2011	Teaching Assistantship, Lehigh University
2010	Warren-York Fellowship, Lehigh University

2010	Research Assistantship, Lehigh University
2004–2005	Presidential Scholarship, Lehigh University
2003–2004	Phi Eta Sigma Scholar
2001–2004	National Society of Collegiate Scholars
2000–2004	Dean's Scholarship, Lehigh University

Skills

Computer Skills:	Stata, gretl, OxMetrics, Maple, LaTeX, SAP SD, SAP MM, SAP WM, Microsoft Office Suite, NVIVO
Web Courseware:	Elluminate, Blackboard, Moodle, eCollege, Angel
Operating Systems:	Windows, Mac OS X, Linux, Solaris

Teaching Experience

2012–Present Instructor, Moravian College, Economics and Business Department

Principles of Economics	Fall 2012, Spring 2013
The Economics of Health and Healthcare	Spring 2013
Labor Economics	Fall 2012

2012 Adjunct Professor, Lafayette College, Economics and Business Department

Money, Financial Intermediation, and the Economy	Spring 2012
Industrial Organization	Spring 2012

2011–2012 Adjunct Professor, Moravian College, Economics and Business Department

Principles of Economics	Fall 2011, Spring 2012
Economics of Health and Health Care	Fall 2011
Industrial Organization	Spring 2012

2011 Adjunct Professor, Cedar Crest College, Business and Management Department

Accounting Information Systems	Fall 2011

2011–2012 Adjunct Professor, DeSales University, ACCESS Department

Money and Banking	Summer 2012 (8 week accelerated class)
Business Computer Applications	Fall 2011 (8 week accelerated class)

2010–2012 Instructor, Lehigh University, College of Business and Economics

Money and Banking	Traditional Classroom	Summer 2012
Principles of Economics	Online Course	Summer 2011
Accounting Information Systems	Lehigh in Prague	Summer 2010

2008–2011 Teaching Assistant, Lehigh University, College of Business and Economics

Money, Banking, and Financial Markets	Spring 2011
Statistical Methods	Summer 2010
Accounting Information Systems	Lehigh in Prague, Summer 2009
Principles of Economics	Fall 2008, Spring 2009, Fall 2009

Work Experience

2012–Present Executive Board Member
Lehigh Valley Research Consortium
Moravian College representative to the Lehigh Valley Research Consortium. As the co-chair of the Community Based Information System, manages and coordinates updates to the on-line community-based research database. Co-author of the Economics section of the annual State of the Lehigh Valley Report.

2009–2010 Independent Contractor
Cengage Learning Inc., South-Western Publishing
Reviewed and corrected the solution manual for *Accounting Information Systems, 7e, 2010* by James A. Hall. Created the solution manual for *IT Auditing, 3e, 2011* by James A. Hall.

2009–2010 Research Assistant
Lehigh University, Department of Economics
Engaged in three separate research projects in the area of applied microeconomics, specifically analyzing the quantity-quality tradeoff within families, health information technology spillovers, and the implementation of health information technology applications. Conducted quantitative data analysis across large databases, including the Taiwan census data from 1980-2000, the American Hospital Association (AHA), the Healthcare Information Management System Society (HiMSS), and the Pennsylvania HealthCare Cost Containment Council (PHC4) databases. Completed qualitative data analysis using interview data

from the Lehigh Valley Hospital. Worked with faculty members in Economics, Finance, and Management to complete research, and drew upon experience as a software implementation consultant to conduct qualitative analysis on the implementation of health information technology applications. Research resulted in two working papers that are currently in the journal article submission phase.

2005–2008 Senior Consultant
IBM, Global Business Services
Developed Enterprise Resource Package (ERP) solutions, specializing in the implementation of SAP Enterprise Applications in a variety of industries, including: consumer package goods (CPG), packaging, and metals. Designed and supported solutions for order management, logistics execution, inventory management, warehouse management, and electronic commerce. Daily tasks included working with clients to understand requirements and subsequently managing requirements within the constraints of the software. While working for a tier one automotive supplier, developed enhancements to the picking and put-away processes in the lean warehouse management system environment. Implemented a system-guided search strategy to meet the put-away requirements set forth by the client. In a different role at a global consumer and commercial products company, designed, tested, and implemented four electronic commerce documents related to the transportation of goods from the client to its customers. In a third role at a packaging and consumer products company, designed and implemented rebate functionality that was far more complex than the standards offered by SAP.

2003–2005 Assistant Project Coordinator
Pacific Institutes of Research, Story Read-Aloud Program
Aided in the implementation of a pilot reading comprehension curriculum in first-grade classrooms across Pennsylvania. Daily tasks included coordinating training, assessment, scheduling, and material distribution to students, teachers, and employees. Assisted the full-time researcher, who was pursuing a PhD in Special Education, by organizing and maintaining the data related to all students' test results.

2002–2003 Worldwide Integrations and Strategic Planning Co-op
Johnson and Johnson, Inc., Ethicon
Worked on a project team implementing new machinery in plants across the United States and its territories. During this process, monitored raw material requirements in plants, and reported updated material requirements to the procurement department and vendors. Designed project impact reports required by the marketing department. During critical financial review periods, analyzed different production scenarios in order to determine the most beneficial options for the project. Prepared and finalized financial data necessary for the Phase I project audit and the Phase II project appropriation.

Publications

Journal Articles, Peer-Reviewed:

1. Mary E. Deily, Tianyan Hu, Sabrina Terrizzi, Shin-Yi Chou, and Chad D. Meyerhoefer, "The

Impact of Health Information Technology Adoption by Outpatient Facilities on Pregnancy Outcomes", *Health Services Research*, 48(1), 2013.

2. Sabrina Terrizzi, Susan Sherer, Chad D. Meyerheofer, Michael Scheinber, and Donald Levick, "Extending the Technology Acceptance Model in Healthcare: Identifying the Role of Trust and Shared Information", *18th Americas Conference on Information Systems Seattle, Washington August 9 -11, 2012*.

Works in Progress

1. "The Effect of Sorority Membership on Disordered Eating and Body Mass Index" with Susan Averett and Yang Wang
2. "Estimating the Price Elasticity of Switching from Branded to Generic Drugs" with Chad Meyerhoefer
3. "Do Generic Substitution Laws Matter? Identifying the Effect of the Tennessee Affordable Drug Act of 2005" with Chad Meyerhoefer
4. "New Evidence on the Sibship Size and Children's Educational Attainment" with Shin-Yi Chou and Hsien-Ming Lien

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Professional Presentations

Organized Conferences

Southern Economic Association Annual Meeting: "The Effect of Sorority Membership on Disordered Eating and Body Mass Index" New Orleans, Louisiana, November 2012.

Americas Conference on Information Systems Annual Meeting: "Extending the Technology Acceptance Model in Healthcare: Identifying the Role of Trust and Shared Information" Seattle, Washington, August 2012.

American Society of Health Economists Annual Meeting: "Estimating the Price Elasticity of Switching from Branded to Generic Drugs" Minneapolis, Minnesota, June 2012.

Eastern Economic Association Annual Meeting, Committee on the Status of Women in the Economics Profession (CSWEP) Session: "Do Generic Substitution Laws Matter? Identifying the Effect of the Tennessee Affordable Drug Act of 2005" Boston, Massachusetts, March 2012.

Eastern Economic Association Annual Meeting: "Estimating the Price Elasticity of Switching from Branded to Generic Drugs" New York City, New York, February 2011.

Eastern Economic Association Annual Meeting: "Spillovers and the Impact of Health Information Technology: Evidence from Pregnancy Outcomes in Pennsylvania" New York City, New York, February 2011.

Eastern Economic Association Annual Meeting: "New Evidence on the Sibship Size and Children's Educational Attainment" Philadelphia, Pennsylvania, February 2010.

Invited Presentations

Lecture at Lafayette College (Department of Economics): "Estimating the Price Elasticity of Switching from Branded to Generic Drugs", December 2011.

Lecture at Lehigh University (Department of Economics): "Estimating the Price Elasticity of Switching from Branded to Generic Drugs", April 2011.

Lecture at Lehigh University (Department of Economics): "Spillovers and the Impact of Health Information Technology: Evidence from Pregnancy Outcomes in Pennsylvania", December 2010.

Lecture at Lehigh University (Department of Industrial and Systems Engineering): "Information Systems and Technology in Healthcare", October 2010.

Service Activities

Peer-Reviewing Activity: Professional Journal

Journal of Health Economics

Americas Conference on Information Systems

Peer-Reviewing Activity: Discussant

Southern Economic Association Annual Meeting. November 2012

Eastern Economic Association Annual Meeting. March 2012

Eastern Economic Association Annual Meeting. February 2011

Teaching Advancement Activities

Book Club Participant: Center for Advancement of Teaching, Moravian College. 2012, 2013

College Service Activities

Executive Board Member, Lehigh Valley Research Consortium

Co-Chair, Community Based Information Systems Database, Lehigh Valley Research Consortium

Co-Advisor, Economics and Business Club, Moravian College

Professional Societies and Affiliations

Eastern Economic Association

Southern Economic Association

American Society of Health Economists

Association for Information Systems