Three Essays in Health Economics

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Dedication

오늘이 있기까지 힘이 되어준 사랑하는 엄마 아빠 동생 우진이에게 감사합니다

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Chapter 1

Introduction

The United States health care system faces difficult challenges regarding access, cost, and quality of health care. This dissertation consists of three essays addressing different topics in health economics aimed to meet some of these challenges.

The first essay investigates the impact of the great recession on hospital capital investment and how hospitals respond to offset the recession effect. Hospital capital investment is important for acquiring and maintaining technology and equipment needed to provide health care. Hospital cutbacks in capital investment may have negative implications for patient outcomes. Most hospitals rely on debt and internal cash flow to fund capital investment. The great recession may have made it difficult for hospitals to borrow thus reducing capital investments. Using the Euler equation with a liquidity constraint to model hospital capital investment is a novel contribution to the literature. I estimate the model with California hospital data and system generalized method of moments. Estimates were decomposed to show the recession effect in terms of investment dollars. Comparing the changes in hospital capital investment between 2006 and 2009 showed that hospitals used cash flow to increase capital investment by $2.5 million other things equal.

The second essay investigates the incremental cost effectiveness of a telecare management intervention for managing pain and depression among patients with cancer. Pain and depression are often undetected and undertreated among patients with cancer. Telecare management has been shown to be effective for managing pain and depression among patients with cancer. Outcomes and cost data from the Indiana Cancer Pain and Depression trial was analyzed to the determine the cost effectiveness of the telecare management intervention. The intervention group was associated with more depression-free days and better quality-adjusted life years than the usual care group.

The third essay investigates how out-of-pocket health care spending trends changed before and during the recession. The great recession slowed the growth of health care spending and its impact may have been different for adults and children. Reduction in children's health care spending for may hinder children's access to routine care which could have adverse implications in the long run. Children with special health care needs are particularly vulnerable to adverse outcomes from inadequate care. Out-of-pocket spending trends of privately insured families with children was examined using the Medical Expenditure Panel Survey data from 2001 to 2009. Out-of-pocket spending for most children was not affected by the recession. But out-of-pocket spending for children with special needs decreased during the recession. Also out-of-pocket spending decreased for adult family members during the recession.

My dissertation contributes to the health economics literature by conducting empirical analysis of the challenges faced by the health care system to guide policy making. Furthermore, my dissertation is interdisciplinary, drawing from the disciplines of economics, finance, health services research, and policy. The results from my dissertation is novel and relevant to each discipline.

Chapter 2

The Great Recession and Hospital Capital Investment

2.1 Introduction

Capital investments include purchases for plant, property, and equipment needed for hospital operations. Hospital capital investment is important for acquiring and maintaining technology and equipment necessary to address patient needs, such as beds, magnetic resonance imaging, and rooms. Cutbacks in capital investment for hospital operations may have negative implications for patient outcomes.

The great recession in the United States began in December 2007 and ended in June 2009 (National Bureau of Economic Research, 2010). The financial crisis made it very difficult for hospitals to borrow money (American Hospital Association, 2010). Not-for-profit hospitals, which comprise about 58% of US community hospitals (American Hospital Association, 2013), rely on debt in the form of bonds and bank loans as the main source of capital to fund capital investments. Investor owned hospitals (21% of US community hospitals) have more flexibility in financing capital investments. In addition to debt they can raise equity by selling stocks. In

2008, nearly half of all non-federal hospitals had put capital projects, including facilities, clinical technology, and information technology, on hold or stopped projects in progress (American Hospital Association, 2009). Also the great recession deteriorated the value of marketable securities held by hospitals. Hospital endowment loss due to recession led to delayed purchase of health IT and cuts to unprofitable services (Dranove et al., 2013).

Policy changes in response to the recession aimed to increase government funding to hospitals. The American Recovery and Reinvestment Act of 2009 (ARRA), which temporarily increased the federal portion of Medicaid payments, was in effect from October 2008 to December 2010, then extended through June 2011. National Health Expenditure Accounts showed that federal Medicaid spending increased 22.0% and state spending decreased 9.8% in 2009 (Martin et al., 2011). Increased federal Medicaid payments allowed states to avoid cuts in Medicaid benefits or provider reimbursement rates (Cassidy, 2010).

The ARRA also enacted the Health Information Technology for Economic and Clinical Health (HITECH) Act. The HITECH Act provided $25.9 billion to promote the adoption and meaningful use of health information technology (PL 111-5, 2009).

Despite federal efforts to improve funding to hospitals, the great recession was detrimental to hospital capital investment. National estimates based on the Truven database showed an increasing trend for mean construction-in-progress between 2005 and 2007, then a flat trend between 2007 and 2009 at about $15 million (Koepke, 2012). Cuts to capital investment were reflected in aging facilities. The average age of plants was about 9.5 years between 2005 and 2008, then it increased to 10.5 years between 2009 and 2011 (Koepke, 2012).

California hospital financial data suggests that the great recession was detrimental to hospital capital investment. California's state GDP declined from 2007 to 2009 (fig. 2.1). Hospital capital investment normalized by capital decreased from 2008 to 2010, reversing the increasing trend from 2003 to 2008 (fig. 2.2). Hospital capital investment remained relatively flat from 2008 to 2010 (fig. 2.3). Hospital capital stock decreased from 2007 to 2008 then increased from 2008 to 2010 (fig. 2.4). The number of hospitals commencing building projects that cost $1 million or more declined from 2007 to 2009 (fig. 2.5). Similarly, the number of hospitals purchasing equipment that cost $500 thousand or more declined from 2007 to 2009 (fig. 2.6).

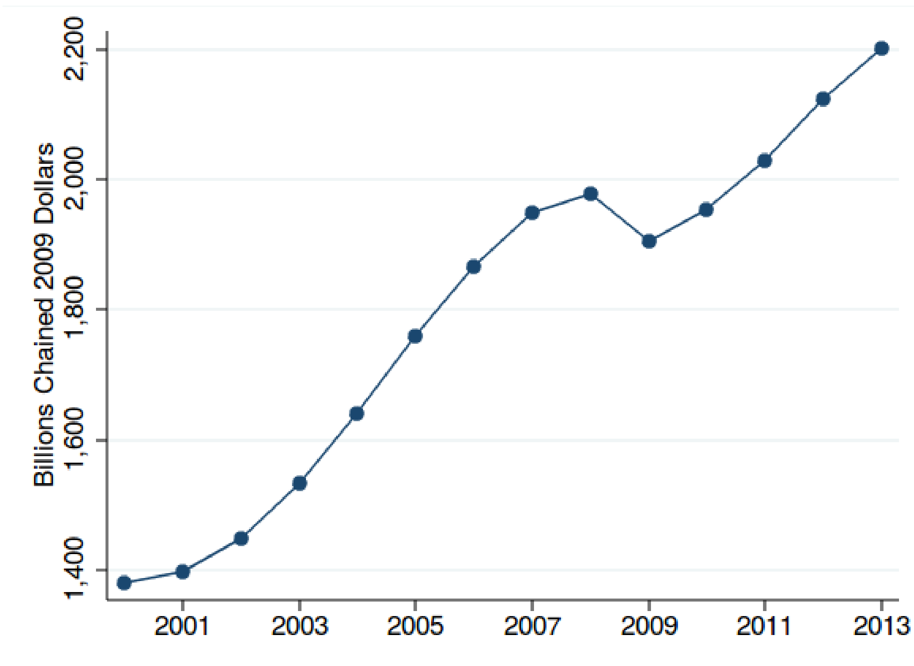

Figure 2.1: California GDP All Industry

Source: Bureau of Economic Analysis

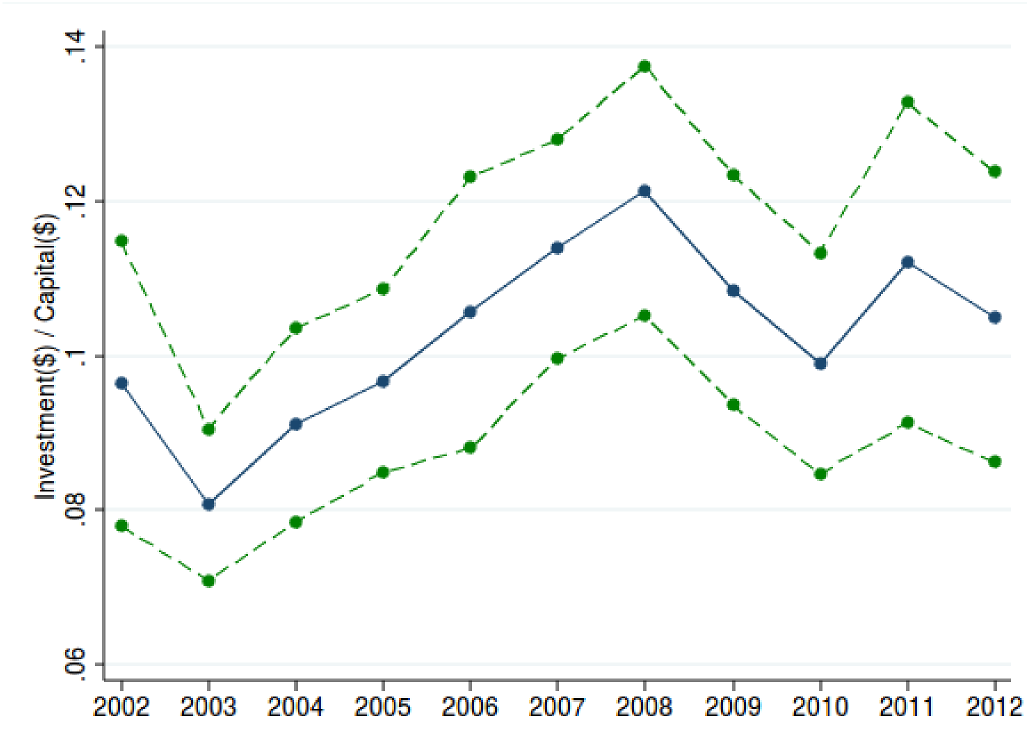

Figure 2.2: Mean Capital Investment per Dollar of Capital with 95% C.I.

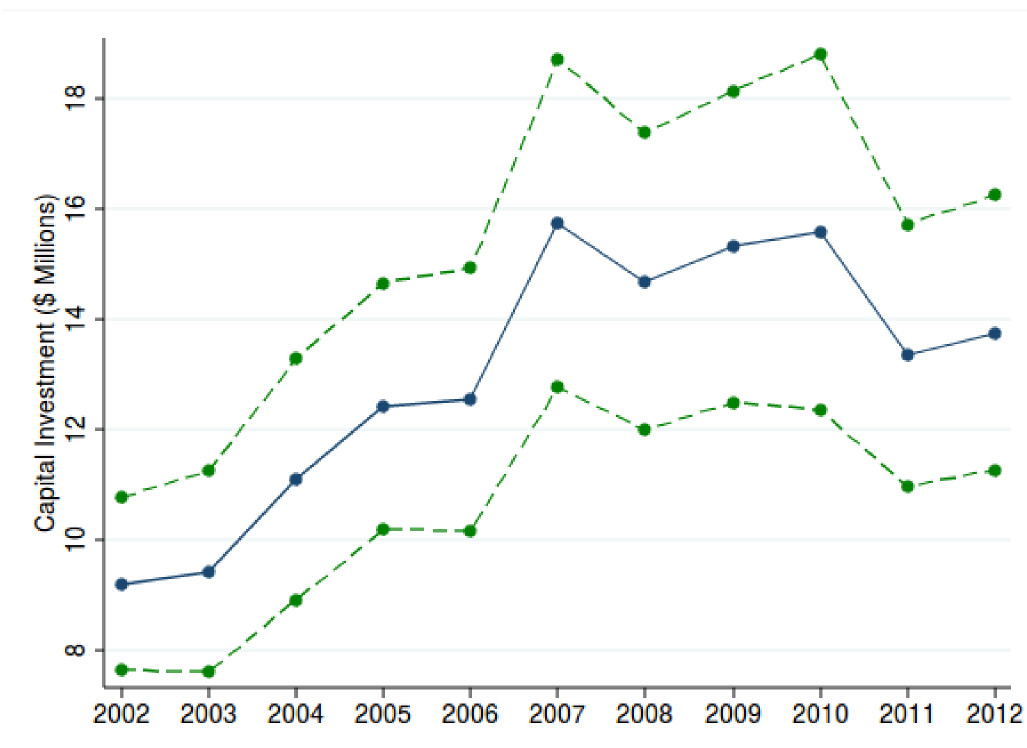

Figure 2.3: Mean Capital Investment with 95% C.I.

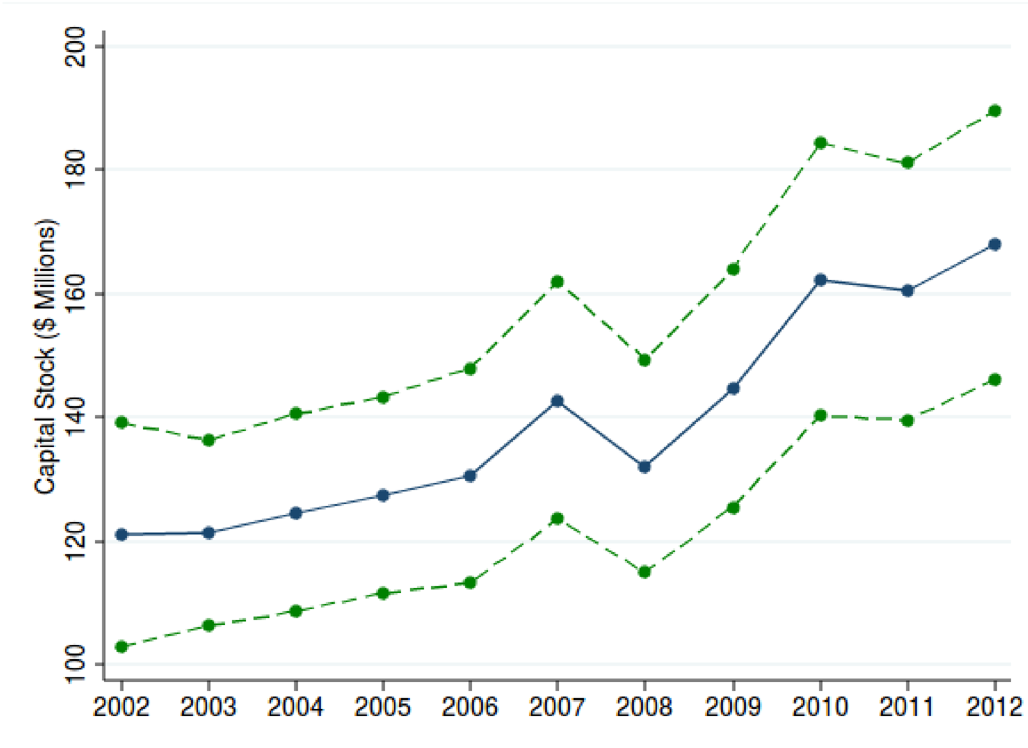

Figure 2.4: Mean Capital Stock with 95% C.I.

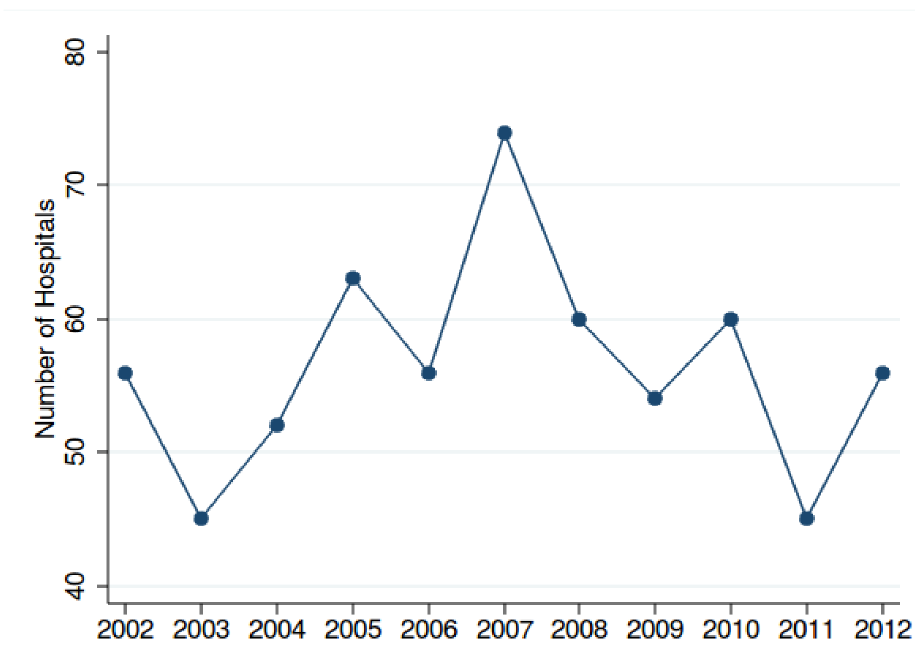

Figure 2.5: Commenced any building projects +$1 million?

Source: OSHPD 28th Year (2002-2003) to 38th Year (2012-2013)

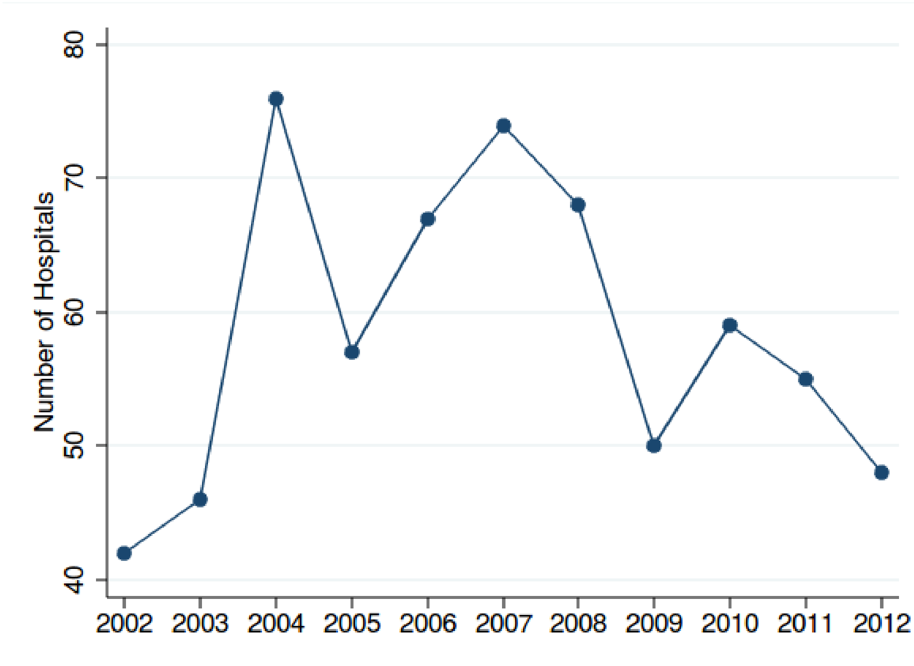

Figure 2.6: Purchased any equipment that cost +$500 thousand?

Source: OSHPD 28th Year (2002-2003) to 38th Year (2012-2013)

The theoretical mechanism through which the recession affected hospital capital investment has not been investigated in the health economics literature. The seminal Modigliani and Miller (1958) theorem showed that in a perfect capital market, the value of the firm is independent of its capital structure. Capital structure is how much of the firm's capital is composed of debt verses equity. In such a case, the value of the firm only depends on the present value of the expected profits from its assets. Therefore, the firm is indifferent between using debt or equity to finance investment. Furthermore, in a perfect capital market the cost of debt and the opportunity cost of internal cash are equal; this makes them perfect substitutes and makes the firm's decision to invest independent of its ability to generate cash flow (Jorgenson, 1963; Hall and Jorgenson, 1967; Jorgenson and Siebert, 1968). A perfectly functioning capital market would allow a firm with low current cash flow, such as a startup company, to invest by raising equity and debt capital if the firm is expected to generate high future profits.

Departing from the perfect capital market model, literature on capital market imperfections has explored how information problems in the capital market constrain firms' ability to borrow and subsequently affect their investment decisions (Fazzari and Athey, 1987; Fazzari et al., 1988; Hoshi et al., 1991; Whited, 1992). Investment models with liquidity constraint hypothesize that when lenders have less information than the firm regarding the firm's financial performance, the firm's cost of borrowing may be drastically higher than the opportunity cost of internal cost. The high cost of borrowing puts a liquidity constraint on the firm. If the firm is liquidity constrained, then investment should be related to the firm's cash flow because the firm must rely more on internal cash to fund investments. These studies have empirically tested the hypothesis on manufacturing firms and their results have been supportive.

The recession may have contributed to the information asymmetry between hospitals and lenders because lenders expected demand for hospital services to fall like the rest of the economy, whereas demand for hospital services may actually have been less affected. The Medicare population is not be affected by the weakened labor market and the loss of private insurance might have been partially offset by the implementation of the Affordable Care Act (ACA) Medicaid expansion.

Information problem during the recession may have discouraged capital investments because lenders limited how much hospitals could borrow, placing a liquidity constraint on hospitals. When unable to borrow debt due to liquidity constraint, hospitals may respond by using their own cash flow to fund investments. This paper aims to address the gap in the literature by modeling hospital capital investment decision under liquidity constraint.

Understanding the impact of the recession on hospital capital investment will help administrators financially prepare to smooth out their investment. If the effect of the recession on capital investment is driven by liquidity constraint, policy changes that mitigate the information asymmetry problem between hospitals and lenders may improve hospital access to debt for capital investments when the next economic crisis hits.

First, I estimated the impact of the great recession on hospital capital investment. Second, I estimated how much cash flow hospitals used to offset the impact of the great recession on hospital capital investment. Lessons from the recession will be valuable because hospitals continue to face financial challenges today. Major credit rating agencies have a negative outlook for the hospital industry in 2015 citing declining operating cash flows and uncertainties over the ACA (Reuters, 2014).

Furthermore, the severity of liquidity constraint might vary by the type of hospital ownership. Ownership differences allow for different financing mechanisms. Not for profit and public hospitals do not have access to equity capital while investor owned hospital do, hence investor owned hospitals are less likely to be liquidity constrained.

Ownership differences in financial disclosure regulations may contribute to liquidity constraint as well. Not for profit hospitals and public hospitals are more likely to be liquidity constrained than investor owned hospital because the municipal bonds they issue are subject to fewer regulations than bonds issued by investor owned hospitals (Government Accountability Office, 2012). Municipal bonds are exempt from the registration and periodic reporting provisions of the Securities and Exchange Commission (SEC). Also, SEC and the Municipal Securities Rulemaking Board (MSRB) are not authorized to require bond issuers to file certain financial information. The Government Accountability Office has documented lenders' criticisms regarding the timeliness, frequency, and completeness of municipal bond disclosures (Government Accountability Office, 2012). The most notable criticism was that municipal bond issuers are not required to provide quarterly financial statements.

2.2 Previous Literature

Empirical test of firm liquidity constraint splits the study sample by predictor of liquidity constraint and separately estimating the effect of liquidity variable (cash flow) on investment controlling for the theoretical determinant of investment (Tobin's Q or marginal product of capital) (Hubbard, 1997).

Poor hospital cash flow led to cutbacks in hospital investments in plant and equipment among community hospitals between 1995 and 2000 (Bazzoli et al., 2007). However it is unclear whether liquidity constraint was driving the relationship. Medicare payment cuts resulting from the Balance Budget Act of 1997 and the growth of Health Maintenance Organizations during that time period may have increased the risk of lending to hospitals but the study does not address liquidity constraint directly.

Liquidity was strongly related to investment among small non-system hospitals (Calem and Rizzo, 1995). System hospitals are less likely to face financing constraints because they can diversify risk by earning revenue from a wider range of services. Having diverse revenue sources mean they are less likely to be affected by disruptions in service lines or fluctuations in demand for services. Health information technology systems can lower information asymmetries, but at a high fixed cost, which system hospitals can spread out over their affiliated hospitals. Also system hospitals may have greater negotiating power against payers and vendors to generate higher profit.

Studies of hospital liquidity constraint focused on cash flow as a measure of financial performance. However hospitals often carry large cash reserves to smooth out fluctuations in revenues and expenses and to improve bond ratings from credit rating agencies (Robinson, 2002). A hospital may compensate for its low borrowing limit by using its cash reserve in addition to cash flow to internally fund capital investment or to improve access to debt from the capital market. Holding a large reserve has negative welfare implications for patients as those funds could have been used for hospital operations had there been no liquidity constraint.

The great recession was a powerful disruption to the national economy. My study will describe hospital capital investment pre-recession, during the recession, and during the recovery to identify liquidity constraint among hospitals during each time period. I contribute to the literature by investigating whether hospitals used cash flow and cash reserves to finance capital investment in response to liquidity constraint driven by the recession. Furthermore hospital ownership differences in liquidity constraint will be addressed.

2.3 Methods

2.3.1 Theoretical Model

In a perfect capital market, the interest rate sets the equilibrium quantity of capital. The neoclassical model of investment (Hall and Jorgenson, 1967; Jorgenson, 1963) has focused on deriving the optimal level of capital for a given rental price of capital. However, hospitals may have been liquidity constrained during the recession. Lenders do not have full information about how the demand for hospital services may be less sensitive to the recession than other services.

Lenders may place a liquidity constraint, by limiting the amount a hospital can borrow, raising the cost of borrowing, or requiring cash reserves as collateral. Liquidity constrained hospitals, unable to borrow debt, may fund capital investments internally with cash. Hence capital investment decision by a liquidity constrained hospital should be sensitive to its cash flow.

Hospital manger's capital investment decision was modeled using a dynamic utility maximization problem (Derivation shown in appendix). The solution to the problem is the Euler equation. The intuition behind the Euler equation is that the hospital maximizes its utility over an infinite time horizon by equating its marginal cost of capital investment of today to the expected discounted marginal benefit of capital investment in the future. Liquidity constraint was added to the maximization problem by adapting the specification of Whited (1992); Gilchrist and Himmelberg (1999).

Value function V maximizes the manager's utility function at time t and the present value of all expected future utilities discounted by discount factor β (eqn. 2.1). U is the hospital manager's utility function to be maximized (eqn. 2.2). It is specified as net profits where cash inflows include operating profits π and borrowing B; cash outflows include adjustment cost C^K, capital investments I^K, and interest expense on debt rD.

$$V(K_t, D_t) = \max_{I_t^K, B_t} U_t + E_t \sum_{s=1}^{\infty} \beta^s U_{t+s} \tag{2.1}$$

$$\begin{aligned} U_t = {} & \pi_t(K_t, L_t, \zeta_t) - C^K(K_t, I_t^K) - I_t^K \\ & - r_t D_t + B_t \end{aligned} \tag{2.2}$$

Operating profits π (flow) is a function of capital K_t, labor L_t, and a random profitability shock ζ_t. Labor L_t is assumed to be perfectly supplied from an elastic market at each time period and does not evolve over time. The price of hospital output and the price of capital are set by the market.

The adjustment cost of capital investment C^K (flow) is typically specified as a function of capital K and capital investment I^K. It is convex in investment to represent how increasing investment incurs growing adjustment costs (Lucas, Jr., 1967; Gould, 1968; Treadway, 1969).

$$C^K(K_t, I_t^K) = \frac{\alpha}{2}\left(\frac{I_t^K}{K_t}\right)^2 K_t \tag{2.3}$$

Hospitals may face convex adjustment cost because its capital stock mostly includes specialized medical equipments and facilities. Increasing capital stock incurs costs because of installation and learning. Decreasing capital stock incurs costs because hospital equipment and facilities are difficult to resell or repurpose (irreversibility) hence costs are incurred when reselling or disposing. The adjustment cost is reciprocal to capital stock because larger stock may allow for economies of scale and reduce the adjustment cost. The empirical specification for the adjustment cost of capital investment (eqn. 2.3) is a function of capital K , capital investment I^K , and a parameter α. Graphically, the adjustment cost (Y-axis) with respect to investment (X-axis) is represented by a parabola where the vertex represents no change in capital stock (zero investment). A positive adjustment cost is incurred when there is a change in capital stock (positive or negative investment) and the adjustment cost rises at an increasing rate with the magnitude of the investment.

Capital K (state variable, stock) represents the total stock of capital. Capital evolves over time through the capital accumulation equation (eqn. 2.4). Capital stock in the next time period K_{t+1} is equal to capital stock K_t , minus depreciation δK_t (depreciation rate δ) , plus capital investment I_t^K at current period. Capital K is restricted to be non-negative because it is a required input for hospital operations (eqn. 2.5). Capital investment I^K (control variable, flow) represents the flow that changes the stock of capital K_t. Capital investment includes expenditures on plant, property, and equipment. Assume constant price of I_t^K, normalized to unity.

$$K_{t+1} = g(K_t, I_t^K) = K_t(1-\delta) + I_t^K \tag{2.4}$$

$$K_t \geq 0 \tag{2.5}$$

Borrowing B_t (control variable, flow) represents the flow that changes the stock of net debt D_t (eqn. 2.6). Borrowing B_t can be positive or negative because a hospital can choose to increase or decrease its net debt. Assume a constant price of B_t, normalized to unity.

$$D_{t+1} = n(D_t, B_t) = D_t + B_t \tag{2.6}$$

The cost of debt or the interest rate required by debt suppliers is $r_t > 0$. The discount factor is $\beta = (\frac{1}{1+R})^s$ where the discount rate R is the hospital's weighted average corporate cost of capital.

Liquidity constraint limits net debt D to be less than or equal to D^* (eqn. 2.7). D^* represents an upper bound on net debt set by creditors.

$$D_t \leq D_t^* \tag{2.7}$$

Bankruptcy constraint specifies net profits U_t to be non-negative (eqn. 2.8). Negative net profits indicate that a hospital is bankrupt where cash inflow is not sufficient to pay for cash outflows.

$$U_t \geq 0 \tag{2.8}$$

The solution to the maximization with respect to investment I_t^K and borrowing B_t yield the following Euler equation.

$$\frac{I_{it}^K}{K_{it}} = E_t\left[\frac{\beta}{\alpha}\left(constant + \frac{1}{\beta} - \left(r_{t+1} + 1 + \frac{\gamma_{it+1}}{1+\lambda_{it}}\right) + MPK_{it+1}\right)\right] \tag{2.9}$$

Capital investment I_{it}^K represents the net changes in capital stock K_{it} at the end of the reporting period. Capital stock K_{it} represents the total stock of capital owned by the hospital at the beginning of the reporting period. Neoclassical theory, assuming perfect information, models investment as a function of marginal product of capital MPK and interest rate r.

However, with asymmetric information in the lending market the borrowing firm is liquidity constrained thus its investment is correlated with firm's financial performance. λ is the Lagrangian multiplier on non-negativity constraint (eqn. 2.8) and γ is the Lagrangian multiplier on liquidity constraint (eqn. 2.7). $\frac{\gamma_{t+1}}{1+\lambda_{it}}$ is non-zero when both constraints are binding, indicating that a hospital is liquidity constrained. $\frac{\gamma_{t+1}}{1+\lambda_{it}}$ is not observed but parameterized with variables correlated with the hospital's financial performance (Whited 1992).

$\left(r_{t+1} + 1 + \frac{\gamma_{it+1}}{1+\lambda_{it}}\right)$ represents the interest expense the hospitals has to pay at $t+1$ for the stock of net debt D_t and borrowing B_t made at time t. Additionally, a hospital expecting a binding liquidity constraint γ_{t+1} would effectively face a higher interest expense at $t+1$. A higher interest expense at $t+1$ would discourage hospitals from borrowing at t, which would increase their risk of bankruptcy at t and decrease capital investment made at t.

2.3.2 Empirical Model

I specified the empirical model based on the theoretical results. The liquidity and non-negativity constraint factor $\frac{\gamma_{t+1}}{1+\lambda_{it}}$ was specified as a function of operating cash flow CF_{it} and liquid assets LA_{it} (eqn. 2.10) which are normalized by capital.

$$\frac{\gamma_{it+1}}{1+\lambda_{it}} = \beta_0 + \beta_1 \frac{CF_{it}}{K_{it}} + \beta_2 \frac{LA_{it}}{K_{it}} \tag{2.10}$$

Operating cash flow measures the net cash inflows and outflows from hospital operations at the end of the reporting period. Operating cash inflows include payments from payors and donations, and operating cash outflows include cash expensed to pay for labor and supplies. Liquid assets include cash reserves and marketable securities which can be used to fund investments directly or used as collateral to lower the cost of debt. Operating cash flow has been used in the literature to capture the impact of financial market imperfections on investment. In the context of hospitals, not for profit hospitals in particular, liquid assets should also be linked to investment in the presence of liquidity constraint.

The marginal product of capital MPK_{it} is the change in profits from a unit change in capital stock. The marginal product of capital captures the effect of the marginal product of capital on investment derived from the neoclassical model. Since the marginal product of capital is unobserved, the average product of capital APK_{it}, specified by operating revenue per capital, was used. (Relationship between MPK and APK shown in appendix).

The interest rate (r_{it+1}) was measured by average interest rate on long term debt. Capital investments are often financed through bonds and bank loans. Including the interest rate in the model should clarify whether the effect of financial variables cash flow and net debt on investment is via affecting the interest rate or via affecting the bankruptcy and liquidity constraint.

The empirical model for $\frac{I^K_{it}}{K_{it}}$ to be estimated is a function of operating cash flow, liquid assets, interest rate, and marginal product of capital (eqn. 2.11). ω_t is year fixed effects. μ_i is hospital fixed effects. υ_{it} is the idiosyncratic error. Significant β coefficients indicate that financial performance is linked to capital investment, which is evidence of liquidity constrain.

$$\frac{I^K_{it}}{K_{it}} = cons + \beta_1 \frac{CF_{it}}{K_{it}} + \beta_2 \frac{LA_{it}}{K_{it}} + \beta_3 r_{t+1} + \beta_4 APK_{t+1} + \omega_t + \mu_i + \upsilon_{it} \tag{2.11}$$

2.3.3 Identification Strategy

System GMM

The estimation model (eqn. 2.11) contains endogenous regressors and unobserved hospital effect that will bias OLS estimates. The regressors operating cash flow, liquid assets, APK, and r are endogenous to unobserved shocks related to capital investment and the direction of bias could be positive or negative. For example, hospitals' service mission to improve the health of the community will exert a negative bias on the effect of operating cash flow. Service activity with a quality objective rather than a profit objective will be negatively correlated with operating cash flow. At the same time, investment will be positively correlated with service activity because equipment and facilities will be needed to carry out the service activity. In contrast, hospitals' reputation will exert a positive bias on the effect of operating cash flow. Hospitals with a good reputation will attract patients thus reputation will be positively correlated with operating cash flow. Also, hospitals will invest more to maintain a good reputation thus reputation will be positively correlated with investments. Unobserved hospital effects, such as the performance of the hospital's manager, may affect operating cash flow and investment. The system generalized method of moments (System GMM) estimator was used to address fixed effects and endogeneity in the estimation model.

System GMM estimates the system of levels and differenced equation using the lags and lag differences of the endogenous regressors as instruments for the endogenous regressors. The estimation model (eqn. 2.11) fits in the system GMM framework as follows. Consider a data generating process with the dependent variable y_t (index i is suppressed for simplification) and endogenous regressor $\mathbf{x_t}$. y_t is $\frac{I_t^K}{K_t}$ and $\mathbf{x_t}$ is $CF, LA, APK, r2$ (eqn. 2.12). The error term ε_t is autoregressive of order p (eqn. 2.13).

$$\begin{array}{l} \text{Levels equation:} \\ \text{Differenced equation:} \end{array} \begin{bmatrix} y_t \\ \Delta y_t \end{bmatrix} = \beta \begin{bmatrix} \mathbf{x}_t' \\ \Delta \mathbf{x}_t' \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \Delta \varepsilon_t \end{bmatrix} \tag{2.12}$$

$$\varepsilon_t \text{ is AR}(p) \quad \varepsilon_t = \sum_{k=1}^{p} \rho_k \varepsilon_{t-k} + \omega_t \tag{2.13}$$

Exogeneity of Instruments

When the endogenous regressor is persistent, lags and lag differences of the endogenous regressors sufficiently removed from the contemporaneous error term are exogenous (derivation shown in appendix). For example, suppose that endogenous x_t is persistent (AR1) and also correlated with the error term ε_t (eqn. 2.14).

$$x_{it} = \alpha x_{t-1} + \varepsilon_t \tag{2.14}$$

If ε_t is AR(0), then in the levels equation, 1 or more period lagged change of

Δx_{t-a}, a > 0 is exogenous to the error term ε_t (eqn. 2.15).

$$\begin{aligned}\Delta x_{t-1} &= (\alpha x_{t-2} + \varepsilon_{t-1}) - (\alpha x_{t-3} + \varepsilon_{t-2}) \\ &= (\alpha x_{t-2} - \alpha x_{t-3}) + (\varepsilon_{t-1} - \varepsilon_{t-2})\end{aligned} \tag{2.15}$$

In the levels equation, $\Delta \mathbf{x}_{t-a}, \forall a > p$ is used to instrument for the endogenous regressors $\mathbf{x}_t$ (eqn. 2.16). In the differenced equation, $\mathbf{x}_{t-(a+1)}, \forall a > p$ is used to instrument for the endogenous regressors $\Delta \mathbf{x}_t$ (eqn. 2.16) (Arellano and Bond, 1991). System GMM combines the moment conditions for the transformed model with the moment conditions for the levels model (Blundell and Bond, 1998). Compared to estimating the differenced equation alone, system GMM improves the finite sample properties regards to bias and root mean squared error.

$$\begin{aligned}E(\Delta \mathbf{x}_{t-a}\varepsilon_t) &= 0, \\ E(\mathbf{x}_{t-(a+1)}\Delta\varepsilon_t) &= 0,\end{aligned} \qquad \forall a > p \tag{2.16}$$

System GMM requires strong assumptions regarding the lags and lag differences of the endogenous regressors. Satisfying the required assumptions to make the system GMM identification strategy work would be considered special circumstances. Validity of the assumptions are rigorously tested later in the paper.

A previous study using system GMM identification strategy for estimating hospital productivity yielded similar results to alternative identification strategies for production functions (Lee et al., 2013). System GMM producing similar results to alternative identification strategies provide support for the validity of using system GMM with hospital financial data.

Strength of Instruments

In the levels equation, lagged change Δx_{t-1} is used to instrument for x_t. Δx_{t-1} is related to x_t by $(\alpha^{-1} - \alpha^{-2})$ (derivation shown in appendix).

$$\Delta x_{t-1} = (\alpha^{-1} - \alpha^{-2})x_t - (\alpha^{-1} - \alpha^{-2})\varepsilon_t + \alpha^{-1}\varepsilon_{t-1} \tag{2.17}$$

In the differenced equation, x_{t-2} is used to instrument for Δx_t. x_{t-2} is related to Δx_t by $\frac{1}{\alpha^2-\alpha}$ (derivation shown in appendix).

$$x_{t-2} = \frac{1}{\alpha^2 - \alpha}\Delta x_t - \frac{1}{\alpha}\varepsilon_{t-1} - \frac{1}{\alpha^2 - \alpha}\varepsilon_t \tag{2.18}$$

Problem of Weak Instruments

Problem of weak instrument arises in both levels equation and differenced equation when there is strong persistence or when α approaches 1. In equation (2.17), if $\alpha = 1$ then $(\alpha^{-1} - \alpha^{-2}) = 0$. Thus Δx_{it} is no longer related to x_{it-2}. In equation (2.18), if $\alpha = 1$ then $(\alpha^2 - \alpha) = 0$. Thus x_{it-2} is no longer related to Δx_{it}. System GMM addresses the weak instrument problem by jointly estimating the system of levels and differenced equation (Blundell and Bond, 1998).

2.3.4 Data

The state of California Office of Statewide Health Planning and Development (OSHPD, 2012) collects financial data from about 450 not for profit and for-profit hospitals in California each year, this study used data from 2002-2011. Participating hospitals report detailed financial information from balance sheets and income statements. OSHPD data includes all non-federal California hospitals. The study sample was limited to short-term general (acute-care) hospitals. Kaiser Permanente hospitals were excluded because they do not report comparable financial data. Hospitals with reporting days less or greater than 365 (less or greater than 366 for leap years) were excluded. 311 hospitals (3,168 observations) remained. Then missing and out of range values, probably resulting from data entry error, were excluded. The remaining 309 hospitals with an unbalanced panel of 2,930 hospital-year observations were analyzed. Dollar amounts were adjusted to 2010 using GDP deflator.

2.4 Results

A descriptive analysis of the study hospitals is summarized in table 2.1. Pooling across ownership types, hospitals had a mean annual capital investment of 18.95 million dollars, capital stock of 178.72 million dollars, and investment per capital ratio of 0.11. Ownership differences showed that investor owned hospital invested relatively more than others with a higher investment per capital ratio. Investor owned hospitals also generated greater returns from a dollar of capital with a higher APK than others. Investor owned hospitals had the smallest capital stock, about a quarter of the size of not for profit hospitals and half the size of public hospitals. The study population was comprised of 58% not for profit hospitals, 20% investor owned hospitals, and 22% public hospitals.

Figure 2.7 shows the investment time trend separately plotted for hospitals with high operating cash flow and low operating cash flow, defined as operating cash flow above and below the median, respectively. High operating cash flow hospitals had an increasing investment trend from 2002 to 2008 then a decreasing trend from 2008 to 2012. Low operating cash flow hospitals increased investment from 2003 to 2007 then decreased from 2007 to 2010.

During the recession I expected hospitals to be liquidity constrained. When liquidity constrained, high operating cash flow hospitals should invest more than low

Table 2.1: Summary Statistics of CA Short-Term General Hospitals, 2002-2012

	All Mean (SD)	NFP Mean (SD)	IO Mean (SD)	Public Mean (SD)
I/K	.11	.11	.14	.1
	(.23)	(.16)	(.42)	(.12)
I (Investments, \$ mil.)	18.95	25.59	6.36	12.72
	(39.86)	(47.14)	(15.12)	(28.99)
K (Capital, \$ mil)	178.72	236.41	60.04	134.83
	(250.1)	(289.95)	(64.36)	(188.36)
CF (Cash Flow, \$ mil)	19.66	24.52	9.35	16.58
	(47.92)	(46.87)	(34.15)	(59.02)
LA (Liquid Ast., \$ mil)	19.54	26.27	1.99	18.45
	(52.92)	(63.37)	(5.23)	(42.49)
APK (Operating Rev / K)	1.71	1.41	2.87	1.42
	(1.36)	(.88)	(2.01)	(1.03)
r (Int. Rate LT Debt, %)	5.77	5.4	8.01	5.66
	(1.96)	(1.73)	(2.53)	(1.43)
N obs	2930	1713	582	635

Source: OSHPD 28th Year (2002-2003) to 38th Year (2012-2013)
In millions of 2011 dollars

operating cash flow hospitals because hospitals are limited in how much they can borrow and must use their own operating cash flow to fund investments. Time trend in figure 2.7 is consistent with this expectation in that during the recession high operating cash flow hospitals invested more than low operating cash flow hospitals. There is a clear separation between high and low operating cash flow hospitals between 2008 and 2010.

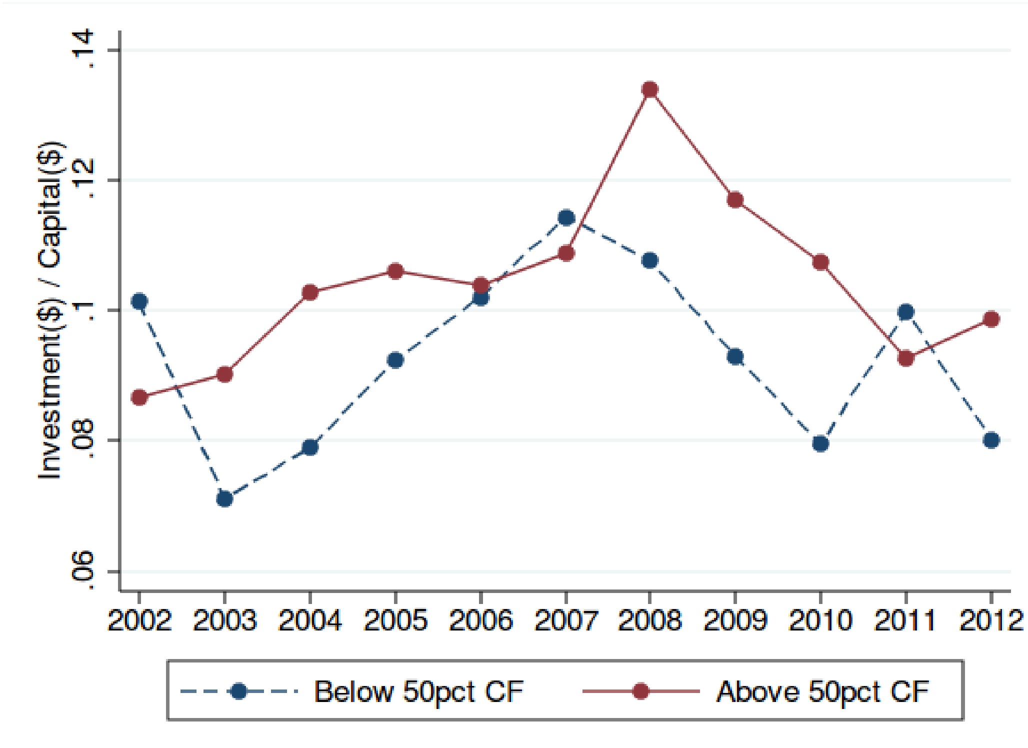

Figure 2.7: Mean Capital Investment per Dollar of Capital by Cash Flow

Source: OSHPD 28th Year (2002-2003) to 38th Year (2012-2013)

I estimated the empirical model (2.11) using system GMM. Estimates are stratified by pre-recession (2002-2006), during recession (2008-2010), and recovery (2011-2012). In addition to GMM estimates, fixed effects estimates are reported for comparison.

Pre-recession period estimates are presented in table 2.2. Operating cash flow and liquid assets were not significantly related to investment per capital for all hospitals, suggesting that hospitals were not liquidity constrained in the pre-recession period. Investment per capital was significantly related to the profitability of capital. The coefficient estimate for APK_{it+1} was significant and positive (.0331 ; p-val $\leq$ 0.001). The GMM estimate for APK_{it+1} was smaller than the FE estimate (.1155 ; p-val $\leq$ 0.001), which implies that managerial performance was positively biasing APK_{it+1}.

Table 2.2: Pre-Recession 2002-2006 Estimates

All I/K_{it}	FE (1)	GMM (2)
CF/K_{it}	-.0168	.0061
	(.0143)	(.0372)
LA/K_{it}	.0625	.2315
	(.0705)	(.1184)
APK_{it+1}	.1155 ***	.0331 ***
	(.0341)	(.0076)
r_{it+1}	-.0021 **	-.0022
	(7.0e-04)	(.0061)
2003	-.0143 *	-.0149
	(.0065)	(.0092)
2004	-.0117	-.0013
	(.0096)	(.0109)
2005	.0078	-.0072
	(.0146)	(.0119)
2006	-.0046	-.0114
	(.0092)	(.0123)
constant	-.0721	.0387
	(.0547)	(.0394)
AB test for AR(2) p-val		.388
Hansen p-val		.12
N instruments		37
N obs	1333	1091
N hospitals	263	250

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Recession period estimates are presented in table 2.3. Operating cash flow was significantly related to investment per capital, suggesting that hospitals were liquidity constrained during the recession. Increasing operating cash flow increased investment per capital (.1309 ; p-val $\leq$ 0.01). The GMM estimate for operating cash flow was larger than the FE estimate (.0932 ; p-val $\leq$ 0.001), which imply quality was negatively biasing operating cash flow.

The coefficient estimate for APK_{it+1} was significant and positive (.0307 ; p-val $\leq$ 0.01). Again, the GMM estimate for APK_{it+1} was smaller than the FE estimate. The APK_{it+1} coefficient during the recession was smaller than the pre-recession estimate, suggesting that investment decisions was less sensitive to the profitability of capital during the recession. Liquidity constrained hospitals would be limited in their borrowing, which may prohibit hospitals from investing even when there are profitable investment opportunities.

Table 2.3: During-Recession 2008-2010 Estimates

All I/K_{it}	FE (1)	GMM (2)
CF/K_{it}	.0932 ***	.1309 **
	(.0217)	(.0454)
LA/K_{it}	-.0435	-.045
	(.0531)	(.0724)
APK_{it+1}	.0527 **	.0307 **
	(.0192)	(.0107)
r_{it+1}	-3.0e-04	-.0014
	(4.7e-04)	(.0114)
2009	.0174 *	-.0227 **
	(.0072)	(.0085)
2010	.0032	-.0115
	(.0077)	(.0096)
constant	.0164	.0712
	(.0328)	(.061)
AB test for AR(2) p-val		.104
Hansen p-val		.215
N instruments		81
N obs	669	664
N hospitals	247	236

* p $\leq$ 0.05, ** p $\leq$ 0.01, *** p $\leq$ 0.001

Recovery period estimates are presented in table 2.4. Operating cash flow and liquid assets were not significantly related to investment per capital, suggesting that hospitals were not liquidity constrained. The coefficient estimate for APK_{it+1} was significant and positive (.0457 units ; p-val ≤ 0.01). The APK_{it+1} coefficient during the recovery was larger than the recession estimate, suggesting that hospitals were able to finance profitable investments by borrowing.

Table 2.4: Recovery 2011-2012 Estimates

All I/K_{it}	FE (1)	GMM (2)
CF/K_{it}	.081	.0807
	(.1102)	(.0767)
LA/K_{it}	-.0461	-.0488
	(.0571)	(.0694)
APK_{it+1}	.0166	.0457 **
	(.0437)	(.0171)
r_{it+1}	-.0089 **	.0215
	(.0033)	(.0301)
2012	.0333	.0244 *
	(.0371)	(.0118)
constant	.127	-.0961
	(.0882)	(.1467)
AB test for AR(2) p-val		.
Hansen p-val		.463
N instruments		56
N obs	890	445
N hospitals	253	237

* p $\leq$ 0.05, ** p $\leq$ 0.01, *** p $\leq$ 0.001

Table 2.5 shows the during-recession GMM estimates by ownership. Not for profit hospital investment was sensitive to operating cash flow (.1878 ; p-val ≤ 0.05). Public hospital investment was sensitive to liquid assets (.0871 ; p-val ≤ 0.05). Investor owned hospital investment was not related to operating cash flow or liquid assets. These results suggest that during the recession, not for profit and public hospitals were liquidity constrained, but investor owned hospitals were not.

Table 2.5: During-Recession 2008-2010 Estimates by Ownership

GMM I/K_{it}	NFP (1)	IO (2)	PUB (3)
CF/K_{it}	.1878 *	.2123	-.0668
	(.0866)	(.1365)	(.0745)
LA/K_{it}	-.1949	-.3568	.0871 *
	(.1073)	(.5883)	(.0406)
APK_{it+1}	.083 *	.0619 *	-.0078
	(.0396)	(.0293)	(.0109)
r_{it+1}	.011	-.095	.0048
	(.0153)	(.0962)	(.0165)
2009	.0011	-.0506	.0015
	(.0094)	(.0554)	(.0166)
2010	-.0033	.1371	.0093
	(.0141)	(.1714)	(.022)
constant	-.0626	.667	.0788
	(.0951)	(.6955)	(.0933)
AB test for AR(2) p-val	.28	.47	.997
Hansen p-val	.217	.441	.481
N instruments	51	27	60
N obs	429	75	160
N hospitals	150	30	57

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

System GMM diagnostic tests supported the validity of the system GMM estimates. In each of the tables presented, the Hansen test of joint validity of the instruments failed to reject the null, showing no evidence that the instruments were not exogenous. Also, over-instrumenting did not appear to be a problem, as the Hansen test statistic was reasonably far from 1.00 (Roodman, 2009). The Arellano-Bond test for AR(2) in first differences failed to reject the null, showing no evidence of AR(1) auto correlation in the levels equation.

The Blinder-Oaxaca Decomposition (Blinder, 1973; Oaxaca, 1973) technique was used to decompose the change in hospital capital investment between pre-recession and during recession. The hospital observations from 2006 were selected as the pre-recession group. Observations from 2009 were selected as the recession group. Using the GMM coefficient estimates from tables 2.2 and 2.3, capital investment was predicted in term of dollars and then separated into the following components.

$$
\begin{aligned}
Y_1 &: \text{Investment (\$ Millions) Recession} \\
Y_0 &: \text{Investment (\$ Millions) Pre-Recession} \\
\Delta E(Y) &= E(Y_1) - E(Y_0) \\
&= (\alpha_1 + \mu_1 + \beta_1 X_1) - (\alpha_0 + \mu_0 + \beta_0 X_0) \\
&= (\alpha_1 - \alpha_0) + (\mu_1 - \mu_0) + (\beta_1 - \beta_0) X_1 + (X_1 - X_0) \beta_0 \\
&= (\alpha_1 - \alpha_0) + (\mu_1 - \mu_0) + \\
&\qquad \left(\beta_1^{CF} - \beta_0^{CF}\right) CF_1 + (CF_1 - CF_0) \beta_0^{CF} + \\
&\qquad \left(\beta_1^{LA} - \beta_0^{LA}\right) LA_1 + (LA_1 - LA_0) \beta_0^{LA} + \\
&\qquad \left(\beta_1^{APK} - \beta_0^{APK}\right) APK_1 + (APK_1 - APK_0) \beta_0^{APK} \\
&\qquad (\beta_1^{r} - \beta_0^{r}) r_1 + (r_1 - r_0) \beta_0^{APK}
\end{aligned}
\tag{2.19}
$$

The effect of the recession through change in the estimated coefficients was captured by $(\beta_1 - \beta_0) X_1$: Coefficients effect. Difference in investment due to the change in the explanatory variables was captured by $(X_1 - X_0) \beta_0$: Change in variables effect. The effect of the recession due to the difference in the estimated intercepts was captured by $(\alpha_1 - \alpha_0) + (\mu_1 - \mu_0)$: Residual effect. Standard errors for decomposition were estimated by block bootstrapping the hospitals.

Table 2.6 summarizes the decomposed change in hospital capital investment between pre-recession and during recession. The residual recession effect is the change in baseline capital investment between the pre-recession and during recession group. The residual recession effect absorbs the change in capital investment unexplained by the predictors in the empirical model. The residual recession effect was not significant.

During the recession, hospital investment was related to operating cash flow, while pre-recession it was not. The operating cash flow coefficient effect (change in capital investment due to the change in the cash flow coefficient pre-recession and during recession) increased capital investment by \$2.5 million (CI:.57,4.44). Change in operating cash flow between the pre-recession group and the recession group was not statistically different. The APK_{it+1} coefficient effect, change in APK_{it+1}, interest rate coefficient effect, change in interest rate were not statistically different between the pre-recession and the recession group.

Table 2.6: Decomposition of Change in Expected Investment Due to the Recession

E(Investment 2009)- E(Investment 2006)	ΔEstimate	[Bootstrap	95% CI]
I. Cash Flow Effect	2.5*	.57	4.44
II. Change in Cash Flow	-.28	-.66	.11
III. Liquid Asset Effect	-2.39	-6.85	2.07
IV. Change in Liquid Asset	.54	-.34	1.43
V. APK Effect	-1.91	-8.02	4.21
VI. Change in APK	.48	-.16	1.13
VII. Interest Rate Effect	11.92	-11.01	34.86
VIII. Change in Interest Rate Effect	-.03	-1.15	1.08
IX. Residual Recession Effect	-9.26	-33.41	14.89
Net Effect	1.59	-1.87	5.04

Notes: * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$
Millions of 2011 Dollars; Bootstrap reps:1000

2.5 Robustness Tests

2.5.1 Validity of GMM Instruments

Overidentifying restrictions in system GMM may be tested by the Hansen J statistic (Hansen, 1982). Rejection of the null hypothesis implies that the instruments violate the orthogonality conditions either because they are not exogenous or because they are being incorrectly excluded from the regression. A large set of excluded instruments weakens the power of the Hansen test. The difference-in-Hansen test or the C test is used to test the validity of a subset of instruments. Rejection of the null hypothesis signals that the subset of instruments are not valid.

Table 2.7 shows the test of instrument exogeneity. The difference-in-Hansen test separately evaluates the exogeneity of instruments for each endogenous regressor. A p-value less than 0.1 suggests that the instrument may be endogenous. The Arellano-Bond test for AR(2) with a p-value less than 0.05 suggests that the error term is serially correlated, thus instruments are invalid. The Hansen test is the overall test of instrument exogeneity and a p-value less than 0.1 suggests that the instrument set may be endogenous (Roodman, 2009). Overall, the test did not find a significant endogeneity problem in the lags and lag differences used as instruments.

Table 2.7: Test of Instrument Exogeneity

	X_{t-2} and ΔX_{t-1} only	X_{t-3} and ΔX_{t-2} only	X_{t-4} and ΔX_{t-3} only	X_{t-5} and ΔX_{t-4} only	X_{t-6} and ΔX_{t-5} only
Diff-in-Hansen Test p-val					
CF/K_{it}	.799	.502	.806	.327	.623
LA/K_{it}	.775	.181	.649	.431	.824
APK_{it+1}	.969	.769	.561	.7	.732
r_{it+1}	.319	.634	.98	.7	.809
Arellano-Bond AR(2) test p-val	.238	.448	.279	.148	.294
Hansen Test p-val	.579	.613	.893	.871	.883
Instruments	85	77	69	61	53

Instruments suspected to be endogenous have a p-val < 0.1

System GMM estimations often use a large set of excluded instruments, weakening the Hansen test (Roodman, 2009). System GMM estimations should be tested for sensitivity to reductions in number of instruments using the Hansen test and the difference-in-Hansen test to ensure that the instruments truly satisfy the orthogonality conditions.

Table 2.8 compares how the system GMM estimates changed with the reduced number of instruments. The system GMM Estimate using all of the available lags and lag differences as instruments is the reference case (column 1). Column 2 reduced the instruments to second to fourth lags and first to third lag differences. Column 3 reduced the instruments to second lag and first lag differences. The coefficient estimates do not appear to be sensitive to reduction in instruments. They are generally in the same direction and magnitude. Also, the reduction of instruments does not reveal an endogeneity problem, as all Hansen test p-values were above 0.1.

Reducing the number of instruments would diminish the effectiveness of system GMM in expunging endogeneity. As the number of instruments decreased going from column 1 to column 3, the coefficient estimate on operating cash flow became smaller. This is consistent with the results suggesting quality may be negatively biasing operating cash flow. The coefficient on APK_{it+1} increased from column 1 to column 3, which is consistent with managerial performance exerting a positive bias.

Table 2.8: Test of Instrument Reduction

All I/K_{it}	GMM all lags (1)	GMM lag 2-4 (2)	GMM lag 2 (3)
CF/K_{it}	.0436	.0362	.0307
	(.0337)	(.0325)	(.0407)
LA/K_{it}	2.8e-04	.0061	-.0456
	(.04)	(.0336)	(.0397)
APK_{it+1}	.0253 ***	.0292 ***	.0406 ***
	(.0068)	(.0083)	(.0062)
r_{it+1}	-.0116	-.0084	-.0062
	(.0083)	(.0064)	(.0089)
AB test for AR(2) p-val	.21	.241	.233
Hansen p-val	.137	.211	.404
N instruments	229	145	85
N obs	2419	2419	2419
N hospitals	280	280	280

Source: OSHPD 28th Year (2002-2003) to 38th Year (2012-2013).
Coefficients for time dummies not shown.
* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

2.5.2 Strength of GMM Instruments

There is no established method in the literature for jointly testing the weakness of the lag and lag differences instrument set in system GMM. Alternatively, a test for weak instruments in two stage least squares regression (Staiger and Stock, 1997; Stock and Yogo, 2002) was adapted for testing the strength of instruments used in system GMM (Wintoki et al., 2012). The adapted F-test indicates the strength of the instruments but inference about their consistency is limited because GMM jointly estimates the levels and differenced equations.

The system of levels and differenced equation were split and tested separately using the F-statistics from the first stage regression. In the levels equation, first stage F-statistics test the strength of lag differences instruments $\Delta\mathbf{x}_{it-(a+1)}$, $\forall a \geq 2$ on the endogenous regressors $\mathbf{x}_{it}$. In the differenced equation, first stage F-statistics test the strength of lag instruments $\mathbf{x}_{it-(a)}$, $\forall a \geq 2$ on the endogenous regressors $\Delta\mathbf{x}_{it}$. An F-statistic less than the 'rule of thumb' critical value 10 is a sign of weak instruments. A Cragg-Daniel test is not reported because it is invalid under robust clustered standard errors.

Table 2.9 presents the results for the test of weak instruments. Operating cash flow, liquid assets, and APK_{it+1} had an F-statistic greater than 10 in either the levels equation or the differenced equation, or both. However, the interest rate suffered from weak instruments. Joint estimation of the levels equation and the differenced equation by system GMM should alleviate the weak instrument problem.

Table 2.9: First Stage F-Test of Weak Instruments

Dependent Variable	F-statistic	p-val
First stage dependent variable is in levels (X_t)		
CF/K	27.73	8.8e-52
LA/K	37.65	3.2e-60
APK_{it+1}	68.25	2.2e-77
r_{it+1}	3.349	2.3e-08
First stage dependent variable is in forward orthogonal deviations (ΔX_t)		
$\Delta CF/K$	8.722	2.2e-24
$\Delta LA/K$	13.25	2.6e-34
ΔAPK_{it+1}	14.54	1.0e-36
Δr_{it+1}	2.474	3.3e-05
Stock-Yogo test critical values		Critical Value
5% max relative bias		21.34
10% max relative bias		11.19
20% max relative bias		5.95
30% max relative bias		4.15

2.5.3 Alternative Specifications

I investigated the robustness of my results against alternative specifications of the empirical model. The effect of cash flow may vary depending on liquid asset. The interaction term for operating cash flow and liquid asset should capture the substitution effect between the two. System GMM estimates for the pre-recession, recession, recovery periods including the interaction term between operating cash flow and liquid asset (appendix table A1, A2, A3) showed consistent results with hospitals being sensitive to cash flow only during the recession period. The interaction term was not significant in the three periods.

Investment may be persistent over time. Dynamic specification (eqn. 2.20) included the lagged dependent and independent variables to test for the presence of an autoregressive(1) error component. The coefficient on the lagged dependent variable was not significant, thus failing to reject the absence of serial correlation in the error term.

$$\begin{aligned}\frac{I^K_{it}}{K_{it}} &= cons + \beta_1\frac{CF_{it}}{K_{it}} - \rho\beta_1\frac{CF_{it-1}}{K_{it-1}} + \beta_2\frac{LA_{it}}{K_{it}} - \rho\beta_2\frac{LA_{it-1}}{K_{it-1}} + \beta_3\frac{CF_{it}}{K_{it}} * \frac{LA_{it}}{K_{it}} \\ &\quad - \rho\beta_3\frac{CF_{it-1}}{K_{it-1}} * \frac{LA_{it-1}}{K_{it-1}} + \beta_4 r_{t+1} - \rho\beta_4 r_t + \beta_5 APK_{t+1} - \rho\beta_5 APK_t \\ &\quad + \rho\frac{I^K_{it-1}}{K_{it-1}} + \omega_t - \rho\omega_{t-1} + \mu_i - \rho\mu_i + \epsilon_{it} \end{aligned} \tag{2.20}$$

The theoretical model and the subsequent empirical model do not explicitly include debt as a predictor of capital investment. However, debt may be correlated with the interest rate, because a lender may evaluate existing debt and interest expenses. Debt is also correlated with capital investment because it is a funding source for capital investments. Including debt as a predictor in the empirical model did not change the coefficient estimates for operating cash flow and APK_{t+1}. Also, debt was not a significant predictor.

The interest rate in the empirical model was defined as the average interest rate on long term debt. Long term debt took about five to ten years to mature and it did not vary greatly from year to year, which may explain why the interest rate was never a significant predictor. Alternatively, I tested average interest expense per debt as a proxy for interest rate and it was not a significant predictor. The problem with average interest expense per debt was that some hospitals had interest expenses greater than debt making the ratio implausible.

Although the recession was dated between 2007 and 2009 nationally, the effect of the recession may have lagged for the hospital industry. A drop in employer sponsored insurance would have lagged behind the recession because the Consolidated Omnibus Budget Reconciliation Act (COBRA) allows people who lost their jobs to continue their coverage. To account for the lag, years 2008 to 2010 was set as the recession period and 2002-2006 was set as the pre-recession period. Year 2007 was excluded because it was a transition period, with 11 months out of the year not in recession. Including 2007 in the pre-recession period did not change the results.

2.6 Discussion

During the recession hospitals' capital investment was linked to operating cash flow, which is an evidence of liquidity constraint. The fixed effects estimates which suffers from endogeneity problem underestimated the relationship between operating cash flow and investment compared to system GMM estimates. The negative bias on operating cash flow may be due to unobserved quality improvement spending.

Liquidity constraint arises when lenders are uncertain about hospitals' ability to service their debt and consequently limit how much hospitals could borrow. Had there been a perfectly functioning capital market, operating cash flow would not have been related to investments. Liquidity constraint drives hospitals to generate large operating cash flows to fund capital investments rather than spending on expenses related to the provision of health care. Hospital management can reduce expenses by cutting hospital staff, delaying wage payments, and closing service lines. Trading off operating expenses for capital investment may have adverse short run consequences. A reduction in hospital staff may worsen patient outcomes by increasing provider error.

The effect of operating cash flow on investment varied by hospital ownership. During the recession, capital investment of not for profit and public hospitals were sensitive to operating cash flow but capital investment of investor owned hospitals were not. These findings suggest that during the recession, not for profit and public hospitals were liquidity constrained but investor owned hospitals were not. Investor owned hospitals can raise equity to fund capital investments, while not for profit and public hospitals can not. This institutional difference makes investor owned hospitals less susceptible to liquidity constraint.

Decomposing the change in hospital capital investment between pre-recession and during recession did not reveal a significant drop in capital investment. The average decrease in capital investment is the change in capital investment holding constant the effects of operating cash flow and other predictors in the empirical model. This change in capital investment unexplained by the model, or the residual effect, includes the net of the pre-recession year fixed effect and the during recession fixed effect.

Thus any policy changes affecting capital investment would be captured by the residual effect. However the large uncertainty around the estimated residual effect makes it unclear how policy changes, such as the government stimulus funds going to hospitals through ARRA, affected hospital capital investment.

Hospitals responded to the recession by using operating cash flow to offset the effect of restricted borrowing. Capital investment was more sensitive to operating cash flow during the recession, which increased capital investment by $2.5 million other things equal. The operating cash flow effect isolates change in capital investment due to the change in coefficient estimate for the pre-recession group and the during recession group.

A liquidity constrained hospital with poor operating cash flow is likely to fall behind on the capital investment necessary for its operations and face the risk of closure. Hospital closure is devastating to a community because access to health care will deteriorate, especially in rural areas where hospitals are far apart. Also, the community's economy will suffer because hospitals are often large employers.

Hospitals with low operating cash flows tend to be small rural hospitals that provide care to underserved populations. During economic recessions when poor financial performance is due to the external environment rather than the hospital's management, access to debt is critical for hospitals to endure the recession. Policy changes that reduce payments to hospitals may discourage liquidity constrained hospitals from investing in capital.

The relationship between APK_{it+1} and capital investment diminished during the recession, although it was not statistically significant. Capital investments may have been forgone during the recession because of greater uncertainty regarding returns from the investment, even though these investments may have been be profitable. The implications of the forgone profitable investment for patient welfare depend on who is the residual claimant of hospital profits. Profits from investment may be returned to the community, which in theory defines not for profit organizations, or may be used to improve the quality of hospital service. Decreased profits from investment would decrease patient welfare because less residual surplus is returned to patients. However, forgoing profitable investment that provides no medical benefit to patients but only generates profits for the hospital manager would be beneficial to patient welfare.

My study provides evidence of liquidity constraint among not for profit and public hospitals during the recession. The theoretical cause of this liquidity constraint is asymmetric information, a market failure that warrants policy intervention. Compared to the private bond market, municipal bond market disclosure requirements have much room for improvement regarding timeliness, frequency, and completeness. The lack of transparency in the financial disclosures of not for profit hospitals may have disastrous consequence such as the failure of the Allegheny Health Education and Research Foundation (AHERF). Policy interventions that mitigate the problem of asymmetric information between hospitals and lenders may alleviate liquidity constraint in economic downturns. Improving hospital access to debt for investing in new equipment and facilities is important for maintaining and improving the quality of hospital services.

Chapter 3

Cost Effectiveness of Telecare Management for Pain and Depression in Patients with Cancer: Results from a Randomized Trial

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3.1 Introduction

Pain and depression are two of the most prevalent and disabling symptoms among patients with cancer yet frequently are undetected and undertreated (Carr et al., 2002; Bottomley, 1998; Caraceni and Portenoy, 1999; Portenoy and Lesage, 1999; Given et al., 2001, 1994; Kurtz et al., 2001; Stommel et al., 2002; Fallowfield et al., 2001; Passik et al., 1998; Sharpe et al., 2004; Cleeland et al., 1994; Cleeland, 1998; Deandrea et al., 2008; Apolone et al., 2009). Telecare interventions have been shown to be effective at managing pain and depression among primary care patients, across a variety of health care settings, from large health systems to rural hospitals (Carr et al., 2002; Bottomley, 1998; Caraceni and Portenoy, 1999; Portenoy and Lesage, 1999; Kroenke, 2007; Sheehan et al., 1996; Wagner et al., 1993; Rost et al., 2001; Cintron and Morrison, 2006). Extending telecare to management of pain and depression in patients with cancer is an emerging area of clinical and research interest spurred by a long-standing failure to adequately manage disabling symptoms among cancer populations (Cleeland, 1998; Deandrea et al., 2008; Apolone et al., 2009).

The Indiana Cancer Pain and Depression (INCPAD) trial evaluated the effectiveness of centralized telecare management coupled with automated symptom monitoring for patients with cancer. The INCPAD trial was conducted in 16 community-based geographically-dispersed urban and rural oncology practices in Indiana and showed that telecare management improved both cancer-related pain and depression over the 12 months of the trial (Kroenke et al., 2010). In the present paper, we investigate the cost effectiveness of the INCPAD telecare intervention. New contributions made by this paper include mapping of information from outcome assessment questionnaires into depression-free days and quality-adjusted life years, accounting for intervention costs, and a regression analysis of the effectiveness measures to allow comparisons with other pain and depression management interventions.

3.2 Methods

3.2.1 Experimental Design and Sample

The INCPAD trial design (Kroenke et al., 2009) and its effectiveness in reducing pain and depression (Kroenke et al., 2010) have been previously described. Patients presenting for oncology clinic visits were screened for depression and pain. Patients who screened positive for depression or pain were contacted for a telephone eligibility interview to determine if they had clinically significant depression or pain. Depression had to be at least moderately severe, defined as a Patient Health Questionnaire nine-item depression scale (PHQ-9) score ≥ 10 and endorsement of either depressed mood and/or anhedonia. Pain had to be: (a) definitely or possibly cancer-related; (b) at least moderately severe, defined as a score of ≥ 6 on the "worst pain in the past week" item of the Brief Pain Inventory. Excluded were individuals who did not speak English, had moderately severe cognitive impairment, schizophrenia or other psychosis, had a pending pain-related disability claim, were pregnant, or were in hospice care. Informed consent and HIPAA release were obtained from eligible patients who desired to participate.

Of the 405 eligible participants who consented to enroll in the study, 202 patients were randomized to the intervention group and 203 to the usual-care group. Randomization was stratified by symptom type: 131 patients had depression only, 96 had pain only, and 178 had both depression and pain. Patient mean age was 58.8 years, and 68% were women. The type of cancer was breast (29%), lung (20%), gastrointestinal (17%), lymphoma or hematological (13%), genitourinary (10%, and other (10%). The phase of cancer was newly-diagnosed (37%), disease-free or maintenance therapy (42%), and recurrent or progressive (20%).

3.2.2 Outcomes

Outcomes were assessed by blinded telephone interviews over 12 months (baseline and at months 1, 3, 6, and 12, with some of the outcomes assessed less frequently). Depression, pain, mental health, and disability outcomes were used to estimate the depression-free days and quality adjusted life years (QALY) associated with the intervention.

Depression-free days (DFD) during the 12-month follow-up period were calculated from the HSCL-20 scores (Lave et al., 1998; Simon et al., 2001). At each assessment, patients received a portion of a DFD for that day according to the following algorithm: if patients had a HSCL-20 score of 0.50 or less, they were coded as having one DFD; if patients had HSCL-20 score of 2.00 or greater, zero DFDs; and if patients scored between 0.50 and 2.00, they were assigned a DFD value between zero and one by linear interpolation (e.g., a HSCL-20 score of 1.25 was coded as 0.5 DFD). DFDs between assessments (intervals of baseline to month 1, month 1 to month 3, etc.) were calculated by averaging the DFDs between the two assessments and multiplying by the number of days between assessments. DFDs between assessments were summed for all assessment intervals to yield the number of DFDs during the 12 month follow-up.

DFDs were calculated two ways, depending on how the missing follow-up assessments were coded. The first measure excluded patients who had missing follow-up assessments or died during the trial. The second imputed DFDs by: (1) carrying the last observation forward to impute the missing follow-up assessment, and (2) including patients who died up to their last assessment prior to death. Patients who died before their month 1 assessment were excluded from imputation.

QALYs were calculated using four methods. First, QALYs were derived from DFDs (Wells and Sherbourne, 1999; Revicki and Wood, 1998; Fryback et al., 1993; Pyne et al., 2010; Unützer et al., 1997; Schoenbaum, 2001). Previous literature estimated that depression corresponds to a 0.2 to 0.4 decrement in quality-of-life weights, so one year of depression would reduce QALYs by the same decrement. The number of depression-free days out of the year would correspond to a proportional reduction in QALYs. For example, a reduction of 30 depression-free days is equivalent to a 0.016 to 0.033 reduction in QALYs, depending on whether 0.2 or 0.4 was used. Second, patient responses to the SF-12 were used to generate preference-based quality-of-life weights (Brazier and Roberts, 2004). Third, a modified EQ-5D survey was construction from the responses to a combination of depression, pain, mental health, and disability items from various questionnaires and used to generate quality-of-life weights (Shaw et al., 2005) (Appendix 1). Fourth, a visual analog scale on a 0-10 scale was used to measure quality of life during the past month at each assessment. Quality-of-life weights at each assessment were rescaled to 0 to 1 and QALYs were calculated by area under the time curves.

3.2.3 Costs

Costs were calculated from a payer's perspective. Intervention cost per patient was determined using provider payroll data and capital expenditure associated with the intervention. The nurse care manager time devoted to each study patient was maintained in a detailed log, and physician time spent in weekly care management conferences and staffing outside of these weekly meetings was determined. Using annual salaries including fringe rates of the physician supervisor and nurse care manager combined with the hours they devoted to the study over the course of the INCPAD trial allowed us to calculate physician and nurse costs. Further details regarding cost determinations are provided in Appendix 2.

Capital expenditures for startup and maintenance of the automated symptom monitoring were included as an intervention cost. Automated symptom monitoring costs can be spread over a number of patients hence intervention cost per patient will decrease with increasing number of patients. Also, after paying these startup costs, subsequent maintenance costs are fairly low. However, the cost of purchasing the automated symptom monitoring may vary depending on the purchasing power of the buyer.

Since INCPAD involved multiple community-based practices across the state of Indiana, it was not possible to obtain prescription or other medical cost data. However, neither patient-reported health care use nor co-interventions differed significantly between the intervention and the usual care group (Kroenke et al., 2010).

3.2.4 Analysis

Incremental intervention costs and effectiveness were calculated separately for (a.) all 202 patients in the intervention group, including those who had only pain, only depression, or both pain and depression; and (b.) the subset of 154 patients in the intervention group with depression, including those with only depression and those with both pain and depression. This is because the cost-effectiveness analyses based upon the SF-12 and EQ-5D used the full sample of 405 patients (202 intervention and 203 control), while the analysis based upon DFDs used the 309 patients with depression (154 intervention and 155 control). Physician and nurse time cost was calculated based on administrative data on annual salary plus fringe and hours spent on the intervention during the year (Appendix 2).

The effect of the intervention on each outcome measure (DFDs, SF-12 quality-of-life weights, visual analog scale, and modified EQ-5D quality-of-life weights) at each assessment timepoint (month 1, 3, 6, and 12 for visual analog scale, DFDs, and the modified EQ-5D; month 3 and 12 for the SF-12) was estimated using OLS regression, controlling for baseline value of the outcome measure, age, gender, education, race, marital status, employment, and income. Each outcome at a given assessment month was modeled separately in cross-sectional regressions. Coefficients of the intervention dummy variable were used to test for significance of the intervention effect. Since the intervention was centralized and telephone-administered to patients throughout the entire state of Indiana, we did not expect an unobserved hospital or clinic level effect in these randomized data. Accordingly, those variables were omitted from the regression.

Based on the regression coefficients, average outcomes (DFD, SF-12 quality-of-life weights, modified EQ-5D quality-of-life weights) for the intervention group and the intervention group were predicted holding the covariates at observed values (Schoenbaum, 2001; Pyne et al., 2010). The area under the curve that captured the predicted quality-of- life weights over time was used to calculate QALYs. As mentioned earlier, the analysis for DFD was done with and without imputation. Analyses for SF-12 and EQ-5D were done only without imputation. Quality-of-life weights derived from the visual analog scale were not significantly different between the intervention and usual care group and therefore no further cost-effectiveness calculations were performed.

3.3 Results

3.3.1 Costs

Table 3.1 summarizes the costs attributable to the intervention. Total physician time cost to treat all intervention patients was $43,226 and the resulting physician cost per patient was $214. Total physician time cost to treat the patients with depression was $43,226 and the resulting physician cost per patient was $281. Total nurse care manager time cost to treat all intervention patients was $71,224 and the resulting total nurse care manager cost per patient was $353. Total nurse care manager time cost to treat the patients with depression was $61,906 and the resulting total nurse care manager cost per patient was $402.

Table 3.1: Costs of INCPAD Intervention for Entire Trial and 12-Month Per Patients Costs*

Intervention component (202 out of 405 intervention)	**Total Trial Costs ($)**	**Per Patient 12-Month Costs ($)**
Physician time	43,226	213.99
Nurse care manager time	71,224	352.59
Automated monitoring start-up/maintenance	78,000	386.14
Total	**192,450**	**952.72**

Intervention component (154 out of 309 depressed)	**Total Trial Costs ($)**	**Per Patient 12-Month Costs ($)**
Physician time	43,226	280.69
Nurse care manager time	61,906	401.99
Automated monitoring start-up/maintenance	78,000	506.49
Total	**183,132**	**1189.17**

* For details regarding cost calculations, see Appendix 2. First column includes total intervention costs for all patients during the 42 months of the trial. Second column is the per patient cost for the 12 months each patient was in the trial.

The cost of the automated monitoring system and its maintenance during the trial was $78,000. Spread out over all intervention patients, monitoring cost per patient was $386. Spread out over the patients with depression, monitoring cost per patient was $506. The sum of the physician, nurse care manager, and monitoring cost was $953 per patient for all intervention patients and $1189 per patient for the patients with depression.

Projected costs of the intervention for new patients enrolled after the trial should decrease because the automated monitoring system is already be set up and only maintenance costs of the system would be required. Post start up, automated monitoring maintenance cost was estimated to be about $20,000 over the 3 years of the trial , which would reduce the incremental cost per new intervention patient treated to about $666 and cost per new depressed patient treated to about $813.

3.3.2 Effectiveness

OLS regression estimated the effect of the intervention on DFDs controlling for baseline characteristics. Table 3.2 summarizes the incremental cost-effectiveness ratios. As previously noted, the regression model for DFD only included the subset of patients who had depression. From the subset of 309 depressed patients, 187 patients had complete follow-up, with 90 in the intervention group and 97 in usual care group. For these patients, predicted average DFD during the 12- month follow-up for the intervention group was 227.38 days and for the usual care group was 167.08 days. Thus, the intervention group was associated with an increase of 60.30 depression-free days (SE=15.38; $p<0.01$) compared to the usual care group. Based on the existing estimates of the increase in quality of life of from 0.2 to 0.4 per additional DFD, the intervention was associated with gain of between 0.033 and 0.066 QALYs.

Table 3.2: INCPAD Incremental Cost Effectiveness Ratios

Effectiveness Metric *	Δ Cost per patient	Δ Effectiveness	Incremental Cost-Effectiveness Ratio
DFD (Complete follow-ups)	1189.17 ($)	60.30 (DFD)	19.72 ($/DFD)
DFD (Complete and imputed follow-ups)	1189.17 ($)	44.12 (DFD)	26.95 ($/DFD)
QALY (derived from DFD complete follow-ups)	1189.17 ($)	.066 QALY to .033 QALY	18,017.73 ($/QALY) to 36,035.45 ($/QALY)
QALY (derived from DFD complete and imputed follow-ups)	1189.17 ($)	.048 QALY to .024 QALY	24,774.38 ($/QALY) to 49,548.75 ($/QALY)
QALY from EQ-5D	952.72 ($)	.088 (QALY)	10,826.48 ($/QALY)
QALY from SF-12	952.72 ($)	.013 (QALY)	73,286.92 ($/QALY)

* DFD = depression-free day. QALY = quality-adjusted life year.

From the subset of 309 depressed patients, 298 patients had either complete or imputed follow-up data on DFDs, with 148 in the intervention group and 150 in usual care group. The intervention group was associated with an increase of 44.12

depression-free days (SE=12.86; $p<0.01$) compared to the usual care group. The predicted average DFD during the 12-month follow-up for the intervention group was 185.81 days and for the usual care group was 141.70 days. Based on the existing estimate of the increase in quality of life in DFDs, the intervention was associated with gain of between 0.024 and 0.048 QALYs.

Quality-of-life weights from SF-12 and modified EQ-5D were also modeled using OLS regression. The regression model for quality-of-life weights included all patients. However, patients included in the regression model decreased over time, due to death or non-response and those with missing data were not imputed. For the SF-12, 405 patients were included at baseline, but diminished to 267 patients at month 12. For EQ-5D, 362 patients were included at baseline, but fell to 211 patients at month 12.

The effect of the intervention on SF-12 based quality-of- life weight was not significant at month 1, but significant at month 12 with intervention group associated with 0.03 point (SE=0.02; $p<0.05$) higher quality-of-life weight. The gain in SF-12 quality of life based on the area under the weight curve over 12 months was 0.013 QALYs. The intervention group was associated with significantly higher quality-of-life weights from the modified EQ-5D at month 1, 3, 6, and 12. Specifically, at month 1, the weights were 0.06 points (SE=0.02; $p < 0.01$) higher; at month 3, 0.08 points (SE=0.03; $p < 0.05$) higher; at month 6, 0.08 points (SE=0.03; $p < 0.05$) higher; at month 12, 0.14 points (SE=0.04; $p < 0.01$) higher. The area under the quality-of-life weight curve showed a gain of 0.088 QALYs.

3.3.3 Cost effectiveness

The reference case incremental cost-effectiveness ratios were calculated including the automated monitoring as a startup cost. For patients with depression who completed the trial without missing follow-ups, incremental cost per DFD gained was $19.72 per DFD, and $18,018 to $36,035 per QALY gained.

For patients with depression who either completed follow-ups or whose follow-up scores were imputed, incremental cost per DFD gained was $26.95, which corresponds to a cost per QALY gained of between $24,774 to $49,549, when evaluated by the range in quality-of-life gains found in the literature. For the modified EQ-5D, the incremental cost for all patients was $10,826 per QALY gained. Cost per QALY gained from the SF-12 was $73,286.

As a sensitivity analysis, post-start cost-effectiveness ratios were projected for new patients who might receive the 12-month intervention after the trial. This assumed similar physician and nurse care manager costs in providing care for a similar number of patients but lower automated monitoring costs due to the fact the system had already been set up and only maintenance costs would be required. startup to reflect lower costs in subsequent years after startup (Tab. 3.3). For patients with depression who completed the trial without missing follow-ups, post-startup incremental cost per DFD gained was $13.48, which corresponds to $12,311 to $24,623 per QALY gained.

Table 3.3: INCPAD Post-Startup Projected Incremental Cost Effectiveness Ratios for New Patients Receiving the Interventions*

Effectiveness Metric†	Δ Cost per patient	Δ Effectiveness	Incremental Cost-Effectiveness Ratio
DFD (complete follow-ups)	812.55 ($)	60.30 (DFD)	13.48 ($/DFD)
DFD (complete and imputed follow-ups)	812.55 ($)	44.12 (DFD)	18.42 ($/DFD)
QALY (derived from DFD complete follow-ups)	812.55 ($)	.066 to .033 (QALY)	12,311.36 ($/QALY) to 24,622.73 ($/QALY)
QALY (derived from DFD complete and imputed follow-ups)	812.55 ($)	.048 to .024 (QALY)	16,622.13 ($/QALY) to 33,856.25 ($/QALY)
QALY from EQ-5D	665.59 ($)	.088 (QALY)	7,563.52 ($/QALY)
QALY from SF-12	665.59 ($)	.013 (QALY)	51,199.23 ($/QALY)

* Post-start-up costs are projected to be $134,450 for 202 new patients receiving the INCPAD intervention , and $125,132 for the subset of 154 new depressed patients receiving the intervention. This is based upon the assumption that physician and nurse care manager times would be the same for treating the same number of new patients for 12 months as in the trial, but that only automated monitoring maintenance (ASM) costs would be needed since the ASM system would already be set up.

† DFD = depression-free days. QALY = quality-adjusted life years

For patients with depression who either completed follow-ups or whose responses were imputed, post-startup incremental cost per DFD gained was $18.42, which corresponds to $16,928.13 to $33,856.25 per QALY gained. Post start-up incremental cost per QALY gained was $7,564 for all patients using the modified EQ-5D weights and $51,199 using the SF-12 quality-of-life weights.

3.4 Discussion

Centralized telecare management coupled with automated symptom monitoring for cancer patients with pain and depression significantly increased depression-free days and associated QALYs compared to usual care. Intervention cost of telecare management was greater than usual care. The range of point estimates for the incremental cost-effectiveness ratio calculated from various outcome measures was within the range of other disease management interventions and generally below $50,000 per QALY (Lave et al., 1998; Simon et al., 2001; Schoenbaum, 2001; Pyne et al., 2010; Katon et al., 2005; Bosmans and Bruijne, 2006).

Effectiveness of the INCPAD intervention may persist beyond conclusion of the intervention. The Improving Mood: Promoting Access to Collaborative Treatment (IMPACT) trial conducted a 12-month collaborative care management program for depressed older primary care patients, and found that effectiveness benefits were sustained at 2-year follow-up and the intervention group had lower healthcare costs during the 4 year follow-up period (Unutzer et al., 2008; Hunkeler et al., 2006). If the improved depression outcomes generated by the INCPAD intervention were to persist beyond the 12 month trial, the incremental cost-effectiveness ratio would be even lower.

Regarding depression-free days (DFDs), our study in patients with cancer compares favorably to 10 previous studies conducted in primary care populations (Tab. 3.4). The latter have shown that a variety of interventions yield annualized gains in DFDs of 25.2 to 58 DFDs (compared to 60.2 DFDs in INCPAD) and a cost per DFD of $2.76 to $35.15 (compared to $19.72 in INCPAD). The cost effectiveness of telecare management also compares favorably with many other cancer treatments. Some new anticancer drugs have costs per QALY exceeding $100,000 to $200,000 (Smith and Hillner, 2011; Hillner and Smith, 2009; Sarin, 2008). Moreover, drivers of increased costs include not only new drugs but also advances in therapeutic radiology, imaging, and other treatment (Meropol et al., 2009; Murphy et al., 2012). In contrast, the estimated cost of the INCPAD intervention ranged from $7500 to $75,000 per QALY, with most CEA methods yielding an estimate under $50,000.

Table 3.4: Incremental Per Patient Costs and Effectiveness of Depression Care Interventions Compared to Usual Care

Study [a]	Year	Intervention	Duration (mo.)	Costs captured [b]			Depression-Free Days Per Patient		Incremental Outpatient Costs Per Patient (dollars)		QALY Method [d]
				Int	Dir	Ind	In Trial	Annualized	Total	Per DFD	
Katon et al [d] [49,50]	1995 1998	Psychiatrist collaborative care	6	✓	✓		15.8	31.6	383	24.24	None
Katon et al [d] [50,51]	1996 1998	Psychologist collaborative care	6	✓	✓		13.4	26.8	471	35.15	None
Schulberg et al [23,52}	1996 1998	Pharmacotherapy or Interpersonal psychotherapy	12	✓	✓	✓	49-58	49-58	-	13.14-17.56	DFD $11,270-$19 510
Katzelnick et al [53,54]	2000 2001	Depression care management	12	✓	✓		47.4	47.4	675	14.24	None
Simon et al [d] [55]	2000	Telephone care management	6	✓	✓		12.6	25.2	130	10.32	None
Simon et al [24]	2001	Stepped collaborative care	6	✓	✓		16.7	33.4	242	14.49	None
Schoenbaum et al [30]	2001	Quality improvement	24	✓	✓		36.5	36.5	-	-	DFD, SF-12 $9,478-$36,467
Katon et al [34]	2005	Collaborative care (late-life)	12	✓	✓		52.6	52.6	-	2.76	DFD $2,519-$5,037
Choi-Yoo et al	2014	Telecare management (cancer)	12	✓			60.3	60.3	1189	19.72	DFD, SF-12, EQ5D, Global QoL $10,829-$73,287

[a] All studies except that by Choi-Yoo were conducted in primary care populations. An additional primary care study by Pyne et al. (2010) showed no significant incremental effect of the intervention on depression-free days.

[b] Int = intervention costs. Dir = other direct health care costs not related to intervention. Ind = indirect costs

[c] If quality-adjusted life years (QALYs) calculated in article, the method (metric) used to calculate QALYs. DFD = depression-free days. SF-12 = Medical Outcome Study 12-item Short-Form. EQ5D = 5-item EuroQoL. Global QoL = single item overall quality of life.

[d] Some of DFD data and/or cost per DFD not in original article(s) but in summary table in Simon et al 2001 article [24]

Our cost-effectiveness analysis has three limitations. First, because the INCPAD trial intervention focused on community-based rural and urban oncology practices (many of which lacked electronic medical records and integrated health care systems), our analysis was limited to intervention costs rather than total health care costs. However, self-reported health care use as well as co-interventions did not differ significantly between intervention and control groups and, indeed, there was a trend for lower rates of hospitalization and emergency department use (two of the more expensive health care use indicators) in the intervention group (Kroenke et al., 2010). Thus, it is unlikely that health care costs were higher in the intervention group. Second, our study found significant improvements in only 3 of the 4 measures investigated. Third, our study used a novel but untested approach that modeled the items and responses for the EQ-5D from the responses to questions from other survey instruments. That this method translated into quality-of-life weight improvements that were consistent with the improvements found using 2 of the other effectiveness measures gave us a level of confidence in the validity of this measure.

Although INCPAD focused on depression and pain, telephone-based management has also proven effective for multiple cancer-related symptoms (Sherwood et al., 2005; Sikorskii et al., 2007). Cancer symptoms frequently cluster so that many patients often have more than one type of symptom (Barsevick et al., 2006; Teunissen et al., 2007; Kroenke et al., 2013). Thus, providing centralized telecare management for a range of cancer-related symptoms might further enhance its cost-effectiveness. Also, increasing the number of patients who can have their symptom management optimized at home without the time and travel costs of coming to the clinic makes the care more convenient and less costly from the perspective of the patient. This was reflected by the high patient adherence to and satisfaction with the telecare intervention in the INCPAD trial (Johns et al., 2011). Given the high symptom burden associated with cancer in all its stages, the responsiveness of symptoms to a cost-effective telecare management approach makes this a promising avenue for improving quality of life in cancer patients.

Chapter 4

Recession Led To A Decline In Out-Of-Pocket Spending For Children With Special Health Care Needs

This paper has been published. Karaca-Mandic, P., Choi Yoo, S. J., and Sommers, B. D. (2013). Recession led to a decline in out-of-pocket spending for children with special health care needs. Health Affairs, 32(6), 1054-1062.

4.1 Introduction

The rate of health care spending growth in the United States declined in the period 2008-10, compared to the prior decade. The recession through decreased household income and savings as well as increased risk of loss both of jobs and of private health insurance was probably one of the main factors in this trend. As consumers held back on their use of health services, out-of-pocket health care spending growth slowed from 2009 to 2010. Consumers' out-of-pocket health care spending increased 1.8 percent from 2009 to 2010, a rate far below the average annual growth of 4.8 percent from 2000 to 2008 (Martin et al., 2012).

The overall slowdown in health care spending growth may mask substantial heterogeneity in terms of whose spending was most affected, which raises several important policy questions. Was spending differentially affected for adults and for children? Although most children are healthy, forgoing routine health care could have long-term adverse implications on children's health.

Furthermore, children with special health care needs require specialized services, and they are at higher risk of adverse outcomes if they do not receive adequate care (Lavarreda et al., 2011). Children with special needs represented about 17.9 percent of all children in 2008, yet they accounted for 47.6 percent of children's total health care expenditures in that year (Davis, 2011). This raises a related question: Did the recession equally affect health care spending for children with and without special health care needs?

These questions are particularly salient for children in families covered by private health insurance (as compared to children with public coverage), because such families have been increasingly subject to higher cost sharing and out-of-pocket burden over the past decade (Cunningham, 2010; Banthin et al., 2008). Previous research has shown that although adults had higher rates of unmet or delayed care because of cost in 2010 than in 2000-with nonelderly adults reporting that they were 66 percent more likely to have had unmet medical needs and 79 percent more likely to have had unmet dental needs in 2010 than in 2000-the rates of unmet need remained stable for children during this ten-year period, reflecting the availability of public coverage for children (Kenney et al., 2012).

However, it is possible that privately insured families experienced greater financial pressure than publicly insured ones to reduce health care use because of the recession. Moreover, these questions have important implications for understanding whether the slowing in health care spending growth was disproportionately borne by those with greater health care needs. Answers to the questions can also provide valuable insights for policy makers considering future options for children's and adults' health care coverage.

In the study reported here, we examined national trends in out-of-pocket spending for privately insured families with children in the period 2001-09. We compared out-of-pocket spending for children with out-of-pocket spending for adults in the same families. We examined children with and without special health care needs separately. We tested whether trends in out-of-pocket health care burden were significantly different before and during the recession. Of course, the recession probably also affected out-of-pocket spending through another mechanism: loss of insurance. However, we focus here on the quality of coverage for those who remained insured for at least part of each year.

4.2 Study Data And Methods

4.2.1 Data

We used the Medical Expenditure Panel Survey (MEPS) 2001-09 Household Component Full Year Consolidated Data files and Person Round Plan files in the Household Component Full Year files. MEPS is a nationally representative survey of the US civilian noninstitutionalized population that provides information on health care access and use, socioeconomic characteristics, employment, access to care, and related topics. More information on the survey can be found through the online MEPS documentation (Agency for Healthcare Research and Quality, 2011b).

4.2.2 Study Sample

Our study population included families with children ages 0-17 who were insured at any time during a given year as dependents on a family member's private health insurance policy. In a sensitivity analysis discussed in more detail below, we also examined children who were covered by private insurance for all twelve months during a year. Consistent with the MEPS definition, the child's family included household members living together, as well as relatives considered usual household members but not present at the time of the interview, such as college students (Agency for Healthcare Research and Quality, 2011b).

Study samples were stratified into children with and without special health care needs via the MEPS special health care needs screening instrument (Maternal and Child Health Bureau, 2007). The Maternal and Child Health Bureau defines children with special health care needs as "those who have or are at increased risk for a chronic physical, developmental, behavioral, or emotional condition and who also require health and related services of a type or amount beyond that required by children generally" (Maternal and Child Health Bureau, 2007).

4.2.3 Out-Of-Pocket Health Care Burden

MEPS estimates of total expenditures per person include payments from all sources (public and private) for services to hospitals and emergency departments; physicians and - providers of dental and other health care; and pharmacies. The questionnaire is comprehensive in the types of services it asks households to report, with the exception of over-the-counter medicines.

The out-of-pocket expenditure variable is the amount paid by the patient or patient's family for services received. Health insurance premiums are not included in out-of-pocket expenditures (Agency for Healthcare Research and Quality, 2011b). We estimated out-of-pocket health care spending for each child and for each adult in the child's family. All dollar measures were adjusted to 2009 US dollars using the urban Consumer Price Index (Bureau of Labor Statistics, 2011).

4.2.4 Statistical Models

We estimated generalized linear models with the logarithm of out-of-pocket spending as the dependent variable, time as the primary independent variable of interest, and multivariate adjustment for the child and family characteristics listed below. The unit of observation was the child-year. Our primary goal was to compare the trend in out-of-pocket spending before and during the recent recession. The National Bureau of Economic Research reported that the recession officially started in December 2007 and ended in June 2009. We used spline modeling, with the regression identifying a linear time trend from 2001 to 2007 and a separate linear time trend from 2007 to 2009 (National Bureau of Economic Research, 2010). Complete details on the methodology can be found in Appendix Exhibits (A8- A11).

We controlled for the following child and family characteristics. Child characteristics were age, sex, race, and ethnicity. Family characteristics were number of adult family members, number of child siblings, highest family member educational attainment, urban status as measured by residence in a Metropolitan Statistical Area, Census region, and the presence of any limitations in activities of daily living or any functional or sensory limitations in family members other than the child.

All analyses accounted for the MEPS complex survey design using the survey commands in the statistical software Stata, version 12. The survey design variables also accounted for observations coming from multiple children in the same family (Sribney, 1998; West, 2011).

4.2.5 Limitations

One limitation of our study was that out-of-pocket spending was broadly defined rather than by specific services. Although it would also be valuable to stratify the analyses by different types of services, our primary goal was to explore the effect of the recession on overall out-of-pocket spending. In additional analyses presented in the Appendix, we distinguished among broad service categories such as inpatient, outpatient, emergency department, prescription drugs, and dental care.

Any reductions in spending might reflect the elimination of either needed or unneeded services, and we were unable to directly distinguish between these two possibilities. However, previous research suggests that adult patients themselves are poor judges of the necessity of treatment for themselves (Goldman DP Zheng Y., 2007) and their children (Leibowitz et al., 1985; Johnson et al., 2006; Karaca-Mandic P Joyce GF,Goldman DP et al., 2012). That means it is reasonable to assume that any general decline in spending resulting from the recession included at least some necessary or recommended medical care.

Another data limitation was that use of health services in MEPS was self-reported and subject to misreporting, as is the case with all self-reported data on health care use (Bhandari and Wagner, 2006). Previous studies of MEPS have showed that although inpatient stays were accurately reported, office visits and emergency department visits were underreported by 19 percent and 30 percent, respectively. However, underreporting occurred across all sociodemographic groups and should not bias our analysis of changes in trends over time (Zuvekas and Olin, 2009b).

Studies have also documented differences between health care expenditures in MEPS and those in the "gold standard" National Health Expenditure Accounts

(Bernard et al., 2012; Zuvekas and Olin, 2009a; Aizcorbe et al., 2012). After adjusting for the differences in underlying population, covered services, and other measurement differences, MEPS total personal health care expenditures were 17.6 percent lower than those in the National Health Expenditure Accounts in 2007. However, MEPS out-of-pocket spending was only 5.5 percent lower than that in the National Health Expenditure Accounts in the same year, and we are unaware of any evidence that this difference has varied over time.

We also compared the out-of-pocket spending for adults versus children, defining adults as anyone in the family over age eighteen-though the most relevant adults for decision making are likely to be the child's parents. Nonetheless, most of the adults in the study families were in fact parents, and we treated these findings in our discussion as primarily related to parental decision making. In a sensitivity analysis, we defined adults in the family as only the child's parents, thus excluding adult siblings and grandparents living in the home. In another sensitivity test, we considered the health insurance eligible units as an alternative to family units. Results were largely similar in all three approaches.

Finally, we examined changes in out-of-pocket trends, after controlling for observed child and family characteristics, in an attempt to quantify the impact of the recession. We attributed the change in spending trends to the recession, but other unmeasured factors may have driven these results. However, we are unaware of other large-scale health policy or economic changes that would affect this population starting in 2008.

4.3 Study Results

4.3.1 Characteristics Of Children And Their Families

Table 4.1 and 4.2 presents the characteristics of the children and their families. Children with special health care needs were older on average and had higher out-of-pocket spending, compared to children without such needs.

Adults in families with special needs children also had higher out-of-pocket spending, compared to those in families without such children. This finding is consistent with other studies that show that caregivers of children with special needs experience higher emotional and physical stress, which is negatively associated with the caregivers' psychological and physical health (Altman et al., 1999; Brehaut et al., 2009, 2011, 2004; Murphy et al., 2007; Singer and Floyd, 2006).

4.3.2 Trends In Out-Of-Pocket Spending Before And During The Recession

For children without special health care needs, out-of-pocket spending increased gradually both before and during the recession, although the the trends were not statistically different (Fig. 4.1). Average out-of-pocket spending for children with special health care needs was substantially higher than for children without such needs (Fig. 4.2). Spending for children with special needs increased over time before the recession but decreased during the recession. The adjusted average out-of-pocket spending was $774 in 2007, which declined to $626 in 2009. Appendix Exhibits A8 and A9 present the marginal effects of spending trends before and during the recession, as well as other control variables on child out-of-pocket spending.

Table 4.1: Non-CSHCN Weighted Descriptive Statistics

	Estimate	(SE)
Age (n=32,736)	8.6	(0.1)
Female (n=16,324)	50.2	(0.4)
Male (n=16,412)	49.8	(0.4)
Adults in family (n=32,736)	2.1	(0.0)
Siblings in family (n=32,736)	1.2	(0.0)
No other family have any limitation (n=24,924)	80.1	(0.4)
Some other family have any limitation (n=6,442)	19.9	(0.4)
No dental insurance (n=9,658)	28.9	(0.5)
Has dental insurance (n=23,078)	71.1	(0.5)
White (n=21,106)	71.0	(0.7)
Black (n=4,340)	9.3	(0.5)
AI/AN (n=432)	1.2	(0.1)
Asian (n=2,431)	6.1	(0.3)
Native Hawaiian/Pacific Islander (n=3,472)	9.9	(0.4)
Multiple races (n=955)	2.5	(0.2)
Not Hispanic (n=25,717)	87.5	(0.5)
Hispanic (n=7,019)	12.5	(0.5)
Highest family edu less than college (n=9,995)	25.6	(0.6)
Highest family edu college (n=15,188)	51.8	(0.6)
Highest family edu 5+ years college (n=5,857)	22.5	(0.6)
Not Metropolitan Statistical Area (n=5,121)	15.5	(0.8)
Metropolitan Statistical Area (n=27,615)	84.5	(0.8)
NorthEast (n=5,103)	18.5	(0.7)
Midwest (n=7,657)	24.3	(0.9)
South (n=11,098)	33.1	(1.0)
West (n=8,878)	24.2	(0.9)
Average Annual Out-of-Pocket Spendings		
Total for child	$276.6	(5.6)
Total for adults	$989.9	(16.0)
Total for adults per child	$478.7	(7.9)

Source: MEPS 2001-2009

Notes:Children between ages 0-17 and their families, with private insurance, non-missing policyholder's OOP premium payment, policy holder lives with the family

Table 4.2: CSHCN Weighted Descriptive Statistics

	Estimate	(SE)
Age (n=7,342)	10.3	(0.1)
Female (n=3,107)	42.8	(0.8)
Male (n=4,235)	57.2	(0.8)
Adults in family (n=7,342)	2.1	(0.0)
Siblings in family (n=7,342)	1.1	(0.0)
No other family have any limitation (n=4,817)	68.6	(0.9)
Some other family have any limitation (n=2,324)	31.4	(0.9)
No dental insurance (n=2,172)	29.0	(0.9)
Has dental insurance (n=5,170)	71.0	(0.9)
White (n=4,913)	74.1	(0.8)
Black (n=955)	8.7	(0.5)
AI/AN (n=67)	0.9	(0.2)
Asian (n=325)	3.3	(0.3)
Native Hawaiian/Pacific Islander (n=823)	10.4	(0.6)
Multiple races (n=259)	2.7	(0.3)
Not Hispanic (n=6,284)	91.2	(0.5)
Hispanic (n=1,058)	8.8	(0.5)
Highest family edu less than college (n=1,881)	22.1	(0.8)
Highest family edu college (n=3,603)	53.1	(1.0)
Highest family edu 5+ years college (n=1,450)	24.8	(1.0)
Not Metropolitan Statistical Area (n=1,142)	14.2	(0.9)
Metropolitan Statistical Area (n=6,200)	85.8	(0.9)
NorthEast (n=1,189)	18.8	(0.9)
Midwest (n=1,886)	25.5	(1.2)
South (n=2,672)	36.6	(1.3)
West (n=1,595)	19.1	(1.0)
Average Annual Out-of-Pocket Spendings		
Total for child	\$685.8	(23.4)
Total for adults	\$1,319.1	(40.2)
Total for adults per child	\$630.9	(15.9)

Source: MEPS 2001-2009

Notes:Children between ages 0-17 and their families, with private insurance, non-missing policyholder's OOP premium payment, policy holder lives with the family

Figure 4.1: Out-of-pocket spending ($) for children without special health care needs

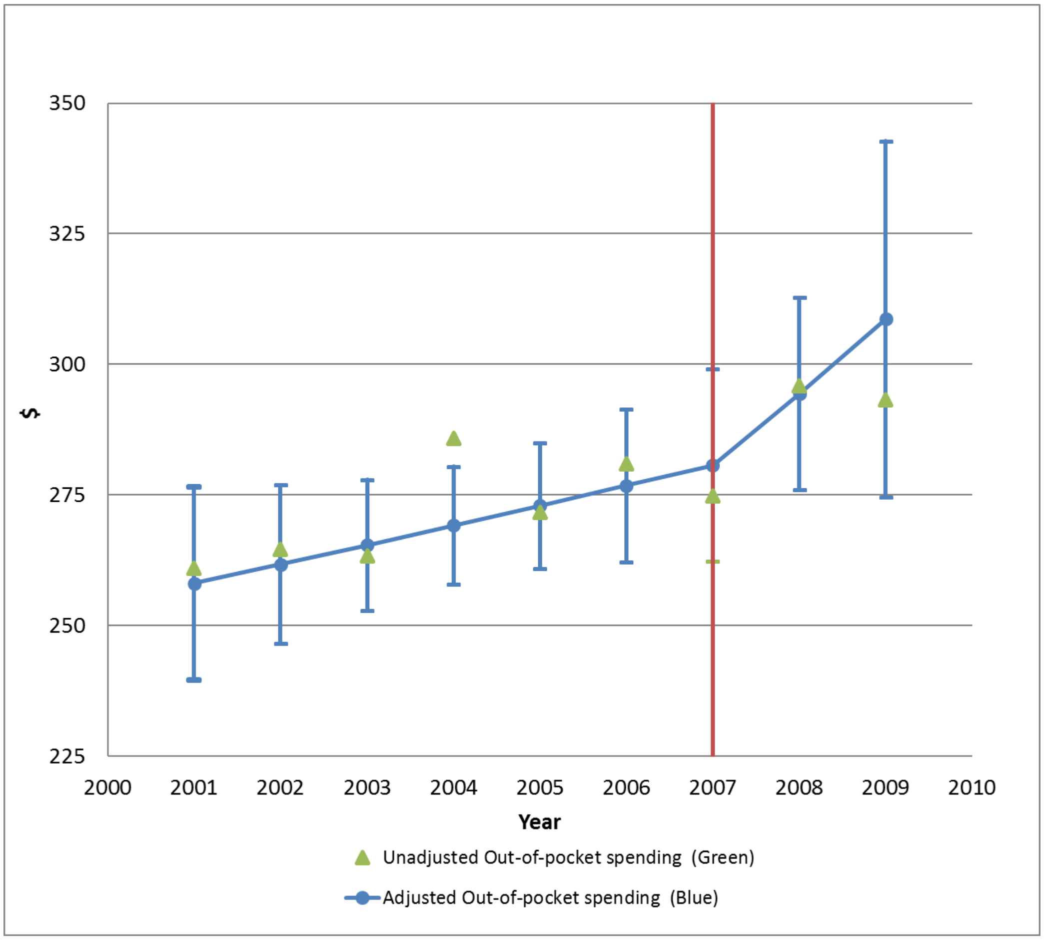
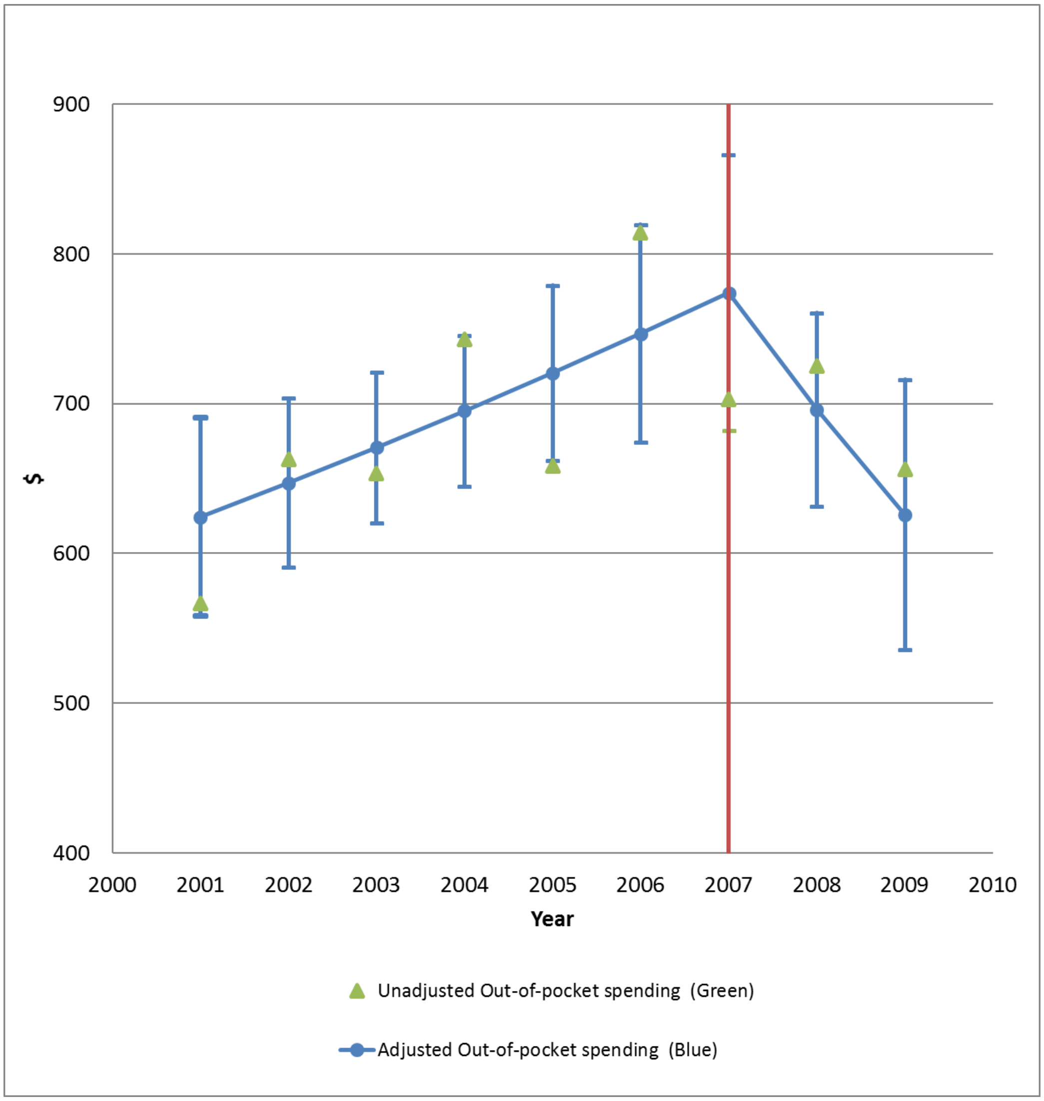


Figure 4.2: Out-of-pocket spending ($) for children with special health care needs



Average annual out-of-pocket spending for adults in the study families increased significantly per adult before the recession, both in families of children without special health care needs (Fig. 4.3) and in families of children with such needs (Fig. 4.4). And in both types of families spending per adult decreased sharply during the recession. Appendix Exhibits A10 and A11 present the marginal effects of spending trends and other control variables on adult out-of-pocket spending.

Figure 4.3: Out-of-pocket spending for adults in families ($ per adult) with children without special health care needs

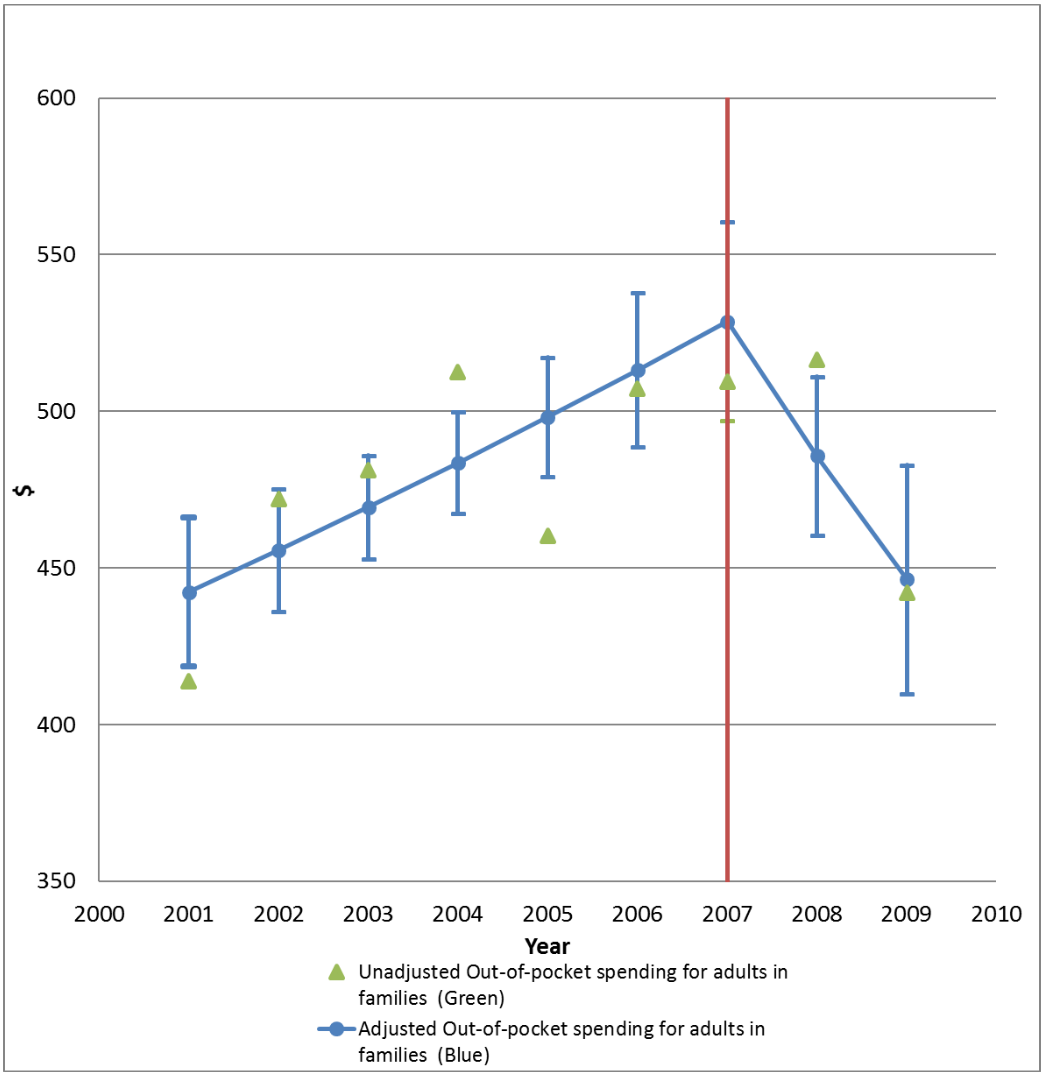
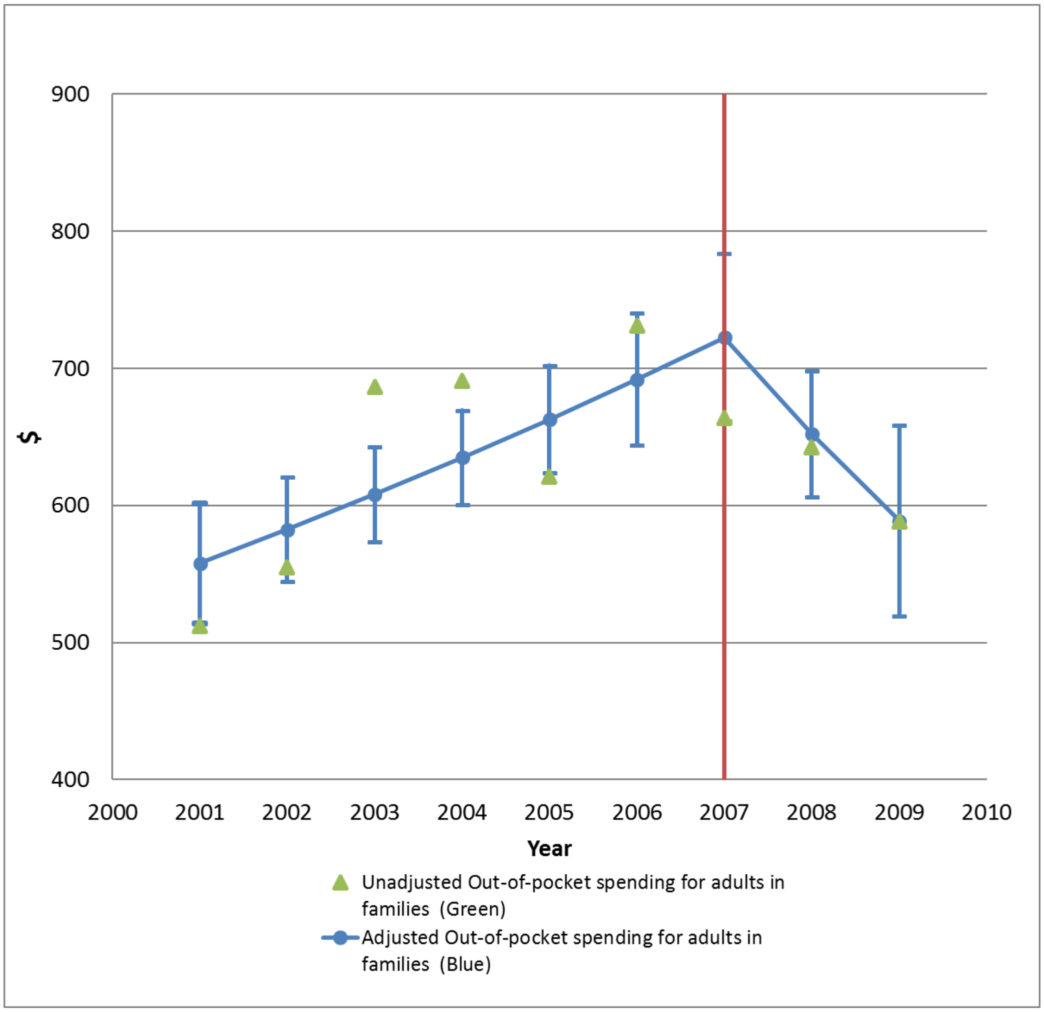


Figure 4.4: Out-of-pocket spending for adults in families ($ per adult) with children with special health care needs



Several sensitivity tests were conducted of our benchmark models. First, we limited the study sample to children who were continuously enrolled in private insurance throughout a given year. Our results were largely unchanged, although among children with special health care needs, the change in out-of-pocket trend associated with the recession was smaller than it was in our benchmark sample, partly as a result of the reduced sample size. This also may suggest that children who are covered continuously with private insurance are better protected from the adverse effects of recession than children whose families lost coverage for part of a year.

A second sensitivity analysis focused only on parents, instead of on all adults in the family. A third analysis considered health insurance eligibility units instead of family units. Our benchmark findings were robust to both of these refinements.

Fourth, we explored the impact of the recession after incrementally including several of its features, such as the employment status of the adults in the family and federal poverty level thresholds. We found that the change in out-of-pocket trends associated with the recession were slightly reduced with the inclusion of unemployment and federal poverty level categories as control variables, but the trends were still similar to those in our benchmark estimates.

However, the employment status of the adults and federal poverty level categories are limited in fully capturing the impact of the recession through unemployment and income. For example, even among the employed, work hours and salary growth were reduced. In addition, the recession probably had adverse effects on savings, housing value, and liquidity. These factors were more immediate, affected households early in 2008, and were not well captured in the available data.

Lastly, we investigated the impact of the recession on total expenditures, family spending on insurance premiums, and out-of-pocket spending and use by broad service categories (inpatient, outpatient, emergency department, and dental care and prescription drugs). During the recession, total expenditure growth increased only for children without special health care needs. Premium spending was reduced. Reductions in out-of-pocket spending growth during the recession for children with special health care needs and adults were primarily driven by reductions in the use of prescription drugs and, to some extent, by reductions in the use of dental care, although trend differences for dental care were significant only for the adults.

Analyses of use outcomes confirm this pattern. Given the small sample size, decomposing health care services into these categories may have limited our power to detect effects in the other use categories.

4.4 Discussion

In our study of families with private health insurance, we found that the recession of 2007-09 was not associated with a decline in out-of-pocket spending for most children. However, adults in those families experienced significant declines in out-of-pocket spending during the recession, suggesting that families may have been forced to reduce parents' spending on health services for themselves to maintain their prior level of spending on services for their children. Although children in general were not significantly affected by the recession, we did find a significant reversal in the spending trend for children with special health care needs. After years of steady increases in out-of-pocket spending for this group, spending declined in 2007-09.

Overall, out-of-pocket spending was determined by two primary factors: service use and insurance benefit design. We were not able to control for benefit design because the MEPS household survey does not contain such information. Evidence suggests that in many cases deductibles and cost-sharing requirements in the private insurance market have been increasing as a proportion of total spending (Cunningham, 2010; Cohen and Martinez, 2012). We found that out-of-pocket spending slowed down during the recession, despite the fact that cost-sharing requirements in many plans were increasing.

Our results suggest that the recession reduced out-of-pocket spending for adults and for children with special health care needs through a reduction in use that was large enough to offset any increased cost-sharing requirements during this period. The reductions in use are concerning, given that previous research has shown an association between forgone care and adverse outcomes, especially for children with special health care needs (Lavarreda et al., 2011; Karaca-Mandic P Joyce GF,Goldman DP et al., 2012; Newacheck et al., 2000). Our findings suggest that dental services and prescription drugs may be particularly vulnerable areas of care during economic downturns.

4.4.1 Policy Implications

Our findings have implications for policy makers in two primary areas. First, the Affordable Care Act may have a major impact on out-of-pocket spending for families with children. The broad Medicaid expansion scheduled for 2014 (for people with incomes of up to 138 percent of the federal poverty level) and cost-sharing subsidies (for those with incomes of up to 250 percent of the level) and tax credits to reduce premiums for insurance through insurance exchanges (for people with incomes of 100-400 percent of the federal poverty level) are likely to reduce the out-of-pocket burden on privately insured families, especially those with lower incomes.

Of the families in our study sample, 28 percent had incomes of less than 100 percent of the federal poverty level. Eight percent had incomes of 100-125 percent of poverty, 20 percent had incomes of 125-200 percent of poverty, and 27 percent had incomes of 200-400 percent of poverty.

Furthermore, the law's elimination of cost sharing for many preventive services applies to all income groups. This provision may be particularly beneficial for children because a higher share of their care is likely to fall under this heading than is the case with adults. Other Affordable Care Act provisions that prohibit health plans from setting lifetime limits on coverage and from excluding care or coverage for preexisting conditions are expected to substantially benefit people of all ages with special health care needs.

Our findings also suggest the importance of considering the impact of policies affecting health coverage in the context of the entire family rather than individuals. Reducing the cost-sharing burden for children's coverage may help parents avoid the difficult decision of whether to cut back on their own care to pay for their children's.

A second area of policy affected by our findings relates to the future of the Children's Health Insurance Program (CHIP). CHIP generally offers coverage to children in low- and middle-income families with more limited cost sharing than private insurance. As of January 2012 twenty-two states required copayments for nonpreventive physician visits for CHIP services covering children whose family income was at least 201 percent of the federal poverty level. These copayments were $5 or less in eleven states, $10 in eight states, and $15-$20 in the remaining three states (Kaiser Family Foundation, 2012).

In contrast, private insurance policies in the group market required, on average, copayments of $23.34 for an office visit in 2011 (Agency for Healthcare Research and Quality, 2011a). Moreover, in private insurance plans the average individual deductible was $1,123 (Agency for Healthcare Research and Quality, 2012) and the average family deductible was $2,220 (Agency for Healthcare Research and Quality, 2012).

However, CHIP is currently funded only through 2015, and its fate after that is highly uncertain. Our findings suggest that private insurance leaves families with children vulnerable during times of economic downturn and may force parents and children with special health care needs to cut back on needed services. The defunding or elimination of CHIP could exacerbate such problems in the future (Kenney et al., 2011).

4.5 Conclusion

We found evidence that the recession of 2007-09 did not affect out-of-pocket health care spending for most children, but it did lead to a sharp reduction in spending for children with special health care needs. Furthermore, adults in families with children also experienced reductions in out-of-pocket spending during the recession, indicating that though health care spending for children in general was not adversely affected during the economic downturn, this may have been at the expense of their parents' health care. Policy efforts to bolster coverage for families with children are needed to protect the health care use of both children and parents during times of economic hardship.

Chapter 5

Conclusion

The three papers in this dissertation investigated topics in health economics to address some of the challenges in the US health care system. The first paper investigated the great recession and hospital capital investment and found evidence of liquidity constraint among not for profit and public hospitals during the recession. Hospital ownership determines what type of financing mechanism is available for capital investment. Not for profit and public hospitals must use cash flow or debt whereas investor owned hospitals also have access to equity. Thus investor owned hospitals are less susceptible to liquidity constraint.

The theoretical cause of liquidity constraint is asymmetric information between the lenders and hospitals, a market failure that warrants policy intervention. Strengthening the financial disclosure requirements in the municipal bond market, where not for profit and public hospitals borrow, may mitigate the information problem between hospitals and lenders and alleviate hospital liquidity constraint in an economic recession.

The theoretical modeling of hospital capital investment and the estimation method for identifying the cash flow effect is a strength of the paper. However, the theoretical model of hospital grossly simplifies the hospital capital investment decision and the study was limited to only California hospitals rather than a national sample of hospitals. Policy changes that overlap with the recession may also have affected hospital capital investment.

The second paper investigated the cost effectiveness of telecare management for pain and depression in patients with cancer. Centralized telecare management combined with automated symptom monitoring for cancer patients with pain and depression was found to be a cost effective intervention for pain and depression in patients with cancer.

The intervention was associated improved quality adjusted life years during the 12 month trial. The intervention group was associated with a yearly increase of 60.3 depression-free days and an increase of between 0.033 and 0.066 quality-adjusted life years compared to the usual care group. The resulting incremental cost per quality-adjusted life year ranged from $18,018 to $ 36,035. The study was limited to community-based rural and urban oncology practices in Indiana, many without electronic medical records, thus cost analysis was limited to intervention costs rather than total health care costs.

The third paper investigated how out of pocket health care spending for children changed during the recession. Out-of-pocket health care spending for most children did not show a change in trend before and during the recession. However, out-of-pocket health care spending sharply declined during the recession among children with special health care needs. Out-of-pocket health care spending of adults in families with children also declined during the recession.

The strength of the paper is using medical expenditure panel survey to make nationally representative estimates on out-of-pocket health care spending. But the medical expenditure panel survey does not provide data on insurance benefit design, which is a determinant of out-of-pocket spending. Another data limitation is that the medical expenditure panel survey is self-reported therefore subject to data misreporting. Previous studies using the medical expenditure panel survey found that underreporting did not vary by sociodemographic characteristics.

The study highlights the vulnerability of children with special health care needs during an economic recession. Also out-of-pocket health care spending of adults in families with children also declined during the recession, suggesting that parents may have been substituting their own health care spending with their children's spending. Health care reform efforts to reduce out-of-pocket spending for children may also save parents from reducing their own health care spending.

My future research aims to extend my understanding of how hospitals respond to financial shocks like the recession to investigate the impact of health care reform on hospital financial performance. The Affordable Care Act includes provisions that reform payments to hospitals, which may have strong implications for hospital financial performance. I want to inform policy discussions around improving patient access to hospital services and containing hospital costs.

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Appendix

1.1 The Great Recession and Hospital Capital Investment

1.1.1 Euler Equation

Value function V that maximizes the manager's utility function at time t and the present value of all expected future utilities discounted by discount factor β. U is the hospital Manager's utility function to be maximized. It is specified as net profits where cash inflows include operating profits π and borrowing B; cash outflows include adjustment cost C^K, capital investments I^K, and interest expense on debt rD.

Capital K (state variable, stock) represents the total stock of capital. Capital evolves over time through the capital accumulation equation (1.3). Capital stock in the next time period K_{t+1} is equal to capital stock K_t , minus depreciation δK_t (depreciation rate δ) , plus capital investment I_t^K at current period. Capital K is restricted to be non-negative because it is a required input for hospital operations (1.8).

Liquidity constraint limits net debt D to be less than or equal to D^* (1.9). D^* represents an upper bound on net debt set by creditors. Bankruptcy constraint specifies the manager's utility function to be non-negative (1.10) such that the cash outflows can not exceed cash inflows. Negative cash flow indicates that a hospital is bankrupt where cash inflow is not sufficient to pay for cash outflows.

$$V(K_t, D_t) = \max_{I_t^K, B_t} U_t + E_t \sum_{s=1}^{\infty} \beta^s U_{t+s} \tag{1.1}$$

Subject to:

$$U_t = \pi_t(K_t, L_t, \zeta_t) - C^K(K_t, I_t^K) - I_t^K \tag{1.2}$$
$$- r_t D_t + B_t$$

$$K_{t+1} = g(K_t, I_t^K) = K_t(1-\delta) + I_t^K \tag{1.3}$$

$$D_{t+1} = n(D_t, B_t) = D_t + B_t \tag{1.4}$$

$$\pi_t(K_t, L_t, \zeta_t) = p_t^Q F(K_t, L_t) - p^L L_t + \zeta_t \tag{1.5}$$

$$C^K(K_t, I_t^K) = \frac{\alpha}{2}\left(\frac{I_t^K}{K_t}\right)^2 K_t \geq 0 \tag{1.6}$$

$$r_t > 0 \tag{1.7}$$

$$K_t \geq 0 \tag{1.8}$$

$$D_t \leq D_t^* \tag{1.9}$$

$$U_t \geq 0 \tag{1.10}$$

We can rewrite the value function (1.1) as a more general Bellman equation V where it is a function of the state variables K_t , A_t, D_t, and with an infinite horizon. Note that the present time utility function U_t is not subject to the expectations operator. This is because at time t, we know the values of today's shock ζ_t.

$$V(K_t, D_t) = \max_{I_t^K, B_t} U_t + E_t[\beta V(K_{t+1}, D_{t+1})] \tag{1.11}$$

Lagrangian for the maximization problem above is written as below with λ_t as the

Lagrange multiplier on the non-negativity constraint (1.10) and γ_t as the Lagrange multiplier on the debt constraint (1.9).

$$\mathcal{L} = U_t + E_t[\beta V(K_{t+1}, D_{t+1})] + \lambda_t U_t + \gamma_t(D_t^* - D_t) \tag{1.12}$$

First order conditions are derived by taking partial derivatives of the Lagrangian with respect to the control variables I_t^K , B_t and the Lagrange multipliers λ_t and γ_t.

Kuhn-Tucker conditions:

$$\frac{\partial \mathcal{L}}{\partial I_t^K} = (1+\lambda_t)\frac{\partial U_t}{\partial I_t^K} + E_t\left[\beta \frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})\frac{\partial g}{\partial I_t^K}(K_t, I_t^K)\right] \leq 0 \tag{1.13}$$

$$I_t^K \geq 0 \tag{1.14}$$

$$I_t^K \frac{\partial \mathcal{L}}{\partial I_t^K} = 0 \tag{1.15}$$

$$\frac{\partial \mathcal{L}}{\partial B_t} = (1+\lambda_t)\frac{\partial U_t}{\partial B_t} + E_t\left[\beta \frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})\frac{\partial n}{\partial B_t}(D_t, B_t)\right] \leq 0 \tag{1.16}$$

$$B_t \geq 0 \tag{1.17}$$

$$B_t \frac{\partial \mathcal{L}}{\partial B_t} = 0 \tag{1.18}$$

$$0 \leq U_t \tag{1.19}$$

$$\lambda_t \geq 0 \tag{1.20}$$

$$\lambda_t U_t = 0 \tag{1.21}$$

$$0 \leq D_t^* - D_t \tag{1.22}$$

$$\gamma_t \geq 0 \tag{1.23}$$

$$\gamma_t(D_t^* - D_t) = 0 \tag{1.24}$$

FOC (1.13) yields (1.25) which then simplifies to (1.26).

$$(1+\lambda_t)\underbrace{\left(-\frac{\partial C_t^K}{\partial I_t^K} - 1\right)}_{\frac{\partial U_t}{\partial I_t^K}} + E_t\left[\beta\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})\underbrace{\frac{\partial g}{\partial I_t^K}(K_t, I_t^K)}_{1}\right] = 0 \tag{1.25}$$

$$(1+\lambda_t)\left(1 + \frac{\partial C_t^K}{\partial I_t^K}\right) = E_t\left[\beta\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})\right] \tag{1.26}$$

FOC (1.16) yields (1.27) which then simplifies to (1.28).

$$(1+\lambda_t)\underbrace{(1)}_{\frac{\partial U_t}{\partial B_t}} + E_t\left[\beta\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})\underbrace{\frac{\partial n}{\partial B_t}(D_t, B_t)}_{1}\right] = 0 \tag{1.27}$$

$$-(1+\lambda_t) = E_t\left[\beta\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})\right] \tag{1.28}$$

Expression for $\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})$ in (1.26) can be derived as follows. First solve for $\frac{\partial V}{\partial K_t}(K_t, D_t)$.

$$\begin{aligned}\frac{\partial V}{\partial K_t}(K_t, D_t) &= (1+\lambda_t)\frac{\partial U_t}{\partial K_t} + E_t\left[\beta\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})\frac{\partial g}{\partial K_t}(K_t, I_t^K)\right] \\ &= (1+\lambda_t)\frac{\partial U_t}{\partial K_t} + E_t[\quad\underbrace{\beta\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})}_{\text{substitue in the left handside of (1.26)}}\quad(1-\delta)] \\ &= (1+\lambda_t)\frac{\partial U_t}{\partial K_t} + \left[(1+\lambda_t)\left(1 + \frac{\partial C_t^K}{\partial I_t^K}\right)(1-\delta)\right] \end{aligned} \tag{1.29}$$

Then we can take the expression for $\frac{\partial V}{\partial K_t}(K_t, D_t)$ in (1.29) one time period forward to yield $\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})$.

$$\begin{aligned}
\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1}) &= (1+\lambda_{t+1})\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left[(1+\lambda_{t+1})\left(1+\frac{\partial C_{t+1}^K}{\partial I_{t+1}^K}\right)(1-\delta)\right] \\
&= (1+\lambda_{t+1})\left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(1+\frac{\partial C_{t+1}^K}{\partial I_{t+1}^K}\right)(1-\delta)\right) \qquad (1.30)
\end{aligned}$$

Inserting the expression for $\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})$ from (1.30) to the FOC (1.26) yields the Euler equation (1.31) which can be rearranged as (1.32):

$$(1+\lambda_t)\left(1+\frac{\partial C_t^K}{\partial I_t^K}\right) = E_t\left[\beta(1+\lambda_{t+1})\left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(1+\frac{\partial C_{t+1}^K}{\partial I_{t+1}^K}\right)(1-\delta)\right)\right] \qquad (1.31)$$

$$1+\frac{\partial C_t^K}{\partial I_t^K} = E_t\left[\beta\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)\left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(1+\frac{\partial C_{t+1}^K}{\partial I_{t+1}^K}\right)(1-\delta)\right)\right] \qquad (1.32)$$

Deriving the expression for $\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})$ in (1.28) is analogous to deriving $\frac{\partial V}{\partial K_{t+1}}(K_{t+1}, D_{t+1})$ shown in equations (1.29) through (1.32). Expression for $\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})$ in (1.28) can be derived as follows. First solve for $\frac{\partial V}{\partial D_t}(K_t, D_t)$.

$$\begin{aligned}
\frac{\partial V}{\partial D_t}(K_t, D_t) &= (1+\lambda_t)\frac{\partial U_t}{\partial D_t} + E_t\left[\beta\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})\frac{\partial n}{\partial D_t}(D_t, B_t)\right] - \gamma_t \\
&= (1+\lambda_t)\frac{\partial U_t}{\partial D_t} + E_t\left[\underbrace{\beta\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})}_{\text{substitue in the left handside of (1.28)}}(1)\right] - \gamma_t \\
&= (1+\lambda_t)\frac{\partial U_t}{\partial D_t} + \left[-(1+\lambda_t)(1)\right] - \gamma_t \\
&= -(1+\lambda_t)(r_t) + \left[-(1+\lambda_t)(1)\right] - \gamma_t \qquad (1.33)
\end{aligned}$$

Then we can take the expression for $\frac{\partial V}{\partial D_t}(K_t, D_t)$ in (1.33) one time period forward to yield $\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})$.

$$\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1}) = -\left(1+\lambda_{t+1}\right)\left(r_{t+1}\right) + \left[-\left(1+\lambda_{t+1}\right)(1)\right] - \gamma_{t+1} \tag{1.34}$$

Inserting the expression for $\frac{\partial V}{\partial D_{t+1}}(K_{t+1}, D_{t+1})$ from (1.34) to the FOC (1.28) yields the Euler equation (1.35).

$$1 = E_t\left[\beta\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)(r_{it+1}+1) + \frac{\gamma_{t+1}}{1+\lambda_t}\right] \tag{1.35}$$

The Euler equations that must be satisfied to maximize the value function are:

$$1 + \frac{\partial C_t^K}{\partial I_t^K} = E_t\left[\beta\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)\left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(1 + \frac{\partial C_{t+1}^K}{\partial I_{t+1}^K}\right)(1-\delta)\right)\right] \tag{1.36}$$

$$1 = E_t\left[\beta\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)(r_{t+1}+1) + \frac{\gamma_{t+1}}{1+\lambda_t}\right] \tag{1.37}$$

Empirical model derived from equation (1.36) is specified as follows. First substitute the LHS with functional form for $\frac{\partial C_t^K}{\partial I_t^K}$, with $C^K(K_t, I_t^K)$ specified below.

$$C^K(K_t, I_t^K) = \frac{\alpha}{2}\left(\frac{I_t^K}{K_t}\right)^2 K_t \tag{1.38}$$

$$\frac{\partial C_t^K}{\partial I_t^K} = \alpha\frac{I_t^K}{K_t} \tag{1.39}$$

Second, linearize the RHS using first order taylor approximation. To simplify the notation, let $\Theta_t = \left(\frac{1+\lambda_{t+1}}{1+\lambda}\right)$ and let $\Omega = \left[\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)\left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(1 + \frac{\partial C_{t+1}^K}{\partial I_{t+1}^K}\right)(1-\delta)\right]\right.$. Then linearize the the RHS using first order taylor approximation around the means of Θ_t and Ω. Expected value of Θ_t should be around 1 assuming hospital's magnitude of liquidity constraint do not vary significantly year to year, thus $\mathrm{E}(\Theta_t) \backsimeq 1$. Then let ω represent the expected value of Ω, thus $\mathrm{E}(\Omega) = \omega$

Let $f(\Theta, \Omega) = \Theta\Omega$ be an infinitely differentiable function around $(\Theta, \Omega) = (1, \gamma)$.

$$\begin{aligned} f(\Theta, \Omega) &\approx f(1, \omega) + f_1(1, \gamma)(\Theta - 1) + f_2(1, \omega)(\Omega - \omega) \\ &\approx \omega + \omega(\Theta - 1) + 1(\Omega - \omega) \\ &\approx constant + \omega\Theta + \Omega \end{aligned} \tag{1.40}$$

Substitute (1.39) and (1.40) into (1.36).

$$\begin{aligned} \frac{I_t^K}{K_t} &= E_t \left[\frac{\beta}{\alpha} \left(constant + \omega\Theta + \Omega \right) \right] \\ &= E_t \left[\frac{\beta}{\alpha} \left(constant + \omega \left(\frac{1 + \lambda_{t+1}}{1 + \lambda_t} \right) + \left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(\frac{\partial C_{t+1}^K}{\partial I_{t+1}^K} \right) (1 - \delta) \right) \right] \end{aligned} \tag{1.41}$$

Substitute $\left(\frac{\partial U_{t+1}}{\partial K_{t+1}} + \left(\alpha \frac{I_{t+1}^K}{K_{t+1}} \right) (1 - \delta) \right)$ in (1.41) with marginal product of capital (MPK) (Gilchrist & Himmelberg 1998). MPK is proxied by

$$MPK = \frac{OperatingRevenue}{TotalCapital} \tag{1.42}$$

which is equivalent to how it is typically specified as sales over capital in the literature.

Empirical model for (1.36) is

$$\frac{I_t^K}{K_t} = E_t \left[\frac{\beta}{\alpha} \left(constant + \omega \left(\frac{1 + \lambda_{t+1}}{1 + \lambda_t} \right) + MPK_{it+1} \right) \right] \tag{1.43}$$

Similarly, empirical model derived from equation (1.37) is specified as the following. Linearize the RHS using first order taylor approximation and replace the expectation with the observed plus error.

$$1 = E_t\left[\beta\left(constant + \omega\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right) + (r_{t+1}+1) + \frac{\gamma_{t+1}}{1+\lambda_t}\right)\right] \tag{1.44}$$

Rearrange (1.44) such that $\omega\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)$ is on the LHS.

$$E_t\left[\omega\left(\frac{1+\lambda_{t+1}}{1+\lambda_t}\right)\right] = E_t\left[\frac{1}{\beta} - \left(constant + r_{t+1} + 1 + \frac{\gamma_{t+1}}{1+\lambda_t}\right)\right] \tag{1.45}$$

Substitute (1.45) into (1.43) yields the empirical model for capital investment.

$$\frac{I_{it}^K}{K_{it}} = E_t\left[\frac{\beta}{\alpha}\left(constant + \frac{1}{\beta} - \left(r_{t+1} + 1 + \frac{\gamma_{it+1}}{1+\lambda_{it}}\right) + MPK_{it+1}\right)\right] \tag{1.46}$$

1.1.2 Marginal Product of Capital (MPK)

Marginal product of capital is unobserved but average product of capital is observed. For any differentiable production function there is a relationship between average product of capital (APK) to the marginal product of capital, $\alpha^K = MPK/APK$, where α^K is the output elasticity of capital in the production function (cite Henderson Quandt). Derivation below shows the substitution for MPK using APK in a Cobb-Douglas production function. APK is measured as $\frac{\text{Operating Revenue}}{\text{Value of Capital}}$.

$$
\begin{aligned}
Y &= F(K,L) && (1.47)\\
F(K,L) &= AK^{\alpha^K}L^{\beta} && (1.48)\\
\max_{K,L} \pi &= pF(K,L) - rK - wL && (1.49)\\
\frac{\partial \pi}{\partial K} &= p\alpha^K AK^{\alpha^K - 1}L^B - r = 0 && (1.50)\\
&\iff \alpha^K AK^{\alpha^K-1}L^B = \frac{r}{p}\\
&\iff \alpha^K \frac{Y}{K} = \frac{r}{p}\\
&\iff \text{MPK} = \frac{r}{p}\\
\frac{\partial \pi}{\partial L} &= p\beta AK^{\alpha}L^{\beta-1} - r = 0 && (1.51)\\
&\iff \beta\frac{Y}{L} = \frac{w}{p}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\text{Operating Revenue}}{\text{Value of Capital}} = \frac{p^Y\text{Hospital Output}}{p^K Capital} &= \frac{p^Y Y}{p^K K} && (1.52)\\
\text{MPK} = \alpha^K \frac{Y}{K} &= \alpha^K \frac{\text{Sales}}{K} && (1.53)\\
p^Y\text{MPK} &= \alpha^K \frac{p^Y\text{Hospital Output}}{Capital} && (1.54)\\
\frac{p^Y}{p^K}\text{MPK} &= \alpha^K \frac{p^Y\text{Hospital Output}}{p^K Capital} && (1.55)\\
\frac{p^Y}{p^K}\text{MPK} &= \alpha^K \frac{\text{Operating Revenue}}{\text{Value of Capital}} && (1.56)\\
\text{Prices are normalized to unity, MPK} &= \alpha^K \frac{\text{Operating Revenue}}{\text{Value of Capital}} && (1.57)
\end{aligned}
$$

1.1.3 System Generalized Method of Moments

Model consists of a system of level and differenced equation (eqn. 1.58). Consider a data generating process with the dependent variable y_t (index i is suppressed for simplification) and endogenous regressor $\mathbf{x_t}$

$$\begin{array}{ll} \text{Levels equation:} & \\ \text{Differenced equation:} & \end{array} \begin{bmatrix} y_t \\ \Delta y_t \end{bmatrix} = \beta \begin{bmatrix} \mathbf{x}'_t \\ \Delta \mathbf{x}'_t \end{bmatrix} + \begin{bmatrix} \varepsilon_t \\ \Delta \varepsilon_t \end{bmatrix} \tag{1.58}$$

Suppose ε_t is autoregressive of order p (eqn. 1.59).

$$\varepsilon_t \text{ is AR}(p) \quad \varepsilon_t = \sum_{k=1}^{p} \rho_k \varepsilon_{t-k} + \omega_t \tag{1.59}$$

In the levels equation, $\Delta \mathbf{x}_{t-a}, \forall a > p$ is used to instrument for the endogenous regressors $\mathbf{x}_{it}$ (eqn. 1.60). In the differenced equation, $\mathbf{x}_{t-(a+1)}, \forall a > p$ is used to instrument for the endogenous regressors $\Delta \mathbf{x}_{it}$ (eqn. 1.60) (Arellano and Bond, 1991).

$$\begin{aligned} &E(\Delta \mathbf{x}_{t-a} \varepsilon_t) = 0, \\ &E(\mathbf{x}_{t-(a+1)} \Delta \varepsilon_t) = 0, \end{aligned} \qquad \forall a > p \tag{1.60}$$

Suppose that endogenous x_t is persistent and its data generating process is AR(1). x_t is correlated with the error term ε_t (eqn. 1.61).

$$x_{it} = \alpha x_{t-1} + \varepsilon_t \tag{1.61}$$

Exogeneity of Instruments

Suppose ε_t is AR(0). Then in the levels equation, 1 or more period lagged change of Δx_{t-a}, a > 0 is exogenous to the error term (eqn. 1.62, 1.63).

$$y_t = \beta x_t + \varepsilon_t \tag{1.62}$$

$$\begin{aligned} \Delta x_{t-1} &= (\alpha x_{t-2} + \varepsilon_{t-1}) - (\alpha x_{t-3} + \varepsilon_{t-2}) \\ &= (\alpha x_{t-2} - \alpha x_{t-3}) + (\varepsilon_{t-1} - \varepsilon_{t-2}) \end{aligned} \tag{1.63}$$

In the differenced equation 2 or more period lagged level of $x_{t-(a+1)}$, a > 0 is exogenous to the differenced error term (eqn. 1.64, 1.65).

$$y_t - y_{t-1} = \beta(x_t - x_{t-1}) + (\varepsilon_t - \varepsilon_{t-1}) \tag{1.64}$$

$$x_{t-2} = \alpha x_{t-3} + \varepsilon_{t-2} \tag{1.65}$$

Suppose ε_t is AR(1). Then in the levels equation, 2 or more period lagged change of Δx_{t-a}, a > 1 is exogenous to the error term (eqn. 1.66, 1.67).

$$\begin{aligned} y_t &= \beta x_t + \varepsilon_t \\ &= \beta x_t + \rho\varepsilon_{t-1} + \varepsilon_t \end{aligned} \tag{1.66}$$

$$\begin{aligned} \Delta x_{t-2} &= (\alpha x_{t-3} + \varepsilon_{t-2}) - (\alpha x_{t-4} + \varepsilon_{t-3}) \\ &= (\alpha x_{t-3} - \alpha x_{t-4}) + (\varepsilon_{t-2} - \varepsilon_{t-3}) \end{aligned} \tag{1.67}$$

In the differenced equation, 3 or more period lagged level of $x_{t-(a+1)}$ a > 1 is exogenous to the differenced error term (eqn. 1.68, 1.69).

$$\begin{aligned} y_t - y_{t-1} &= \beta(x_t - x_{t-1}) + (\varepsilon_t - \varepsilon_{t-1}) \\ &= \beta(x_t - x_{t-1}) + \rho(\varepsilon_{t-1} - \varepsilon_{t-2}) + (\varepsilon_t - \varepsilon_{t-1}) \end{aligned} \tag{1.68}$$

$$x_{t-3} = \alpha x_{t-4} + \varepsilon_{t-3} \tag{1.69}$$

Strength of Instruments

In the levels equation, lagged change Δx_{t-1} is used to instrument for x_t. Δx_{t-1} is related to x_t by $(\alpha^{-1} - \alpha^{-2})$, the change in the effect of current x on past x (eqn. 1.70).

$$\begin{aligned}\Delta x_{t-1} &= x_{t-1} - x_{t-2} \\ &= (\alpha^{-1} x_t - \alpha^{-1}\varepsilon_t) - (\alpha^{-2} x_t - \alpha^{-2}\varepsilon_t - \alpha^{-1}\varepsilon_{t-1}) \\ &= (\alpha^{-1} - \alpha^{-2}) x_t - (\alpha^{-1} - \alpha^{-2})\varepsilon_t + \alpha^{-1}\varepsilon_{t-1} \qquad (1.70)\end{aligned}$$

In the differenced equation, x_{t-2} is used to instrument for Δx_t. x_{t-2} is related to Δx_t by $\frac{1}{\alpha^2-\alpha}$. First, Δx_t can be expressed in terms of x_{t-2} (eqn. 1.71).

$$\begin{aligned}\Delta x_t &= x_t - x_{t-1} \\ &= (\alpha x_{t-1} + \varepsilon_t) - (\alpha x_{t-2} + \varepsilon_{t-1}) \\ &= (\alpha^2 x_{t-2} + \alpha\varepsilon_{t-1} + \varepsilon_t) - (\alpha x_{t-2} + \varepsilon_{t-1}) \\ &= (\alpha^2 - \alpha) x_{t-2} + (\alpha - 1)\varepsilon_{t-1} + \varepsilon_t \qquad (1.71)\end{aligned}$$

Then rearrange to put x_{t-2} on the left hand side (eqn. 1.72).

$$\begin{aligned}x_{t-2} &= \frac{1}{\alpha^2 - \alpha}\left(\Delta x_t - (\alpha - 1)\varepsilon_{t-1} - \varepsilon_t\right) \\ &= \frac{1}{\alpha^2 - \alpha}\Delta x_t - \frac{1}{\alpha}\varepsilon_{t-1} - \frac{1}{\alpha^2 - \alpha}\varepsilon_t \qquad (1.72)\end{aligned}$$

1.1.4 Alternative Specification: GMM estimates with Cash Flow and Liquid Assets Interaction Term

Table A1: Pre-Recession 2002-2006 Estimates with Interaction Term

All I/K_{it}	FE (1)	GMM (2)
CF/K_{it}	-.0351	.0231
	(.0186)	(.0563)
LA/K_{it}	-.0084	.227
	(.0621)	(.1793)
$CF/K_{it} * LA/K_{it}$	.1675	-.383
	(.1116)	(.4823)
APK_{it+1}	.1129 **	.038 ***
	(.0343)	(.007)
r_{it+1}	-.002 **	-.0194
	(6.3e-04)	(.0134)
2003	-.0113	-.0201
	(.0063)	(.0128)
2004	-.0081	-.016
	(.0097)	(.0158)
2005	.0123	-6.6e-04
	(.0139)	(.0134)
2006	-8.3e-04	-.0122
	(.0092)	(.0192)
constant	-.0654	.1465
	(.0549)	(.0783)
AB test for AR(2) p-val		.424
Hansen p-val		.297
N instruments		46
N obs	1333	1091
N hospitals	263	250

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table A2: During-Recession 2008-2010 Estimates with Interaction Term

All I/K_{it}	FE (1)	GMM (2)
CF/K_{it}	.0979 ***	.0847 **
	(.0189)	(.0324)
LA/K_{it}	-.0263	.0873
	(.0866)	(.0919)
$CF/K_{it} * LA/K_{it}$	-.0351	-.2505
	(.1107)	(.2242)
APK_{it+1}	.0525 **	.0256 *
	(.0196)	(.0125)
r_{it+1}	-3.2e-04	-.0156
	(4.7e-04)	(.0237)
2009	.0176 *	-.0108
	(.007)	(.0073)
2010	.0033	.0212
	(.0076)	(.0346)
constant	.0148	.1494
	(.0325)	(.1268)
AB test for AR(2) p-val		.226
Hansen p-val		.476
N instruments		86
N obs	669	664
N hospitals	247	236

* $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

Table A3: Recovery 2011-2012 Estimates with Interaction Term

All I/K_{it}	FE (1)	GMM (2)
CF/K_{it}	.1209	-.0505
	(.1669)	(.1032)
LA/K_{it}	-.0286	-.0866
	(.049)	(.067)
$CF/K_{it} * LA/K_{it}$	-.0856	.2443
	(.1321)	(.1594)
APK_{it+1}	.0219	.0361 **
	(.0479)	(.0123)
r_{it+1}	-.009 **	.0453
	(.0033)	(.0289)
2012	.0345	.0339 *
	(.0383)	(.0141)
constant	.1142	-.1906
	(.1007)	(.1483)
AB test for AR(2) p-val		.
Hansen p-val		.372
N instruments		62
N obs	890	445
N hospitals	253	237

* p $\leq$ 0.05, ** p $\leq$ 0.01, *** p $\leq$ 0.001

1.2 Cost Effectiveness of Telecare Management for Pain and Depression in Patients with Cancer: Results from a Randomized Trial

1.2.1 Effectiveness Metrics

Converting DFD to QALY (Schoenbaum, 2001)

-0.2 to -0.4 QALY = 1 year of depression

X / (DFD/365) year of depression = - 0.2 to -0.4 QALY / 1 year of depression
Solve for X
Where:
Y = incremental DFD / 365

60.30/365 = 0.1652
44.12/365 = 0.1209

0.1652 * -0.2 = -0.0330 QALY
0.1652*-0.4 = -0.0661 QALY

0.1209 * -0.2 = -0.0242 QALY
0.1209 * -0.4 = -0.0484 QALY

1.2.2 Incremental Cost-Effectiveness Ratio (ICER)

DFD

DFD ICER = 1249.68/60.30= 20.72

DFD imputed

DFD imputed ICER = 1249.68/47.25 = 26.45

SF-12

ΔQALY = Area between the curves
Area under intervention curve from month3 to month12 – Area under control curve from month3 to month12

ΔQALY = Area inside big triangle – Area inside small triangle

ΔQALY = (QOL_intervention *0.75year)/2 – (QOL_control*0.75year)/2
(.647 * 0.75)/2 - (.613*0.75)/2 = .013

SF6 ICER = 952.72/.013 = 73286.92

EQ-5D

ΔQALY = Area between the curves
ΔQALY = (Area under intervention curve from month0 to month1 – Area under control curve from month0 to month1) + (Area under intervention curve from month1 to month3 – Area under control curve from month1 to month3) + (Area under intervention curve from month3 to month6 – Area under control curve from month3 to month6) + (Area under intervention curve from month6 to month12 – Area under control curve from month6 to month12)

ΔQALY = (Area inside big trapezoid – Area inside small trapezoid) + (Area inside big trapezoid – Area inside small trapezoid) + (Area inside big trapezoid – Area inside small trapezoid) + (Area inside big trapezoid – Area inside small trapezoid)

ΔQALY = [(.404+.49) *(1/12)/2 – (.411+.427)*(1/12)/2] +[(.49+.534) *(2/12)/2 – (.427+.458)*(2/12)/2]+[(.534+.558) *(3/12)/2 – (.458+.477)*(3/12)/2]+[(.558+.574) *(6/12)/2 – (.477+.437)*(6/12)/2] = .088

EQ-5D ICER = 952.72/.088= 10826.48

1.2.3 Detailed INCPAD Cost Determination

Table A4: Aggregate projected post-startup costs - 202 theoretical new intervention patients

Intervention component (202 intervention)	**Costs ($)**
Physician time	43,226
Nurse care manager time	71,224
Automated monitoring start-up/maintenance	78,000
Total	**192,450**

Table A5: Aggregate projected post-startup costs - 154 theoretical new intervention patients

Intervention component (154 depressed)	**Costs ($)**
Physician time	43,226
Nurse care manager time	61,906
Automated monitoring start-up/maintenance	78,000
Total	**183,132**

Table A6: Aggregate projected post-startup costs - 202 theoretical new intervention patients*

Intervention component (202 intervention)	**Costs ($)**
Physician time	43,226
Nurse care manager time	71,224
Automated monitoring maintenance	20,000
Total	**134,450**

Table A7: Aggregate projected post-startup costs - 154 theoretical new intervention patients*

Intervention component (154 depressed)	**Costs ($)**
Physician time	43,226
Nurse care manager time	61,906
Automated monitoring maintenance	20,000
Total	**125,132**

* Projected post-startup costs would be the costs for all new patients receiving the intervention after the study. Physician and nurse time is estimated to be the same for the same number of patients buy automated monitoring costs are only maintenance since system is already setup.

Physician costs: $43,226

- Weekly care management conferences: 456 hr
- Staffing outside care management conferences: 590+585 min = 1175 min ~ 20 hr
- Training nurse manager: 8 hr
- Total hrs: 484 hr
- Physician hourly costs: $89.31, calculated as follows:
    - $214,354 annually with 22% fringe, $175,700 without fringe
    - Hrs per year: 50 per week X 48 weeks = 2400 hr
    - Hourly costs: 214,354/2400 = $89.31
- Total physician costs: 484 X $89.31 = $43226.04

Nurse care manager costs: $71,224 all patients; [$61,906 depressed only]

- Total time outside of care manager conference: 1401 hr
- Total time outside care manager conference (depressed only): 1157 hr
- Weekly care management conferences: 456 hr
- Training time: 8 hr
- Total hrs: 1865 hr
- Total hrs (depressed only): 1621 hr
- Nurse hourly costs: $38.19, calculated as follows:
    - $73,322 annually with 22% fringe, $60,100 without fringe
    - Hrs per year: 40 per week X 48 weeks X 40 = 1920 hr
    - Hourly costs: 73,322/1920 = $38.19
- Total nurse costs (all patients): 1865 X $38.19 = $71,224
- Total nurse costs (depressed only): 1621 X $38.19 = $61,906

Automated symptom monitoring costs: **$78,000**

- Possibly an overestimate since most of cost ($50,000) is start-up, and once in place this could continue to provide care for thousands of patients at low maintenance costs. Thus, a sensitivity analysis is to estimate post-start-up incremental costs as well.

Calculating weekly care management conference hours: 456 hr

- 336 hours → 42 months
    - 30 month enrollment & 12-mo follow-up (March 2006 through August 2009)
    - 2 hrs per week for 12 months (first 4 mo and last 8 mo of study period) and 3 hrs per week for 30 months.
    - 48 work wks/12 mo → (48 wk x 2 hr) + (120 wk x 3 hr) = 96 hr + 360 hr = 456 hr

Nurse care manager time outside weekly staffing conference

- All 202 intervention patients = 1,401 hours
    - [Nurse B: 57,946 min / 60 = 965.8 hrs] + [Nurse S: 26,128 min/ 60 = 435.5 hrs]
- 154 depressed patients only = 1,157 hours
    - [Nurse B: 47,199 min / 60 = 786.7 hrs] + [Nurse S: 22,211 min/ 60 = 370.2 hrs]

1.3 Recession Led To A Decline In Out-Of-Pocket Spending For Children With Special Health Care Needs

Table A8: Out-of-pocket spending for children without special health care needs, estimates of marginal effects

Child out-of-pocket \$, in 2009 dollars	(1)E[∂y/∂x]	(2) SE	(3) P-value
Before-recession slope	3.86	(2.55)	0.13
During-recession slope	13.11	(9.30)	0.16
Age	21.93***	(1.17)	0.00
Gender (ref: female)	-5.74	(8.78)	0.51
Number of family adults	-23.91***	(8.01)	0.00
Number of child siblings	-40.23***	(4.88)	0.00
Some family have limitation (ref: No family limitation)	40.20***	(12.30)	0.00
Unknown (ref: No family with limitations)	99.19***	(31.44)	0.00
Black (ref: White)	-169.57***	(10.74)	0.00
Asian/NH/PI (ref: White)	-97.50***	(15.92)	0.00
Other (ref: White)	-69.85***	(21.05)	0.00
Hispanic (ref: Not-Hispanic)	-107.36***	(10.43)	0.00
College (ref: Less than college)	64.59***	(11.02)	0.00
5+ Years college (ref: Less than college)	135.65***	(15.88)	0.00
Unknown (ref: Less than college)	1.04	(23.81)	0.97
MSA status (ref: Not MSA)	25.90**	(10.94)	0.02
Midwest (ref: North East)	4.70	(15.69)	0.76
South (ref: North East)	4.10	(14.51)	0.78
West (ref: North East)	-14.57	(16.05)	0.36

Observations: 31,905

*** p<0.01, ** p<0.05, * p<0.1

Source: Medical Expenditure Panel Survey 2001-2009, Children ages 0-17 and their families with private insurance; 31,905 observations.

Notes:

1.The estimates are based on generalized linear models (gamma family and log link) with out-of-pocket health care measures as the dependent variable *(y*). Log link function was selected based on Box-Cox test and gamma family was selected based on the generalized linear model family test. Box-Cox test finds the maximum likelihood estimate of λ such that $y^{\lambda} = \frac{y^{\lambda}-1}{\lambda}$. If $\hat{\lambda}=0$, the appropriate functional form is $\ln(y) = X\beta + \varepsilon$; if $\hat{\lambda}=0.5$, the appropriate functional form is $\sqrt{y} = X\beta + \varepsilon$ and if $\hat{\lambda}=1$, the appropriate functional form is $y = X\beta + \varepsilon$. We estimated $\hat{\lambda}=0.037$, suggesting that the log link is appropriate. After specifying the appropriate scale of estimation, the GLM family test determines the relationship between $E[y\backslash x]$ and $Var[y\backslash x]$ by estimating the parameters $\propto$ and $\delta$for the specification $Var[y\backslash x] = \propto E[y\backslash x]^{\delta}$. Estimate of $\delta = 0$ suggests Gaussian family; $\delta = 1$ Poisson family; $\delta = 2$ Gamma family; and $\delta = 3$ inverse Gaussian family. We estimated $\delta = 1.78$ suggesting the use of Gamma family.

2. The spline model identifies a linear time trend from 2001-2007 (before-recession slope) and a separate linear time trend from 2007-2009 (during recession slope). The year 2007 serves as the "knot" in this model, because this indicates the beginning of the recession, in December 2007.

3. For continuous variables the coefficient estimates represent average ∂y/∂x, for factor variables the coefficient estimates represent average discrete first difference from the base category

4. Each year increase was associated with a change of $3.86 (SE $2.55, p=0.13) in out-of-pocket in the period before the recession, and $13.11 (SE $9.30, p=0.16) during the recession. The difference between the before/during the recession period had a p-value of 0.39. Adjusted average out-of-pocket (SE) were: 2001: $258.12 ($9.41), 2002: $261.76 ($7.71), 2003: $265.44 ($6.36), 2004: $269.18 ($5.72), 2005: $272.97 ($6.11), 2006: $276.81 ($7.42), 2007: $280.71 ($9.34), 2008: $294.35 ($9.38), 2009: $308.66 ($17.36).

Table A9: Out-of-pocket spending for children with special health care needs, estimates of marginal effects

Child out-of-pocket $, in 2009 dollars	(1)E[∂y/∂x]	(2) SE	(3) P-value
Before-recession slope	24.69**	(10.27)	0.02
During-recession slope	-73.27**	(33.41)	0.03
Age	37.03***	(4.20)	0.00
Gender (ref: female)	-65.73*	(36.34)	0.07
Number of family adults	-39.02	(29.32)	0.18
Number of child siblings	-59.38***	(17.23)	0.00
Some family have limitation (ref: No family limitation)	10.44	(34.91)	0.76
Unknown (ref: No family with limitations)	200.41	(183.17)	0.27
Black (ref: White)	-309.59***	(52.04)	0.00
Asian/NH/PI (ref: White)	145.42	(162.82)	0.37
Other (ref: White)	58.44	(120.24)	0.63
Hispanic (ref: Not-Hispanic)	-49.41	(83.85)	0.56
College (ref: Less than college)	178.28***	(41.17)	0.00
5+ Years college (ref: Less than college)	408.15***	(52.69)	0.00
Unknown (ref: Less than college)	-58.52	(62.47)	0.35
MSA status (ref: Not MSA)	61.55	(42.06)	0.14
Midwest (ref: North East)	14.33	(55.48)	0.80
South (ref: North East)	81.97	(59.79)	0.17
West (ref: North East)	-34.83	(64.36)	0.59

Observations: 7,185
*** p<0.01, ** p<0.05, * p<0.1
Source: Medical Expenditure Panel Survey 2001-2009, Children ages 0-17 and their families with private insurance; 7,185 observations.

Notes:

1.The estimates are based on generalized linear models (gamma family and log link) with out-of-pocket health care measures as the dependent variable *(y)*. Log link function was selected based on Box-Cox test and gamma family was selected based on the generalized linear model family test. Box-Cox test finds the maximum likelihood estimate of λ such that $y^{\lambda} = \frac{y^{\lambda}-1}{\lambda}$. If $\hat{\lambda}=0$, the appropriate functional form is $\ln(y) = X\beta+\varepsilon$; if $\hat{\lambda}=0.5$, the appropriate functional form is $\sqrt{y} = X\beta+\varepsilon$ and if $\hat{\lambda}=1$, the appropriate functional form is $y = X\beta+\varepsilon$. We estimated $\hat{\lambda}=0.059$, suggesting that the log link is appropriate. After specifying the appropriate scale of estimation, the GLM family test determines the relationship between $E[y\backslash x]$ and $Var[y\backslash x]$ by estimating the parameters $\propto$ and δ for the specification $Var[y\backslash x] =\propto E[y\backslash x]^{\delta}$. Estimate of $\delta = 0$ suggests Gaussian family; $\delta = 1$ Poisson family; $\delta = 2$ Gamma family; and $\delta = 3$ inverse Gaussian family. We estimated $\delta = 1.51$, suggesting that either the Gamma family or Poisson family are appropriate.

2.The spline model identifies a linear time trend from 2001-2007 (before-recession slope) and a separate linear time trend from 2007-2009 (during recession slope). The year 2007 serves as the “knot” in this model, because this indicates the beginning of the recession, in December 2007.

3.For continuous variables the coefficient estimates represent average ∂y/∂x, for factor variables the coefficient estimates represent average discrete first difference from the base category

4. Each year increase was associated with a change of $24.69 (SE $10.27, p=0.02) in the period before the recession, and $-73.27 (SE $33.41, p=0.03 during the recession. The difference between the before/during the recession period had a p-value of p=0.01. Adjusted average out-of-pocket (SE) were: 2001: $624.36 ($33.7), 2002: $647.14 ($28.72), 2003: $670.74 ($25.57), 2004: $695.21 ($25.67), 2005: $720.57 ($29.71), 2006: $746.86 ($37.08), 2007: $774.1 ($46.81), 2008: $696.01 ($32.96), 2009: $625.79 ($45.96).

Table A10: Out-of-pocket spending for adults, ($ per adult), in families with children without special health care needs, estimates of marginal effects

Adult out-of-pocket $ per adult, in 2009 dollars	(1)E[∂y/∂x]	(2) SE	(3) P-value
Before-recession slope	14.26***	(3.78)	0.00
During-recession slope	-40.60***	(12.00)	0.00
Age	4.03***	(1.13)	0.00
Gender (ref: female)	9.16	(9.91)	0.36
Number of family adults	-73.95***	(10.80)	0.00
Number of child siblings	-30.23***	(7.78)	0.00
Some family have limitation (ref: No family limitation)	264.62***	(21.48)	0.00
Unknown (ref: No family with limitations)	241.90***	(41.91)	0.00
Black (ref: White)	-190.50***	(17.36)	0.00
Asian/NH/PI (ref: White)	-140.46***	(27.76)	0.00
Other (ref: White)	-99.92***	(33.39)	0.00
Hispanic (ref: Not-Hispanic)	-153.85***	(16.66)	0.00
College (ref: Less than college)	117.17***	(15.31)	0.00
5+ Years college (ref: Less than college)	175.52***	(20.74)	0.00
Unknown (ref: Less than college)	-8.25	(33.50)	0.81
MSA status (ref: Not MSA)	17.74	(18.46)	0.34
Midwest (ref: North East)	33.00	(22.97)	0.15
South (ref: North East)	46.33**	(21.61)	0.03
West (ref: North East)	37.05	(26.16)	0.16

Observations: 31,891

*** p<0.01, ** p<0.05, * p<0.1

Source: Medical Expenditure Panel Survey 2001-2009, Children ages 0-17 and their families with private insurance; 31,891 observations.

Notes:

1.The estimates are based on generalized linear models (gamma family and log link) with out-of-pocket health care measures as the dependent variable *(y)*. Log link function was selected based on Box-Cox test and gamma family was selected based on the generalized linear model family test. Box-Cox test finds the maximum likelihood estimate of λ such that $y^{\lambda} = \frac{y^{\lambda}-1}{\lambda}$. If $\hat{\lambda}=0$, the appropriate functional form is $\ln(y) = X\beta+\varepsilon$; if $\hat{\lambda}=0.5$, the appropriate functional form is $\sqrt{y} = X\beta+\varepsilon$ and if $\hat{\lambda}=1$, the appropriate functional form is $y = X\beta+\varepsilon$. We estimated $\hat{\lambda}=0.13$, suggesting that the log link is appropriate. After specifying the appropriate scale of estimation, the GLM family test determines the relationship between $E[y\backslash x]$ and $Var[y\backslash x]$ by estimating the parameters $\propto$ and $\delta$for the specification $Var[y\backslash x] = \propto E[y\backslash x]^{\delta}$. Estimate of $\delta = 0$ suggests Gaussian family; $\delta = 1$ Poisson family; $\delta = 2$ Gamma family; and $\delta = 3$ inverse Gaussian family. We estimated $\delta = 1.49$ suggesting the use of either Gamma family or Poisson family.

2. The spline model identifies a linear time trend from 2001-2007 (before-recession slope) and a separate linear time trend from 2007-2009 (during recession slope). The year 2007

serves as the “knot” in this model, because this indicates the beginning of the recession, in December 2007.

3. For continuous variables the coefficient estimates represent average $\partial y/\partial x$, for factor variables the coefficient estimates represent average discrete first difference from the base category.

4. Each year increase was associated with a change of \$14.26 (SE \$3.78, $p< 0.01$) in the period before the recession, and \$-40.6 (SE \$12, $p< 0.01$) during the recession. The difference between the before/during the recession period had a p-value of $p<0.01$. Adjusted average out-of-pocket (SE) were: 2001: \$442.31 (\$12.08), 2002: \$455.65 (\$9.91), 2003: \$469.39 (\$8.42), 2004: \$483.55 (\$8.25), 2005: \$498.13 (\$9.73), 2006: \$513.16 (\$12.49), 2007: \$528.64 (\$16.07), 2008: \$485.73 (\$12.92), 2009: \$446.31 (\$18.6).

Table A11: Out-of-pocket spending for adults, ($ per adult), in families with children with special health care needs, estimates of marginal effects

Adult Out-of-pocket $ per adult, in 2009 dollars	(1)E[∂y/∂x]	(2) SE	(3) P-value
Before-recession slope	27.29***	(6.66)	0.00
During-recession slope	-64.86***	(24.34)	0.01
Age	7.80***	(2.52)	0.00
Gender (ref: female)	-80.59***	(22.60)	0.00
Number of family adults	-52.72**	(26.62)	0.05
Number of child siblings	-26.04	(17.06)	0.13
Some family have limitation (ref: No family limitation)	333.45***	(36.64)	0.00
Unknown (ref: No family with limitations)	-17.13	(51.56)	0.74
Black (ref: White)	-262.52***	(29.28)	0.00
Asian/NH/PI (ref: White)	-112.21	(85.48)	0.19
Other (ref: White)	67.21	(122.05)	0.58
Hispanic (ref: Not-Hispanic)	-171.30***	(31.12)	0.00
College (ref: Less than college)	140.53***	(31.58)	0.00
5+ Years college (ref: Less than college)	213.96***	(38.86)	0.00
Unknown (ref: Less than college)	5.59	(53.28)	0.92
MSA status (ref: Not MSA)	8.34	(40.43)	0.84
Midwest (ref: North East)	109.08**	(43.94)	0.01
South (ref: North East)	124.41***	(35.85)	0.00
West (ref: North East)	88.33*	(45.21)	0.05

Observations: 7,181
*** p<0.01, ** p<0.05, * p<0.1
Source: Medical Expenditure Panel Survey 2001-2009, Children ages 0-17 and their families with private insurance; 7,181 observations.
Notes:

1.The estimates are based on generalized linear models (gamma family and log link) with out-of-pocket health care measures as the dependent variable (y). Log link function was selected based on Box-Cox test and gamma family was selected based on the generalized linear model family test. Box-Cox test finds the maximum likelihood estimate of λ such that $y^{\lambda} = \frac{y^{\lambda}-1}{\lambda}$. If $\hat{\lambda}=0$, the appropriate functional form is $\ln(y) = X\beta + \varepsilon$; if $\hat{\lambda}=0.5$, the appropriate functional form is $\sqrt{y} = X\beta + \varepsilon$ and if $\hat{\lambda}=1$, the appropriate functional form is $y = X\beta + \varepsilon$. We estimated $\hat{\lambda}=0.16$, suggesting that the log link is appropriate. After specifying the appropriate scale of estimation, the GLM family test determines the relationship between $E[y\backslash x]$ and $Var[y\backslash x]$ by estimating the parameters $\propto$ and $\delta$for the specification $Var[y\backslash x] =\propto E[y\backslash x]^{\delta}$. Estimate of $\delta = 0$ suggests Gaussian family; $\delta = 1$ Poisson family; $\delta = 2$ Gamma family; and $\delta = 3$ inverse Gaussian family. We estimated $\delta = 1.86$ suggesting the use of Gamma family.

2. The spline model identifies a linear time trend from 2001-2007 (before-recession slope) and a separate linear time trend from 2007-2009 (during recession slope). The year 2007 serves as the "knot" in this model, because this indicates the beginning of the recession, in December 2007.

3.For continuous variables the coefficient estimates represent average $\partial y/\partial x$, for factor variables the coefficient estimates represent average discrete first difference from the base category

4. Each year increase was associated with a change of \$27.29 (SE \$6.66, $p< 0.01$) in the period before the recession, and \$-64.86 (SE \$24.34, $p< .01$) during the recession. The difference between the before/during the recession period had a p-value of $p<0.01$. Adjusted average out-of-pocket (SE) were: 2001: \$557.88 (\$22.34), 2002: \$582.44 (\$19.41), 2003: \$608.07 (\$17.53), 2004: \$634.84 (\$17.53), 2005: \$662.78 (\$19.96), 2006: \$691.95 (\$24.59), 2007: \$722.41 (\$30.91), 2008: \$652.11 (\$23.39), 2009: \$588.65 (\$35.5).