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Essays in Applied Microeconomics

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To my son Jonathan Aryan, who I love up to the sky and back

To my dear mother, my humble gratitude for your devotion and sacrifices

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ABSTRACT

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This dissertation comprises essays in Applied Microeconomics with focus in Health and Regional Economics. The first investigates a neo-classical hospital production model for cost and quality implications by payment source in the context of the 2010 Affordable Care Act. The second essay demonstrates positive crime effects induced by Hurricane Katrina population migration. Specifically, the first essay evaluates hospital cost efficiencies emanating from changes in public reimbursement levels and/or shifts in hospital care demand or health care budgets. Using 2000-2008 data from Tennessee Joint Annual Reports of Hospitals, hybrid generalized translog multi-product cost functions were estimated with controls for multi-dimensional quality, diagnostic mix, and hospital heterogeneity. The production technology cost model, accounting for technological change and geographic effects, was estimated using the Iterative Seemingly Unrelated Regressions methodology. Factor demand elasticities, alternative conceptual measures of the elasticities of substitution, scale and scope economies were evaluated. This is the first study to quantify opportunities for exploiting scope economies by payer type (e.g., Medicaid/Tenncare with private payers). Policy implications were explored. Using a natural experiment, the second essay tests an empirical link between the forced evacuation and crime types countywide and in Houston, TX, while avoiding concerns of endogeneity due to selection or simultaneity. Few prior economic studies of Katrina probed impacts on host labor markets or on evacuees' labor and schooling outcomes, overlooking potential effects on local crime in spite of anecdotal evidence. To ensure identification with a Difference-In-Difference specification, the number of evacuees going to a metropolitan area was instrumented by its distance to New Orleans, LA. Katrina immigration was found to raise the incidence of murder and non-negligent manslaughter, robbery, and motor vehicle theft. The analysis of Houston post-shelter consequences of Katrina on crime showed increased murder, aggravated assault, illegal possession of weapons, and arson. While the regional analysis was based on the Current Population Survey and data from the Federal Bureau of Investigation, the Houston study used data provided by the Police Department. Robustness checks evaluating self-selection utilized the Displaced New Orleans Resident Pilot survey. It remained undetermined whether the crimes were committed by evacuees, or triggered by their presence.

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INTRODUCTION

In the chapters that follow, the fields of Health and Regional Economics are intertwined under Applied Microeconomics to examine, separately, the effects of changes due to the recent implementation of the 2010 Patient Protection and Affordable Care Act on hospital industry and the consequences of forced population migration arising from the catastrophic Hurricane Katrina natural disaster on various crime types in the areas of destination for evacuees.

Differences in hospital care expenditures and outcomes suggest possible existence of unexploited opportunities for improving cost economies, which have become crucial in the view of increased demand for hospital care and expected reductions in health care budgets. Using the Iterative Seemingly Unrelated Regressions Estimation (ISURE) technique, translog multi-product cost functions are estimated with many controls for care quality, hospital-specific diagnostic mix, and other heterogeneities. We employ a rich 2000-2008 panel data set of 117 hospitals in the state of Tennessee (U.S.) to model the production technology cost structure for measures of output by payers, while accounting for geographic, technological change, and other effects. We present estimates for own- and cross-price factor demand elasticities, alternative conceptual measures of pair-wise factor substitutions (Allen-Uzawa, Morishima, and Shadow), economies of scale, and scope economies. The data rejected Hicks-neutrality hypothesis and technological progress is energy- and supplies- using and marginally labor-saving. The scale-augmenting portion of technical change effect is mostly due to diseconomies of scale in production of patients with private insurance. Production exhibits increasing returns to scale. Opportunities for cost-efficiency exist through scope economies (for example, Medicaid/TennCare insurance with private payers). Dual hospital accreditation by general (JCAHO) and specialized (ACSCC) agencies increases cost, while holding joint membership in state and national hospital associations decreases cost. Policy implications are explored with reference to the 2010 Affordable Care Act implementation.

The following chapter examines crime effects induced by Hurricane Katrina by exploiting a plausible exogenous change in population levels in areas of relocation of evacuees. Using a Difference-in-Differences approach, we estimate the effects of migration due to Hurricane Katrina on crime rates across the United States between 2003 and 2007. To account for possible endogeneity between the socio-economic characteristics of a host city and evacuees, we instrument the number of evacuees going to a certain metropolitan area by its distance to New Orleans, LA. The results suggest that immigration of Katrina evacuees led to a more than 13% increase in murder and non-negligent manslaughter, an almost 3% increase in robbery, and a 4.1% increase in motor vehicle theft. We also examine Houston, TX, home to a large number of comparatively more disadvantaged evacuees, and find dramatic increases in murder (27%) and aggravated assault (28%) coupled with increases in illegal possession of weapons (32%) and arson (41%) in areas lived by evacuees. While these estimated effects are substantial, it remains undetermined whether the crimes were committed by evacuees, or were triggered by their presence.

CHAPTER I: QUALITY-ADJUSTED MULTI-PRODUCT HOSPITAL COST STRUCTURE BY PAYER TYPE[*†]

[*] This work was completed under the supervision of Dr. Albert A. Okunade.

[†] A version of the research presented in this chapter was submitted for publication in the *Health Economics*. Earlier versions were presented at the 49th annual meeting of the Missouri Valley Economic Association (Memphis, TN, Oct. 2012), and at the 81st annual meeting of the Southern Economic Association (Washington, DC, Nov. 2011).

Introduction

The U.S. is continuing its piecemeal implementations of the 2010 Patient Protection and Affordable Care Act (ACA) and the Health Care and Education Reconciliation Act, a broad-sweeping healthcare system reform since the 1965 passage of the Medicare and Medicaid Act. The ACA is designed to provide coverage for a percentage of the uninsured and improved coverage for those with pre-existing conditions among other provisions. Given the massive health care resource shifts involved, economists and policymakers are keenly interested in provider operational efficiency implications of the emerging reform. As the reform will push outward the demand for hospital care, it becomes essential for providers to strive consistently for higher productivity while maintaining low costs. Hospitals bill patients or patients' payers for the health services they provide and, as a result of increased activity, enjoy increased revenues. More insured due to Obama's Health Care Act, more revenues. However, hospitals do not operate in perfectly competitive markets. Hospitals have local market power, benefit from third party agreements, detain asymmetric information about patients, and enjoy barriers to entry. The industry is highly regulated, which makes it difficult or illegal for hospitals to turn away low-paying patients. The severity of medical conditions is outside of hospitals' control. In this environment, higher profits or the very survival of providers depend on cost minimization efforts.[1]

Moreover, due to the performance incentives for provider reimbursements regarding outcome or value-based (and not volume-based) purchasing of care, it is crucial that U.S. hospitals operate at least cost for a given output level. Productivity or cost efficiency

[1] Medicare prospective payment system (PPS) was designed to promote efficiency in resource utilization by rewarding hospitals that would maintain costs below the PPS rates and by penalizing hospitals with higher costs.

changes are linked to changes in for-profit or non-profit performance (bottom line) goals.[2] Value-based medical care and amenities produced at least cost will increasingly become the main driver of contracted purchases of care by various payers (Blue-Cross/Blue-Shield and other private insurances, Commercial insurance, Medicaid, and Medicare).

As competition among hospitals continues to intensifies, offering quality medical services and amenities while maintaining suppressed costs becomes crucial. However, in absence of any rewards for process improvement in the current reimbursement system, that entertains lower payments for Medicaid and minority populations, quality disparities among hospitals are expected to continue to increase.

In addition to the nature of the demand for services and the characteristics of the factor markets, the impact of reimbursement policies is an important determinant of hospital costs. With a revived interest in the reduction of the size of the public sector, concerns have been voiced over the rising share of national resources consumed by health care costs. This might translate for hospitals in reductions of payments for Medicare and Medicaid patients.

In the view of potential changes in public reimbursement levels and/or shifts in demand for hospital care or health care budgets, this paper develops a parametric production cost model to evaluate hospital production cost efficiencies. Using Shepherd's duality theorem, insights are gained into the underling multi-product technology structure

[2] Grifell-Tatje and Lovell (1999) developed an analytical framework for decomposing hospital profit performance change into productivity change effect (includes a technical change effect and an operating efficiency effect), an activity effect (comprising product mix, resource mix and scale effects), and a price effect. The analytical framework is flexible for applications to various scenarios, including also not-for-profit settings. As of January, 2014, 27% of all US registered community hospitals are for-profit or investor owned and 73% are not-for-profit (American Hospital Association, *http://www.aha.org/research/rc/stat-studies/fast-facts.shtml*, 2014).

of hospital production by payment source and we explore its characteristics while accounting for differential quality standards and patient mix. The panel dimension of the data allows for investigations of technological change, total factor productivity, alternatively defined pair-wise factor substitution tendencies (based on isoquant shapes), and possibilities of scale and scope economies. We specify a hybrid transcendental logarithmic flexible functional form (translog) multi-product hospital production cost model and present a battery of hypotheses tests for homotheticity, homogeneity, constant returns to scale, and unitary elasticity of substitution technologies. Finally, we examine the effects of geographic variation in factor availability and/or input prices on hospital production costs.

The flexible form hospital cost model by source of payment accounting for multiple quality indicators and case-mix variations across hospitals using recent panel data is innovative. The study findings employing 2000-2008 panel data of 117 Tennessee hospitals (1,053 observations), could inform healthcare resource policy decision-making in other U.S. states contending with similar health system reform changes (Richardson & Yilmazer, 2013), while also yielding insights into novel research on modeling hospital production cost structure.

The balance of this study proceeds as follows. Section 2 reviews relevant literature on hospital production. Section 3 presents a theoretical model and the econometric estimation approach. Section 4 describes the data and methods for analysis. Section 5 presents empirical results. Section 6 concludes with study findings and policy implications.

Literature Review

Hospital Output Measures

Cost is a function of output and other factors. Hospitals produce heterogeneous outputs that are difficult to measure. Cowing and Holtmann (1983) employed annual patient-days by diagnostic categories including medical-surgical, maternity, pediatrics, other in-patient care, and emergency room (ER) visits. Conrad and Strauss (1983) made a seminal attempt to distinguish between inpatient days by insurance types, and partitioned patient-days into age groups, e.g., Medicare, non-Medicare and child inpatient days. Breyer (1987) proposed a specification with three global output categories of cases, patient-days, and staffed beds. While patient-days can account for a large portion of the variation in total cost, this measure of hospital output raises some concerns. Patient-days might not have uniform effects on costs[3] or might be endogenous to costs as hospitals can technically manipulate treatment durations. Moreover, in a PPS, patient-days might measure profit-driven choices of management rather than demand (Ellis & McGuire, 1996). Cases treated adjusted for differences in case mix, length of stay, and severity of ailments, might better capture the hospital production and associated costs.

Disaggregation of medical cases range from simple breakdowns into outpatient visits and inpatient admissions to more elaborate stratifications. Grannemann *et al.* (1986), separating inpatient admissions from patient-days and emergency visits from other outpatient visits, found distinct marginal cost estimates for the two dimensions of inpatient care. Scuffham *et al.* (1996) measured output as admissions and length of stay, and controlled for variation in individual practices. Magnussen (1996), using outpatient

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[3] The initial hospital-days incur disproportionally higher costs, given diagnostic tests, possible surgical procedures, and intensive care needed to stabilize acute conditions.

visits, long-term patient-days, and limited stay inpatient activity, found significant changes in efficiencies for changes in output specification.

The correlation between health status and insurance type suggests that patients covered by different insurers might require different treatment intensities. Grannemann *et al.* (1986) used sources of hospital revenue as independent shifters of the cost function. Conrad and Strauss (1983) reported Medicare patients as using less expensive resources and having higher average length of stay than non-Medicare patients in every diagnostic group. Hospitals react differently to Medicare and Medicaid payment mechanisms (McKay *et al.*, 2002/2003; Meltzer *et al.*, 2002; Rosko & Mutter, 2008). Bilodeau *et al.* (2000) found that outpatient visits and teaching status had no effects on variable. However, most hospital cost models capture inpatient and outpatient outputs (Rosko & Mutter, 2008). Minor outpatient surgeries require no hospitalization. Outpatient care is rising due to payer mandates and improved technology of care. As a result, this study defines hospital output as payer type, with payer-specific admissions and outpatient visits (including ER visits) as distinct products.

Hospital Quality Measures

Standard theory posits production cost to vary with (input, process and output) quality. Hospital quality of care depends on payer type (Doyle, 2005). Hospitals tend to produce varying quality output levels with different amounts of factor inputs, depending on payer mix. Patients covered under less generous third-party insurers receive lower services quality (Dor & Farley, 1995). Meltzer *et al.* (2002) found differences in resources usage, as measured by charges, between Medicare and private patients with identical diagnosis.

However, omission of explicit measures of care quality suggests that past results must be interpreted with caution (Folland & Hofler, 2001; McKay *et al.*, 2002/2003).

Adequate adjustment for care quality is a difficult task. Hospital quality has structural, process, and outcome dimensions (Donabedian, 2003; Romano & Mutter, 2004). Structural measures, encompassing conditions under which hospital care is provided and resources used for treating patients, include teaching status (Ayanian & Weissman, 2002), membership status, number or proportion of specialists on the medical staff, location and hospital accessibility (Keeler & Ying, 1996). Staff characteristics may capture aspects of inpatient care and hospital residency training provided by the hospital (Custer & Willke, 1991). However, these measures are limited in explaining observed variability in care processes and outcomes. Major teaching hospitals can produce low-quality care or use excessive testing and consultation for simple cases and changes in quality measured this way may be unobserved over short time periods. Process measures of quality reflect better the activities providers perform (how they evaluate and treat patients) in health care production (Romano & Mutter, 2004) but are difficult or costly to collect. Outcome measures of quality, including risk-adjusted mortality rates and readmission indexes (Carey, 2000), infant mortality index and in-hospital mortality rates, might be endogenous to costs if associated with lower spending per patient in hospitals that are under-providing essential care. Using outcome measures of quality in cost models is only appropriate if patient characteristics are fully accounted for (Rosko & Mutter, 2008).

Structural and process-related quality controls that are likely to be associated with hospital-level differences in quality and care complexity are used in this study. First, we employ variables traditionally used as quality controls such as teaching status and inpatient occupancy rate. Teaching hospitals perform more complex, innovative, or unusual medical procedures that might not be captured by the volume or case-mix controls. Occupancy rate has been used as a measure of quality on the argument that when admissions approach full capacity, overuse of hospital resources yield lower overall care quality (Friedman & Pauly, 1981).

Next, hospital accreditations and memberships may have differential effects on production through altering decisions of hospital administrators. Quality is likely to increases with greater number of hospital accreditations and memberships as more intense emphasis is placed on maintaining high quality standards. However, to obtain an accreditation, hospitals must meet efficiency requirements or standards via maintaining lower costs, which could be at the expense of lower care quality. Hospitals affiliated with medical schools are likely to engage more heavily in medical research and teaching than institutions with approvals for residencies, while both endeavors may increase costs and be correlated with output case-mix. The direction of this effect could be reversed if hospitals that offer graduate medical education increase patient exposure to inexperienced care, therefore decreasing the service quality provided. The quality-increasing effects of medical education may dissipate in hospitals approved as schools of nursing as usage of inexpensive nursing personal in training is expected to depress care quality and push the costs down.

Hospital Ownership, Location, and Technological Change

Costs and care quality are linked to ownership status, although the theoretical underpinning of this hypothesis is inconclusive. Ownership type could affect access to factor markets or for-profit hospitals might also pursue profit-maximization (Rosko 1999) through cost inefficiencies and increasing quality by payment source.[4] Contrasting earlier results (e.g., Becker & Sloan, 1985), Grannemann *et al.* (1986) found for-profit to have higher costs than not-profit hospitals.

Technical progress can influence cost efficiency. In a translog cost analysis of hospital pharmacies, Okunade (2001) found that information technology could improve cost efficiency and spur gains in productivity. Finally, hospital location reflects variation in the availability and prices of production factors. Studies capturing geographic disparities suggest cost efficiency differences across regions within a health care system (Okunade & Suraratdecha, 2006).

Specification of Hospital Cost Model and Empirical Methodology

The neo-classical cost function predicts that hospitals minimize costs by choosing the optimal vector of input factors X, given that input prices and outputs are exogenous, i.e. the vector of factor prices W is competitively determined in a factor market free from monopsonistic pressures. Hospital production, denoted by $f(\cdot)$, is fully described by its cost minimizing dual:

$\min_X W'X = C(Y(Q), W, Z)$, subject to $f(X; Y(Q)) = Y(Q)$,

where $Y(Q)$ is the output vector, W is the factor price vector, Q and Z include quality controls and cost shifters. Supposed $C(\cdot)$ is a well-behaved cost function with non-decreasing marginal costs ($C'(\cdot) > 0$, $C''(\cdot) \geq 0$) and linearly homogeneous in input prices. Efficient production requires the inputs to be set at cost minimizing levels: $X_i^*(Y(Q), W, Z), \forall i = 1, \ldots$, where X_i^* is the long-run optimal input bundle for hospital i.

[4] See Sloan (2000) for a detailed review of the impact of ownership status.

If production includes a portion of capital that behaves as a fixed input and cannot fluctuate in response to unexpected realizations of demand, the cost minimizing assumption is violated (Bilodeau *et al.*, 2009).

Estimating hospital cost requires explicit designation of the state of the equilibrium. Let K represent the fixed capital and W_v and $W_k$be vectors of variable and fixed inputs prices. Short-run total cost is given by the following expression:

$C^S = C_v(Y(Q), W_v, K, Z) + W_k'K.$

A test for long-run equilibrium is performed by using the envelope condition, which relates short- and long-run costs. By taking partial derivative with respect to k_i, the long-run conditions are: $\partial C_v(Y(Q), W_v, K, Z)/\partial k_i = -w_{ki}, \forall i = 1, \ldots$, which implies that the variable cost saved by substituting the last unit of the fixed input for variable inputs must be equal to the marginal cost of that unit of capital. If $\partial C_v/\partial K < -w_{ki}$, investment in capital is at a sub-optimal level, while the opposite implies that hospital has excessive k_i. By solving for optimal $k_i^*, \forall i = 1, \ldots$ and substituting K^* back into the short-run cost, we get $C^S = C_v(Y(Q), W_v, K^*, Z) + W_k'K^*$, which can be rewritten as $C^S = C(Y, W_v, W_k, K^*; Q, Z)$, to obtain the long-run cost: $C^L = C(Y, W; Q, Z)$.

Since the true functional form is unknown, a flexible function is postulated to reduce misspecification. The translog has sufficient flexibility to model entities with multiples outputs and inputs, does not assume additivity and homogeneity, and allows variability of factor demand elasticities and scale economies (Berndt & Christensen, 1973; Caves *et al.*, 1980).[5] Alternative forms, including the Cobb-Douglas, involve estimation of fewer parameters but are restrictive when describing hospital behavior in ways unrelated to cost

[5] Translog is a local second-order Taylor series approximation of any arbitrary twice-differentiable function (Caves *et al.*, 1980).

minimization or technology. With *n* outputs and *m* aggregate inputs and including non-neutral and scale augmenting technical change, we approximate hospital cost as:[6]

$$Ln(C) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \, lnY_i + \sum_{j=1}^{m} \beta_j \, lnW_j +$$

$$1/2 \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_{ij} lnY_i lnY_j + 1/2 \sum_{i=1}^{m} \sum_{j=1}^{m} \beta_{ij} lnW_i lnW_j +$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \gamma_{ij} lnY_i lnW_j + \delta_t T + 1/2 \, \delta_{tt} T^2 + \sum_{j=1}^{m} \delta_{tj} T \, lnW_j + \sum_{i=1}^{n} \delta_{ti} T \, lnY_i + \Theta Z + \epsilon,$$

where $ln(C), lnY_i, \forall i = 1, \dots, n$, and $lnW_i, \forall i = 1, \dots, m$, are natural logarithms of the mean-scaled values of total cost, outputs by payer, and input prices respectively.[7] Z is a matrix of controls accounting for hospital specific characteristics. T is an annual time index and ϵ is a stochastic disturbance.

Using Shephard's lemma, we derive the factor demand functions: $X_i = \partial C / \partial W_i \, , \forall i = 1, \dots, m$. In logarithmic form, the cost share of the *i*th factor input S_i, can be expressed as: $S_i = (W_i / C) X_i, \forall i = 1, \dots, m$. The input share equations are: $S_i = \beta_i + \sum_{j=1}^{m} \beta_{ij} lnW_j + \sum_{j=1}^{n} \gamma_{ij} lnY_j + \sum_{j=1}^{m} \delta_{tj} T + u_i, \forall i = 1, \dots, m$, with $\sum_{i=1}^{m} S_i = 1$ and only $(m - 1)$ independent equations. We obtain parameter estimates of a three-equation system via ISURE (Iterative Seemingly Unrelated Regressions Estimation) to avoid singularity and gain efficiency. Following Conrad and Strauss (1983), Vita (1990), and Bilodeau *et al.* (2000) among others, we delete the share equation of energy and intermediate medical

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[6] Subscripts *h* and *t* represent the hospital and year respectively.

[7] We substitute arbitrarily small positive values for zero values of outputs based on the transformation ln $(Y + \varepsilon) \sim Y$ (Weninger, 2003). Sensitivity tests performed by varying the value of ε, from 1 to $10^{(-6)}$ show that this approach is not sensitive to the value chosen. An alternative way is to apply a Box-Cox transformation to zero outputs given by: ln $(Y) \sim {(Y_{it}^{\lambda} -)}/{\lambda}$.

supplies from the cost share system. We specify additive disturbances with joint normal distribution.

For the trans-long cost function to be a well-behaved cost the following must hold:

i. non-decreasing in input prices: $\partial lnC/\partial lnW_i \geq 0, \forall i = 1, \ldots, m$[8]

ii. non-decreasing in outputs: $\partial lnC/\partial lnY_i \geq 0, \forall i = 1, \ldots, n$

iii. symmetry: $\beta_{ij} = \beta_{ji}, \forall i \neq j$ [9]

iv. linear homogeneous of degree one in input prices imposed as:

$\sum_{i=1}^{m} \beta_i = 1, \forall i = 1, \ldots, m$

$\sum_{i=1}^{m} \beta_{ij} = \sum_{j=1}^{m} \beta_{ij} = 0, \forall i, j = 1, \ldots, m$

$\sum_{j=1}^{m} \gamma_{ij} = 0, \forall i = 1, \ldots, n,\ j = 1, \ldots, m$

$\sum_{j=1}^{m} \delta_{tj} = 0, \forall j = 1, \ldots, m$

v. non-negative[10], concave, continuous and differentiable in input prices.

The restrictions $\gamma_{ij} = 0, \forall i = 1, \ldots, n,\ j = 1, \ldots, m$ are necessary and sufficient for homotheticity. A homothetic structure is homogeneous if and only if output elasticity of cost is constant or $\alpha_{ij} = 0, \forall i, j = 1, \ldots, n$, and the degree of homogeneity is equal to $1/\sum_{i=1}^{n} \alpha_j$. If the dual production has constant returns to scale (CRS), an additional restriction must hold: $\sum_{i=1}^{n} \alpha_{ij} = 1$. We do not impose *a priori* any restrictions and

[8] In addition to the monotonicity in factor prices and output levels, this assumption ensures that the estimated cost share must be positive for each input *i*.

[9] This assumption implies that the cost function is twice-differentiable and the Hessian matrix is symmetric. It is differentiable only when it is continuous. This condition is based on Young's theorem and it is necessary for the derivation of the conditional factor demands.

[10] This states that hospitals cannot provide care without incurring some positive costs. Since the dependent is the natural log of hospital total costs, the non-negativity condition is automatically satisfied.

formally verify the properties of the cost function and the assumption of long-run equilibrium. Complete testing of the theoretical properties of hospital cost functions is typically not performed in previous research even though the verification of these properties -such as concavity in input prices and monotonicity in all variables- is a necessary condition for the validity of any empirical cost analysis.[11]

When assessing the degree of input responsiveness to exogenous factor wage changes, it is important to select conceptually appropriate measures of elasticity to draw inferences regarding substitution possibilities in hospital production (Okunade, 1999). Alternative definitions are not equivalent when production is nonhomothetic and involves at least there inputs (Blackorby & Russell, 1989).

The price elasticity of the *i*th factor demand given by: $\eta_{ij} \equiv \partial lnX_i/\partial lnW_j = X_{ij}\left(W_j/X_i\right), \forall i, j$, is not symmetric (Okunade, 2003). The symmetric Allen-Uzawa partial elasticities can be derived from the cost function (Uzawa, 1962): $\sigma_{ij}^{A-U} = CC_{ij}/C_iC_j,\ \forall i \neq j, i, j = 1, \dots, m$, where $C_i = \partial lnC(\cdot)/\partial lnW_i$ is the ith input share as defined previously.[12] In the translog framework, substitutions between factors *i* and *j* are given by: $\sigma_{ij}^{A-U} = (\beta_{ij} + S_iS_j)/S_iS_j$, and $\sigma_{ii}^{A-U} = [\beta_{ii} + S_i(S_i - 1)]/S_i^2, \forall i \neq j, i, j = 1, \dots, m$. Numerically, the σ_{ij}^{A-U} show the proportional change in the quantity used of the ith input weighted by the its factor cost share, due to a proportionate change in the price of the jth input. By substituting for total cost we get: $\sigma_{ij}^{A-U} = \left(W_jX_j/S_j\right)X_{ij}/X_iX_j = \eta_{ij}/S_j, \forall i, j = 1, \dots, m$, where $\eta_{ij}$is the

[11] In most studies, monotonicity is the only property tested (Bilodeau *et al.*, 2000).

[12] $S_i = W_iX_i/WX, \forall i = 1, \dots, m$.

cross-price elasticity of the ith factor demand. Using the partial σ_{ii} and σ_{ij}, we compute own- and cross-price elasticities of the ith factor demand as $\eta_{ii} = \beta_{ii}/S_i + S_i - 1, \forall i = 1, \dots, m$, and $\eta_{ij} = \beta_{ij}/S_i + S_j, \forall i \neq j, i, j = 1, \dots, m$.

The Allen-Uzawa concept is difficult to interpret, is inconsistent with the Hicksian definition, and imposes the invariance of factor demands with respect to which input price changes (Blackorby & Russell, 1989). However, it is used to calculate more meaningful measures such as Morrishawa ealsticities given by:

$\sigma_{ij}^{M} = \partial ln(X_i/X_j)/\partial\, lnW_j = W_iC_{ij}/C_j - W_iC_{ii}/C_i = S_j(\sigma_{ij}^{A-U} - \sigma_{JJ}^{A-U})$, where C_j is the jth input cost share, and $C_{ij} = \partial^2 C(\cdot)/\partial W_i \partial W_j$. Morrishawa is a non-symmetric, two-factor, one-price sufficient statistic for assessing the effects of input price changes on relative factor shares by substituting between factors along an isoquant. It is intimately related to input price elasticities $\sigma_{ij}^{M} = \eta_{ij} - \eta_{jj}, \forall i, j = 1, \dots, m$.

The Shadow elasticity σ_{ij}^{S} is a special form of Hicks two-factor, two-price elasticity of factor substitution $\partial ln(X_i/X_j)/\partial ln(W_j/W_i)$ calculated as:

$\sigma_{ij}^{S} = (S_iS_j)/(S_i + S_j)[2\sigma_{ij}^{A-U} - \sigma_{ii}^{A-U} - \sigma_{jj}^{A-U}]$. The Shadow elasticity captures how input ratio used in production respond to changes in relative factor prices.

Rather than assuming technological change neutrality, we test for the possibility that productivity growth is biased in favor of specific inputs or is due to scale increases. Estimates of the uncontaminated rate of technical progress are obtained from the expression: $\dot{T} = \partial lnC/\partial T = (\delta_t + 1/2\, \delta_{tt}T) + \left(\sum_{j=1}^{m} \delta_{tj} lnW_j\right) + (\sum_{i=1}^{n} \delta_{ti} lnY_i)$.

A test for improving technology is executed by checking whether the mean of $\delta_t + 1/2\, \delta_{tt}T$, which represents the true trend in technology, is greater than zero (Stern, 1995). The second and the third parenthesized terms in the decomposed technical effects expression represent factor bias and scale-augmenting components respectively. Typically, evaluation of productivity growth is done under the assumption of CRS technology. Here, hypothesis related to the nature of the scale economies are tested rather than imposed on the postulated model.

By separating inpatient admissions/discharges and outpatient care by type of payer, we estimate distinct measures of economies of scale and scope by sources of reimbursement.

If output *i* is varied, while other outputs and input prices are held constant, partial scale economies is measured as: $SCE_i = (C/Y_i)/(\partial C/\partial Y_i) = 1/(\partial lnC/\partial lnY_i) = AC_i/MC_i, \forall i = 1, \dots, n$. If estimated marginal cost for output i is less than the average incremental costs, there are partial scale economies in the production of admissions and outpatient visits by payer *i*. Overall scale economies is computed as: $SCE = 1 - \partial lnC/\partial lnY = 1 - \sum_i^n(\partial lnC/\partial lnY_i)$; a positive value indicate presence of scale economies.

Economies of scope, $ESCOPE$, exist if $C(Y_i, Y_j) < [C(Y_i, 0) + C(0, Y_j)], \forall i, j; i \neq j$. Sufficient condition for scope economies to occur is: $\partial^2 C(\cdot)/\partial Y_i\, \partial Y_j < 0, \forall i, j; i \neq j$, which requires that the MC_i declines when the production of output by payer *j* is increased.

Previous estimates of scale and scope economies are inconsistent possibly due to wide variation in outputs measurement, use of long- or short-run cost functions, inclusion or omission of input prices and different model specifications (Smet, 2002). Dranove (1998) found limited evidence of scale economies for mid-sized hospitals (200 beds). Fournier and Mitchell (1992), Carey (1997), Dor and Farley (1996), Dranove (1998), Gaynor and

Anderson (1995), and Preyra and Pink (2006) found stronger evidence of scale economies. Conrad and Strauss (1983) reported evidence of CRS for North Carolina hospitals. Vita (1990) recalculated the Cowing and Holtmann (1983) scale parameter and found slight diseconomies. Grannemann *et al.* (1986) and Keeler and Ying (1996) found no scale economies for inpatient care and weak scale diseconomies for all levels of output. The empirical evidence on the presence of hospital scope economies is also mixed. Cowing and Holtmann (1983) found little support that the long-run cost is characterized by weak cost complementarities (Vita, 1990). However, others show prevalence of significant scopes in hospital production (Custer & Willke, 1991; Fournier & Mitchell, 1992; Preyra & Pink, 2006; Scott & Parkin, 1995).

Data and Descriptive Statistics

The 2000-2008 data are from Joint Annual Reports of Hospitals for the state of Tennessee (USA), a sample ensuring a common institutional and regulatory environment. Omitted from analysis are the structurally diverse psychiatric, pediatric, long-term care and rehabilitation hospitals serving specialized populations. They would have uniquely different production cost structures. Total cost is calculated as the sum of payroll expenses and employee benefits, depreciation and interest, energy, and other non-payroll expenses including supplies, purchased services, and other non-operating expenses. All values denominated in dollars are adjusted for inflation using the general healthcare CPI.

Hospital Outputs and Case Mix Index

Given that the concept of output in hospital sector is of an ambiguous nature, an appropriate approach is to identify observable intermediate products that form the basis of payment for hospital services and use them as proxies for output. Thus, hospital outputs are defined as inpatient admissions and outpatient services including ER visits, by source of payment: Self-pay, Private insurance (includes Blue Cross/Blue Shield and Commercial Insurance), Medicaid/Tenncare, Medicare, and other non-government insurance (Workers Compensation).[13]

Differences of severity, duration, or distribution of medical conditions require adjustments for patient heterogeneity based on the assumption that the more difficult illnesses are more input demanding than less serious ones.

Medicare Case Mix Index (MCMI) based on the Diagnosis Related Group (DRG) classification system developed by Medicare is predominantly used to control for patient burden of illness (Rosko & Mutter, 2008). The DRG system classifies hospital cases into 999 groups, each including patients that are similar clinically and are expected to use similar amounts of hospital resources.[14] The MCMI represents hospital average DRG relative weight calculated by summing the DRG weights for Medicare discharges and dividing by the number of discharges. The Medicare system is used for payment calculations and is partly based on treatment decisions for patients. However, the MCMI is a relatively weak measure of differences in sickness among patients (Carey, 2000).[15] If

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[13] Payer classification varies over time. Cover TN, Cover Kids, and Access TN, are included under Medicaid/TennCare.

[14] The groups are assigned by a "grouper" program based on diagnoses, procedures, age, sex, discharge status, and the presence of complications or comorbidities.

[15] In 2009, only 119 hospitals (70% of all the hospital in Tennessee) were registered with Medicare.

hospitals strategically classify patients across DRGs to maximize payments, using the MCMI would inject a bias known as the "DRG bias creep".

We build hospital-specific inpatient mix index (Vita, 1990; Grannemann *et al.*, 1986). Using historical Medicare DRG relative weights that reflect the resources used to treat a specific diagnose and cross walk files[16], and accounting for changes over time in the classification systems, we obtain aggregated weights by Major Diagnostic Categories (MDC) and incorporate discharge information to define the inpatient case mix index as follows: $CMI_{it} = \sum_{d=1}^{26}(weight_{dt})(discharges_{dit})/\sum_{d=1}^{26}(discharges_{dit})$, where $d = 1, \dots, 26$ represent the MDCs, and $i = 1, 2, \dots, 171$ and $t = 2000, 2001, \dots, 2008$ are indexes for individual hospitals and time. Hospitals do not report admissions in the "PRE" category as defined by Medicare, which includes resource-intensive major surgical procedures, mainly transplants.[17] We reassign the medical cases included in the "PRE" category to corresponding MDCs according to the type of transplant.

We control for outpatient severity by including the proportion of ER visits, assuming that the emergent cases are the most severe outpatient cases. The complexity of the ER cases could be due to patients' characteristics (uninsured people who defer seeking treatment until a disease reaches a critical stage) or their emergent nature (sudden trauma

[16] The Medicare cross walk files that link the CMS DRGs version 24 to MS DRGs version 25 via MDCs.

[17] Examples of procedures classified under Medicare category "PRE" include: "Heart transplant or implant of heart assist system", "Liver transplant with MCC or intestinal transplant", "Lung transplant", "Simultaneous pancreas/kidney transplant", "Bone marrow transplant", "Pancreas transplant", "Tracheostomy for face, mouth and neck", etc.

arising from accidents or crime). The index is weighted by the size of the emergency department as:

$sickop_{it} =$

$(er\ visits_{it}/outpatient\ visits_{it})\left[(1/T_i)\sum_t^{T_i} er\ visits_t/(1/N)\sum_i^N er\ visits_i\right]$, where T_i is periods by hospital i, and N is the sample observations. This is a proxy for the acuity of hospital outpatient workload. Because $log(1+x) \cong x$ if x is sufficiently small and CMI_{it} and $sick\_op_{it}$ are in the range of 1.5 and 0.4 respectively, we do not take the log of these indexes.

Input Prices

While in theory, hospitals are price-takers in the labor market, the average annual salary per employee reflects hospitals' choices regarding the number and skill-mix of personnel. Hospital labor incorporates (1) Medical personnel (physicians and dentists), (2) Medical and dental residents (medical and dental interns), (3) Trainees (medical technology, x-ray therapy, administrative), (4) Registered and licensed practical nurses, (5) Contracted nursing services (include staff from nursing registries, service contract, and temporary help agencies), and (6) All other personnel. Unlike previous studies disregarding employee benefits due to data limitations, labor costs are correctly defined based on full compensation (salaries plus employees benefits: social security, group insurance, and retirement benefits).[18] Wages are calculated by dividing payroll expenses

[18] Compensations paid as professional fees (medical, dental, legal, auditing, consultant, etc.) or for contracted nursing services (for stuff from nursing registries, service contracts, and temporary help agencies) are not included in labor costs, since wages for this personnel are paid independently of the hospital.

by the full-time equivalent (FTE) of current personnel and deflating by annual average medical CPI.[19]

The flow of capital services as a resource is difficult to assess due to timing of expenditures and charges for depreciation. A convenient approach uses beds as a proxy for fixed inputs and assumes constant level of investment in all assets (such as medical equipment per bed) across hospitals (Vita, 1990). Folland and Hofler (2001) find that hospital beds performs similar in cost estimations to a composed measure of capital cost that allows equity and debt rates to differ and inflation to be nonzero. However, the comprehensive data allows for a more appropriate definition of capital input as the value of net fixed plant and equipment assets (building, equipment, land, etc.) per licensed adult and pediatric bed. The price of capital is calculated as depreciation expenses plus annual interest payments per unit of capital.[20] Long-term beds are excluded as they differ from acute care beds in terms of technology embodied and capital invested.

Lastly, we include energy, supplies, purchased services and other non-operating expenses, henceforth classified as supplies expenses. Hospitals procure supplies in competitive markets, and given the purchasing power of the average hospital, it is reasonable to assume that non-labor inputs prices are exogeneous. Furthermore, the quantity of supplies consumed is assumed to be proportional to total average beds staffed and used during the operational year. Thus, the price of supplies is obtained by dividing

[19] Full-time employees are those whose regularly scheduled workweek is 40 hours or more and exclude agency and contract staff. Full-time equivalents (FTE) are calculated as the number of hours worked by part-time employees per week divided by 40 hours per week.

[20] Grannemann *et al.* (1986) and others maintain that the price of capital measured as depreciation should be included when a long-run total hospital cost function is estimated.

expenses on energy, supplies, purchases services, and other non-operating expenses by the number of staffed beds.

Quality, Technological Change, and Geographic Controls

Approval by the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) has been previously used as an imperfect proxy for quality. We introduce a quality indicator based on joint accreditations by the JCAHO[21] and the American College of Surgeons Commission on Cancer (ACSCC) to capture heterogeneity in costs across hospitals potentially due to variations in the requirements for meeting differing quality standards. If, indeed, having a "specialized" accreditation increases quality we expect a positive coefficient on this index in the cost model. However, the ACSCC accreditation could have a negative effect on costs if it raises demand by signaling high quality or attracting cancer patients, which allows hospitals to perform complicated procedures and offer prolonged treatments with increased reimbursements, or places pressures on reaching and maintaining high efficiency levels to eliminate waste. Almost all hospitals (94.6%) are members of the state-wide Tennessee Hospital Associations (THA), of which 63.5% are members of the Hospital Alliance of Tennessee (HAT). We account for the effect of having a double membership with THA and the American Hospital Association (AHA). Having medical school affiliation or the American Medical Association (AMA) approval for residencies is captured by including interns or residents. Lastly, we include an indicator for hospitals approved as nursing schools for registered or licensed practical nurses.

Production is defined not only by quantities of inputs used but also by the stock of inputs available to meet fluctuating demand. Since capacity may have option value

[21] The vast majority of hospitals in the sample are JCAHO accredited (95.5%).

(Zweifel & Breyer, 1997), we adjust for the size of the inpatient facility by adding dummies for licensed adult and pediatric beds grouped into categories, 1-99, 100-199, and >200, with the small class as the reference category. While licensed beds show potential capacity, inverse of the inpatient occupancy rate (patients admitted typically on September, 30) measures actual excess capacity (Gaynor & Anderson, 1995). High occupancy may enhance cost efficiency and low occupancy tends to raise unit fixed costs. As the inverse occupancy rate increases, the relative share of fixed factors increases and the coefficient on this rate shows the cost of empty beds. By showing how inpatient resources are allocated, occupancy may reflect quality of treatment. Including the time-trend, its nonlinear effects, and interactions with outputs and input factors capture how technical change affects costs. The time index is used as a proxy for exogenous Hicks-neutral technology change that affects hospital costs. Moreover, the trend estimate could capture basic shifts in demand, input factors, or hospital behaviors and must be interpreted as an upper bound of the effect of technology on costs. Quadratic time effects and interactions with outputs and wages are added to allow for non-Hicks-neutral technical changes. These terms represent effects on costs that are not accounted for by input usage (capital, labor, and other non-operating expenses), scale changes, hospital-specific factors, or environmental changes (regulations, etc.).

Finally, ownership is measured using investor-owned and government-owned hospitals as separate indicators, with non-governmental not-for-profit being the excluded category. Dummies for East and West Divisions in Tennessee are included (Middle Division is the reference). Table 1 presents a description and descriptive statistics of the basic variables used in this study.

Table 1. Definitions and descriptive statistics of variables in the cost model

Components of the Cost Model		Sample Size	Sample Mean	Standard Deviation
Total Variable Cost				
C*	Total hospital cost= total payroll expenses + total nonpayroll expenses (employee benefits, depreciation expenses, interest expenses, energy, and other nonpayroll expenses such as supplies, purchased services, and other nonoperating expenses)	1,176	70,536.37	113,000.00
Output Measures				
Y_1	Admissions/discharges self-paid	1,096	5,636.62	10,435.52
Y_2	Admissions/discharges with private insurance (Blue Cross/Blue Shield and Commercial Insurance)	1,096	28,247.52	51,655.91
Y_4	Admissions/discharges with Medicare	1,096	16,319.98	22,878.16
Y_5	Admissions/discharges with other non-government insurance (includes Workers Compensation)	1,096	3,143.38	6,212.29
Variable and Quasi-fixed Inputs				
w_L	Labor Wage: (Total Payroll Expenses + Employee Benefits) / FTE Personnel	1,176	654.00	942.57
expenses labor*	Salaries paid to all personnel: physicians and dentists, medical and dental residents/interns, trainees (medical technology, x-ray therapy, administrative), registered and licensed practical nurses and nursing services, contracted nursing services (staff from nursing registries, service contract, and temporary help agencies), auxiliary personnel, pharmacy, administration and management, and other. Employee Benefits include social security, group insurance, and retirement benefits.	1,175	34,046.46	52,800.00

Table 1. Definitions and descriptive statistics of variables in the cost model

Components of the Cost Model		Sample Size	Sample Mean	Standard Deviation
Variable and Quasi-fixed Inputs – cont.				
w_K	Price of capital = Capital expenses / Value of net fixed plant and equipment assets (including land, building, and equipment)	1,176	170.95	182.35
expenses capital*	Depreciation expenses and interest expenses	1,175	6,291.34	8,770.70
w_S	Price of supplies = Supply expenses / Average staffed beds in use over the course of the reporting period	1,176	129.85	146.50
expenses supply*	Energy expenses, supplies, purchased services, other non-operating expenses, etc.	1,175	30,258.61	53,300.00
Additional Controls: Case Mix				
cmi	Hospital specific case mix index for admissions/discharges	1,176	1.572	0.28
sick_op	Proportion of total outpatient visits admitted through the Emergency Room	1,063	0.406	0.16
sick_payer*i*	Proportion of outpatient visits by payer *i* admitted through the Emergency Room			
	sick_self	1,034	0.840	1.01
	sick_mcaid	1,045	6.126	166.05
	sick_mcare	1,045	0.291	0.57
	sick_priv	1,043	0.370	0.41
	sick_other	983	1.290	11.18
Quality Measures				
qaccreditations	Accredited by the Joint Commission on Accreditation of Healthcare Organizations and the American College of Surgeons Commission on Cancer	1,152	0.167	0.37
qmemberships	Member of the Tennessee Hospital Association and the American Hospital Association	1,176	0.699	0.46

Table 1. Definitions and descriptive statistics of variables in the cost model

Components of the Cost Model		Sample Size	Sample Mean	Standard Deviation
Quality Measures – cont.				
qnursing	Member of the Tennessee Hospital Association and functions as a State Approved School of Nursing for Registered Nurses or Licensed Practical Nurses	1,170	1.836	1.07
qteaching	Hospital uses medical and/or dental interns and/or residents (has the American Medical Association Approval for Residencies and/or has a Medical School Affiliation)	1,068	15.613	69.14
Other Controls				
occupancy	Inverse of occupancy rate (hospital patients at the time of survey response)	1,051	3.202	7.13
ssize	Hospitals with < 100 beds	1,176	0.469	0.50
msize	Hospitals with > 100 and <200 beds	1,176	0.261	0.44
lsize	Hospitals with >200 beds	1,176	0.270	0.44
for-profit	Investor-owned for-profit hospital	1,176	0.321	0.47
not-for-profit	Nongovernmental, not-for-profit hospital	1,176	0.475	0.50
public	Government-non-federal and government federal hospital	1,176	0.202	0.40
east	Located in the Eastern Grand Division of TN	1,176	0.372	0.48
west	Located in the Western Grand Division of TN	1,176	0.247	0.43
middle	Located in the Middle Grand Division of TN	1,176	0.382	0.49
trend	Hicks-neutral technical change	1,176	5.059	2.58
Cost Shares = Variable Cost for Input / Total Variable Cost				
x_1	Cost share of labor (physicians, dentists, technicians, nursing, and administrative personnel)			
x_2	Cost share of capital			
x_3	Cost share of supplies			

Notes: Based on JARH 2000-2008 data; $*10^3$ dollars. All dollar amounts are deflated by medical CPI.

Total cost for the typical hospital is about $70.53 million of which 48.2%, 8.9%, and 42.5% are spent on labor, capital, and supplies respectively. On average, 5,636 admissions are self-paid, 28,247 have private insurance, 23,614 have Medicare, 16,319 have TennCare/Medicaid and 3,143 have other payers. The average hospital employs 16 residents and interns, and has an inverse occupancy rate of 3.2. About 20% of hospitals are government owned, 47.5% are not-for-profit, and 32% are for-profit hospitals. Nearly 47% of the hospitals have less than 100 licensed beds. About 37% of the sample hospitals are located in the Eastern Division and almost a fourth of the hospitals are located in the Western Division. While capital spending does not vary significantly with size, hospitals with less than 100 beds spend 53.1% of total costs on labor compared to 48.9% of total expenditure allocated for payroll expenses by hospitals having more than 200 beds (Table 2).

Table 2. Descriptive statistics of factor cost shares by hospital size

Variable	Sample Size	Sample Mean	Standard Deviation	Min. Value	Max. Value
	Total Licensed Adult and Pediatric Beds < 100				
Cost Share of Labor	550	0.531	0.108	0.016	0.908
Cost Share of Capital	551	0.091	0.062	0.001	0.599
Cost Share of Supplies	551	0.379	0.099	0.029	0.931
	100<=Total Licensed Adult and Pediatric Beds < 200				
Cost Share of Labor	307	0.499	0.069	0.337	0.669
Cost Share of Capital	307	0.105	0.049	0.008	0.336
Cost Share of Supplies	307	0.396	0.068	0.216	0.580
	Total Licensed Adult and Pediatric Beds>=200				
Cost Share of Labor	318	0.489	0.073	0.162	0.811
Cost Share of Capital	318	0.091	0.034	0.027	0.229
Cost Share of Supplies	318	0.420	0.079	0.071	0.740
	Pooled Sample				
Cost Share of Labor	1175	0.511	0.092	0.016	0.908
Cost Share of Capital	1176	0.095	0.053	0.001	0.599
Cost Share of Supplies	1176	0.395	0.088	0.029	0.931

Notes: Based on JARH 2000-2008 data; All dollar amounts are deflated by medical CPI.

The share of supplies in total costs is 41.9% cost in large hospitals, which is larger compared to 37.9% in hospitals with less than 100 beds.

Empirical Results

Main Findings

We estimate as system of equations comprising of a multi-output-multi-input hybrid translog cost function and the corresponding cost shares using the 3SLS-ISURE technique to allow individual hospital disturbances to be correlated across equations.[22] The data is transformed to avoid unit sensitivity of the coefficients on the non-multiplicative terms (Stern, 1995).[23] Linear homogeneity in factor prices, and symmetry of the matrix of second partial derivatives are *a priori* imposed. A Hausman specification test ($p < 0.05$) suggests that hospital outputs can be treated as exogenous. For robustness purpose, alternative specifications were estimated subject to various definitions of fixed capital and quality. The results obtained were consistent and did not vary in significant ways.

The assumption of long-run equilibrium is verified by estimating a variable hospital cost function taking as given the capital stock and treating licensed beds as a quasi-fixed factor. The fixed input is defined as the dollar value of fixed assets and equipment per licensed bed. Consistent with long run equilibrium the estimated coefficient for fixed capital is negative and significant (Table 3), which contradicts the over-capitalization result in found in earlier studies (Cowing & Holtmann, 1983; Vita, 1990; Fournier & Mitchell, 1992).

[22] The ISUR estimation is performed in STATA 11 (College Station, TX, USA) with the iteration option. It iterates over the estimated disturbance covariance matrix and parameter estimates until the parameter estimates converge.

[23] This procedure affects only the constant term, which means that no transformation of the dependent variables is necessary.

Table 3. Testing the envelope condition for long-run hospital cost minimization

Self-paid	0.020	Other*Price Supplies	0.009
	(0.062)		(0.007)
Private Insurance	0.269***	Price Labor	0.494***
	(0.057)		(0.006)
Medicare	0.612***	Price Supplies	0.506***
	(0.085)		(0.006)
Medicaid/Tenncare	-0.008	Price Labor Squared	0.046***
	(0.073)		(0.003)
Other Payers	0.094***	Price Supplies Squared	0.046***
	(0.018)		(0.003)
Self Squared	0.093**	Price Labor*Price Supplies	-0.046***
	(0.030)		(0.003)
Private Squared	0.525***	Fixed Capital	-0.057**
	(0.082)		(0.019)
Medicare Squared	-0.027	Public	-0.075*
	(0.060)		(0.037)
Medicaid Squared	-0.011	For-profit	0.075*
	(0.083)		(0.035)
Other Squared	0.073***	East Division	-0.094**
	(0.015)		(0.036)
Self*Private	-0.105	West Division	0.092*
	(0.095)		(0.038)
Self*Medicare	-0.010	Case Mix Index	0.106
	(0.081)		(0.086)
Self*Medicaid	0.282***	Sick Outpatients	0.623***
	(0.060)		(0.070)
Self*Other	-0.022	JCAHO and ACSCC Accredited	0.208***
	(0.021)		(0.043)
Private*Medicare	-0.018	Memberships THA and AHA	-0.120***
	(0.093)		(0.033)
Private*Medicaid	-0.654***	State Approved Nursing School	-0.033
	(0.110)		(0.039)
Private*Other	0.046	Teaching	0.176***
	(0.027)		(0.044)
Medicare*Medicaid	0.280**	Inverse Occupancy	-0.001
	(0.094)		(0.002)
Medicare*Other	-0.042	Trend	0.030
	(0.031)		(0.032)
Medicaid*Other	0.018	Trend Squared	-0.004
	(0.025)		(0.006)
Self*Price Labor	-0.001	Trend*Price Labor	0.001
	(0.002)		(0.001)
Self*Price Supplies	-0.017	Trend* Price Supplies	-0.055***
	(0.012)		(0.005)

Table 3. Testing the envelope condition for long-run hospital cost minimization

Private*Price Labor	-0.031*** (0.003)	Trend*Self	0.012 (0.009)
Private*Price Supplies	-0.072*** (0.014)	Trend*Private	0.037*** (0.009)
Medicare*Price Labor	0.012*** (0.003)	Trend*Medicare	-0.024 (0.014)
Medicare*Price Supplies	0.027* (0.013)	Trend*Medicaid	-0.019 (0.012)
Medicaid*Price Labor	0.021*** (0.003)	Trend*Other	-0.002 (0.002)
Medicaid*Price Supplies	0.054*** (0.013)	Constant	17.181*** (0.172)
Other*Price Labor	-0.002** (0.001)	System R Squared	0.9083

Notes: Based on JARH 2000-2008 data; *10^3 dollars. All dollar amounts are deflated by medical cpi. Standard errors are presented in parenthesis. # p<0.15, * p<0.10, ** p<0.05, *** p<0.01.

Hypotheses tests on restricted technologies, including homotheticity, homogeneity, CRS, and unitary elasticity of substitution were conducted using the *Likelihood Ratio* (*LR*) statistic given by:

$$-2log\Lambda = N\left[log|\widehat{\Omega_r}| - log\widehat{|\Omega_u|}\right],$$

where *N* is the observations, and$|\Omega_r|$ and $|\Omega_u|$ are determinants of the estimated error covariance matrices for the unrestricted and restricted models, respectively. These tests suggest that the operational data of hospital health production is inconsistent with the restricted technology forms (Table 4).

Rejecting homotheticity in outputs implies nonlinear expansion paths indicating that the optimal input bundle varies with outputs levels. Consequently, hospital management can reduce costs by optimally re-organizing input factor ratios as demand expands. Prior, to estimating elasticities of substitution and price elasticities of demand from cost-minimizing factor demand equations, we must determine whether the underlying production technology is Cobb-Douglas. Based on the *LR* test defined above, the calculated ratio obtained ($\chi^2(33) = 1181.49$) rejects the hypothesis that the underlying technology is Cobb-Douglas at the 1% significance level. This result confirms that a flexible model allowing for non-homotheticity, non-unitary elasticities of factor substitution, and non-constant pairwise factor substitutions is required to represent the structure of hospital production of care.

Table 4. Tests statistics for restricted hospital cost technology structures

	Null Hypothesis	Number of Restrictions	Critical χ^2	P-value	Test Decision at 1%
Constant Returns to Scale	$\sum \alpha_i$=1 $\sum \alpha_{ij} = 0$ $\sum \gamma_{ij} = 0$	10	52.13	0.000	Reject the Null
Unitary Elasticity of Substitution	$\beta_{ij} = 0$	3	147.44	0.000	Reject the Null
Homotheticity	$\gamma_{ij} = 0$	12	233.26	0.000	Reject the Null
Homotheticity and Unitary Elasticity of Substitution	$\gamma_{ij} = 0$ $\beta_{ij} = 0$	15	644.74	0.000	Reject the Null
Homogeneity	$\gamma_{ij} = 0$ $\alpha_{ij} = 0$	17	286.55	0.000	Reject the Null
Homogeneity and Unitary Elasticity of Substitution	$\gamma_{ij} = 0$ $\alpha_{ij} = 0$ $\beta_{ij} = 0$	20	693.28	0.000	Reject the Null

*Note*s: Estimates based on hybrid translog with Hicks technical change and controls (Model 3). Hypothesis testing uses *LR* likelihood tests. Errors are corrected via bootstrapping.

Table 5 presents the translog estimated coefficients of hospital cost models that include increasing degrees of control for differences in hospital characteristics.

The baseline model incorporating technical progress (Model 1) is further, evaluated against the models accounting for hospital heterogeneity (Model 2) and (Model 3). The restricted specifications are rejected in favor of the model with controls and controls for outpatient mix by payer type (Table 6). However, the small root mean square error suggests that these models produce modest prediction errors (0.323 and 0.282 respectively).

The resulting cost function is non-decreasing in outputs and input prices, homogeneous of degree one in factor prices, and concave in factor prices (Hessian $\{\beta_{ij}\}$ is symmetric and satisfies the negative semi-definiteness condition). The coefficients are in line with expectations and satisfy the positivity conditions for 95.4% of the observations (Table 5). Mean factor shares are equal to own-price coefficients and lie in the unit interval. Estimated output elasticities of the typical hospital are positive and significant for private insurance, Medicare, and other payers suggesting that a 10% increase in the number of patients covered by these payers leads to a cost increase of 1.6%, 4.8%, and 0.9% respectively. Medicare admissions, emergency room and other outpatient visits have the largest measured impact on hospital costs followed by privately insured, *ceteris paribus*.

Table 5. 3SLS-ISURE estimates of the hybrid translog cost models with patient mix, quality, trend, and other controls

	Model A	Model B	Model C
Self-paid	0.105	0.014	0.049
	(0.061)	(0.051)	(0.055)
Private Insurance	0.454***	0.228***	0.155**
	(0.057)	(0.048)	(0.053)
Medicare	0.362***	0.322***	0.477***
	(0.075)	(0.073)	(0.077)
Medicaid/Tenncare	-0.097	0.025	0.013
	(0.072)	(0.061)	(0.065)
Other Payers	0.097***	0.057***	0.086**
	(0.019)	(0.015)	(0.030)
Self Squared	0.129***	0.068**	0.990***
	(0.036)	(0.025)	(0.216)
Private Squared	0.094***	0.562***	0.277**
	(0.013)	(0.067)	(0.086)
Medicare Squared	0.202***	-0.073	-0.592**
	(0.048)	(0.050)	(0.221)
Medicaid Squared	-0.030	0.116	0.248***
	(0.091)	(0.070)	(0.064)
Other Squared	0.043*	0.055***	0.128
	(0.017)	(0.013)	(0.097)
Self*Private	0.218*	-0.133	-0.330**
	(0.088)	(0.079)	(0.119)
Self*Medicare	-0.243***	0.143*	0.195
	(0.064)	(0.067)	(0.136)
Self*Medicaid	0.275***	0.092	-0.107
	(0.063)	(0.051)	(0.106)
Self*Other	-0.003	0.003	-0.113*
	(0.023)	(0.017)	(0.057)
Private*Medicare	-0.077	-0.187*	0.132
	(0.085)	(0.078)	(0.146)
Private*Medicaid	-0.211*	-0.528***	-0.575***
	(0.105)	(0.091)	(0.135)
Private*Other	0.063*	0.048*	0.197**
	(0.026)	(0.022)	(0.073)
Medicare*Medicaid	0.082	0.253**	0.644***
	(0.085)	(0.077)	(0.123)
Medicare*Other	-0.064**	-0.084**	-0.306***
	(0.024)	(0.026)	(0.078)
Medicaid*Other	0.022	0.015	0.134*
	(0.025)	(0.021)	(0.063)
Self*Price Labor	-0.001	-0.001	0.012**
	(0.002)	(0.002)	(0.004)

Table 5. 3SLS-ISURE estimates of the hybrid translog cost models with patient mix, quality, trend, and other controls

	Model A	Model B	Model C
Self*Price Supplies	0.003*	0.003*	-0.001
	(0.001)	(0.001)	(0.003)
Private*Price Labor	-0.013	-0.010	-0.047**
	(0.013)	(0.010)	(0.018)
Private*Price Supplies	-0.027***	-0.029***	-0.029***
	(0.002)	(0.003)	(0.004)
Medicare*Price Labor	0.013***	0.018***	0.017***
	(0.002)	(0.002)	(0.003)
Medicare*Price Supplies	-0.041**	-0.068***	0.063*
	(0.014)	(0.011)	(0.025)
Medicaid*Price Labor	0.022***	0.013***	0.005
	(0.002)	(0.002)	(0.005)
Medicaid*Price Supplies	-0.012***	-0.020***	-0.019***
	(0.002)	(0.002)	(0.004)
Other*Price Labor	0.018	0.027*	0.013
	(0.012)	(0.011)	(0.016)
Other*Price Supplies	0.008**	0.019***	0.024***
	(0.003)	(0.003)	(0.004)
Price Labor	-0.006**	-0.005*	-0.006
	(0.002)	(0.002)	(0.003)
Price Supplies	0.023	0.051***	-0.025
	(0.012)	(0.011)	(0.014)
Price Labor Squared	-0.002**	-0.002**	-0.012***
	(0.001)	(0.001)	(0.002)
Price Supplies Squared	0.002***	0.003***	0.010***
	(0.000)	(0.000)	(0.002)
Price Labor*Price Supplies	0.014*	(0.000)	-0.003
	(0.006)	(0.006)	(0.015)
Fixed Capital	0.112***	0.102***	0.102***
	(0.004)	(0.004)	(0.005)
Fixed Capital Squared	0.473***	0.484***	0.483***
	(0.005)	(0.006)	(0.007)
Fixed Capital*Price Labor	0.416***	0.415***	0.415***
	(0.005)	(0.006)	(0.007)
Fixed Capital*Price Supplies	0.021***	0.010***	0.006**
	(0.002)	(0.002)	(0.002)
Self*Fixed Capital	0.053***	0.033***	0.019***
	(0.003)	(0.003)	(0.003)
Private*Fixed Capital	0.066***	0.062***	0.054***
	(0.003)	(0.003)	(0.003)
Medicare*Fixed Capital	-0.004*	0.009***	0.014***
	(0.002)	(0.002)	(0.002)

Table 5. 3SLS-ISURE estimates of the hybrid translog cost models with patient mix, quality, trend, and other controls

	Model A	Model B	Model C
Medicaid*Fixed Capital	-0.017***	-0.019***	-0.021***
	(0.002)	(0.002)	(0.002)
Other*Fixed Capital	-0.049***	-0.043***	-0.033***
	(0.003)	(0.003)	(0.003)
Trend	-0.005	0.063*	0.066**
	(0.029)	(0.026)	(0.025)
Trend Squared	0.003	-0.007	-0.008
	(0.006)	(0.005)	(0.005)
Trend*Price Labor	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)
Trend* Price Capital	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Trend* Price Supplies	-0.061***	-0.041***	-0.040***
	(0.006)	(0.004)	(0.004)
Trend*Self	0.022*	0.014	-0.002
	(0.010)	(0.008)	(0.009)
Trend*Private	0.031**	0.027***	0.027**
	(0.010)	(0.008)	(0.009)
Trend*Medicare	-0.029*	-0.016	-0.027*
	(0.012)	(0.011)	(0.012)
Trend*Medicaid	0.014	-0.020	-0.003
	(0.012)	(0.010)	(0.011)
Trend*Other	-0.004*	0.000	0.002
	(0.002)	(0.002)	(0.005)
Public		-0.035	-0.010
		(0.031)	(0.029)
For-profit		0.022	0.072**
		(0.030)	(0.028)
Medium Size (100<Beds<200)		0.381***	0.319***
		(0.033)	(0.032)
Large Size (200<Beds)		0.784***	0.634***
		(0.049)	(0.048)
East Division		-0.069*	-0.100***
		(0.030)	(0.028)
West Division		0.006	(0.013)
		(0.032)	(0.031)
Case Mix Index		0.173*	0.150*
		(0.071)	(0.073)
Sick Outpatients		0.448***	
		(0.059)	
Accreditations JCAHO & ACSCC		0.102**	0.099**
		(0.037)	(0.034)

Table 5. 3SLS-ISURE estimates of the hybrid translog cost models with patient mix, quality, trend, and other controls

	Model A	Model B	Model C
Memberships THA & AHA		-0.049	-0.056*
		(0.027)	(0.025)
State Approved Nursing School		-0.01	-0.049
		(0.033)	(0.030)
Interns & Residents		0.176***	0.112**
		(0.037)	(0.035)
Inverse Occupancy		-1.005***	-1.068***
		(0.112)	(0.115)
Sick Self Outpatients			0.024
			(0.028)
Sick Medicaid Outpatients			0.000***
			(0.000)
Sick Medicare Outpatients			0.475***
			(0.058)
Sick Private Outpatients			0.189**
			(0.062)
Sick Other Outpatients			0.010*
			(0.004)
Constant	17.934***	16.804***	16.869***
	(0.070)	(0.148)	(0.149)
System R Squared	0.8281	0.9366	0.9527

Notes: Bootstrapped standard errors are presented in parenthesis. * $p<0.10$, ** $p<0.05$, and *** $p<0.01$ indicate significance at 90%, 95%, and 99% confidence levels, respectively.

The hospital-specific inpatient CMI controls for unobserved differences in patient population that increase costs. The outpatient severity is also cost-increasing on overall (Model 2), and by insurance groups except for the self-paid (Model 3). Not surprisingly, the share of Medicare emergencies appears to be the most responsible for the cost-augmenting effects of case severity.

Table 6. Hypothesis tests of restricted vs. unrestricted models

Null Hypothesis	Likelihood Ratio Statistic	Number of Restrictions	P-value	Decision at 1%
Cobb-Douglas vs. Flexible Translog with no Controls	2901.37	15	0.000	Reject the Null
Flexible Translog with no Controls vs. Flexible Translog with Hicks Technological Trend	112.50	9	0.000	Reject the Null
Flexible Translog with Hicks Technological Trend vs. Flexible Translog with Controls	1365.80	18	0.000	Reject the Null
Flexible Translog with Controls vs. Flexible Translog with Controls and Patient Mix by Payer	27.01	5	0.001	Reject the Null

Notes: Estimates based on the hybrid flexible translog model with Hicks technical change and controls. Hypothesis testing uses *LR* likelihood tests based on bootstrapped errors.

Joint JCAHO and ACSCC accreditations have significant positive effect on costs possibly through imposing greater quality standards or signaling differential higher quality. This suggests that ACSCC or similar "specialized" accreditations rather than JCAHO should be used to proxy hospital quality. State (THA) and national (AHA) hospital organizational memberships decrease costs perhaps due to pressures placed on hospitals to implement cost-saving and efficiency-increasing measures. An approved nursing school status is cost-decreasing, but not statistically significant. As expected (see, Hogan, Franzini, & Boex, 2000; Lopez-Casasnovas & Saez, 1999), medical school affiliation is cost-increasing.

For-profit status increases cost, a finding in line with past findings suggesting that investor-owned hospitals have higher costs than not-for-profit hospitals (Grannemann *et al.*, 1986). Not-for-profit hospitals are more likely to invest in cost-saving production processes (e.g., centralized management, electronic records, etc.), which enables production of care at lower costs than their for-profit counterparts. The bed size effects on costs indicate that relative to hospitals with less than 100 beds, medium and large classes have appreciably higher costs in the order of 31.9% and 63.4%, respectively. Compared with hospitals buying factors from local markets in Middle Tennessee, those located in the Eastern region incur lower costs, while those in the West have significantly higher cost.

Derived Input Demands and Pair-wise Factor Substitutions

Table 7 displays information on the degree of isoquant curvature at the mean expansion point. The Table 7a shows estimated own- and cross-price elasticities (η_{ii}) of substitution. The off-diagonal elements in Tables 7b, 7c, and 7d represent estimates of the Allen-Uzawa (σ_{ij}^{A-U}), Morishima (σ_{ij}^{M}), and Shadow (σ_{ij}^{S}) pair-wise factor substitution elasticities among inputs.

The positive and statistically significant own-price elasticities (η_{ii}) suggest that the inputs are relatively inelastic to variations in own-prices (Table 7a). Capital shows greater own-price sensitivity than labor and supplies as it is expected to be more easily substituted for other inputs. Estimated cross-price effects are symmetric. As expected, capital-labor substitution suggests that introducing new forms of capital-intensive technologies decreases hospital demand for labor.

Table 7. 3SLS-ISURE estimates of conceptually different measures of elasticities

	Capital	Labor	Energy and supplies
7a.	Own and Cross-Price Elasticities of Input Demand (η_{ij})		
Capital	-0.835110*** (0.022851)	0.622980*** (0.024888)	0.212131*** (0.023244)
Labor	0.132084*** (0.005820)	-0.478922*** (0.008525)	0.346838*** (0.007759)
Energy and supplies	0.052284*** (0.006784)	0.403198*** (0.010145)	-0.455482*** (0.009859)
7b.	Allen-Uzawa Partial Elasticities of Substitution (σ_{ij}^{A-U})		
Capital	-8.162177*** (0.494779)	1.290962*** (0.045866)	0.511016*** (0.054943)
Labor		-0.992440*** (0.028283)	0.835522*** (0.015330)
Energy and supplies			-1.097243*** (0.036564)
7c.[i]	Morishima Elasticities of Factor Substitution (σ_{ij}^{M})		
Capital	0	1.101902*** (0.026527)	0.667613**** (0.027140)
Labor	0.967195*** (0.024174)	0	0.802320**** (0.013520)
Energy and supplies	0.887395*** (0.025282)	0.882120**** (0.013705)	0
7d.[ii]	Shadow Elasticities of Factor Substitution (σ_{ij}^{S})		
Capital	0	0.990760*** (0.022506)	0.843936*** (0.023881)
Labor		0	0.839222*** (0.012931)
Energy and supplies			0

Notes: Elasticities are computed at the mean of actual cost shares. Bootstrapped errors are computed in parentheses. Statistical significance at the 0.01, 0.05, and 0.10 levels are indicated as ***, **, *, respectively.

[i] Conceptually, the Morishima own-substitution elasticities (i.e. the diagonal elements) are zero.
[ii] Similar to Morishima, Shadow own-substitution elasticities (i.e. the diagonal elements) are zero.

The diagonal entries of Table 7b suggest that own-price Allen-Uzawa factor demands are downward sloped. The relative demand for labor appears inelastic, which is consistent with the notion of shortage of nurses and physicians. The estimated cross-price elasticities show a relatively high degree of substitutability between capital and labor, capital and energy, supplies and other non-operating inputs, and labor and energy, supplies and other non-operating inputs. Capital inputs such as computerized medical devices, etc., can reasonably be expected to substitute for hospital manpower needs. Moreover, expansion of capital stock through adopting advanced technologies generally cuts down on energy, supplies and other non-operating inputs. Similar to the Allen-Uzawa findings, the positive and statistically significant Morishima substitution elasticity estimates (Table 7c) signal that input factors behave as long-run substitutes. Capital and labor are strongest substitutes ($\sigma_{lk}^{M} < \sigma_{kl}^{M} < \sigma_{kl}^{A-U}$), followed by labor and energy, supplies and other non-operating inputs ($\sigma_{ls}^{M} < \sigma_{ls}^{A-U} < \sigma_{sl}^{M}$), and capital and energy, supplies and other non-operating inputs ($\sigma_{ks}^{A-U} < \sigma_{ks}^{M} < \sigma_{sk}^{M}$). Morishima estimates offer insights for evaluating the effects of increases in labor wages on hospital production. Specifically, the σ_{kl}^{M} estimate suggests that a 1% increase in real wage of medical staff reduces their usage to increase the capital-labor ratio by 1.10%. Finally, estimates of the Shadow substitution tendencies for input factors reinforce those of the Morishima estimates (Table 7d). The Shadow elasticity of capital with respect to energy, supplies and other non-operating inputs is the largest in magnitude, while the Allen elasticity of capital is the smallest.

Decomposed Technical Change [26]

Productivity gains from technological change is 0.0028 (*std. err*. = 0.0062) or 0.28% for the 2000-2008 period of study, but it is not statistically different from zero ($P > |z| = 0.187$). Technical progress is decomposed as follows: 0.0284 (*std. err.* = 0.0061) or 2.84% productivity gains due to pure effects ($P > |z| = 0.000$), -0.0391 (*std. err.* = 0.0043) or -3.91% losses due to factor bias ($P > |z| = 0.000$), and -0.0028 (*std. err.* = 0.0062) or 0.28% losses due to scale augmentation *(*$P > |z| = 0.644$*).*

Energy and medical supplies, constituting more than a third (38.5%) of factor costs, is the largest driver of factor productivity growth. The estimates reflect technical progress as supplies-using and marginally worker-saving. We reject the Hicks-neutrality hypothesis: $H_0: \delta_{tj} = 0, \forall i, (i = 1,2,3)$ at.01 significance level ($\chi^2(3) = 84.71$). The scale-augmenting component of the composite technological effect is not significantly different from zero. This could be due to the scale-augmenting effects due to private patients being cancelled by the shrinking effects due to decreased population of Medicare patients.

Scale and Scope Economies

We compute a global measure of the scale economies (*SCE*) as one minus the proportionate change in all outputs (Table 8).

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[26] Standard errors of the decomposed technical change effects are corrected by bootstrapping.

Table 8. Hypothesis tests of the economies of scale estimates for inpatients admissions and outpatient visits by payer type

Overall Economies of Scale	Estimated Parameter	Chi2(1)	Prob > Chi2	Significantly different from 0
	0.2199*** (0.059)	13.87	0.000	0.000
Partial Economies of Scale				
Self-paid	20.2184 (22.468)	0.73	0.392	0.368
Private insurance	6.4689*** (2.219)	6.07	0.014	0.004
Medicare	2.0960*** (0.336)	10.62	0.001	0.000
Medicaid/Tenncare	74.4817 (362.433)	0.04	0.839	0.837
Other Payers	11.6893*** (4.056)	6.95	0.008	0.004

Notes: Estimates based on the hybrid flexible translog model with Hicks technical change and controls. Hypothesis testing uses *LR* likelihood tests based on bootstrapped errors. * p<0.10, ** p<0.05, and *** p<0.01 indicate significance at 90%, 95%, and 99% confidence levels, respectively.

The parameter estimate of $SCE = 0.2199$ $(std. err. = 0.0590)$ is significant and nonnegative ($\chi^2(1) = 13.87$), indicating increasing returns to scale.[27] A proportional rise in outputs (1%) results in a less than proportional (0.78%) increase in costs of the average hospital. We evaluate the extent of *SCE* at the 25% and 75% of average production and obtain estimated scales of 1.3168 $(std. err. = 0.1872)$ and 0.4475 $(std. err. = 0.0515)$ respectively, suggesting diminishing operational scale advantages as the output increases perhaps due to capacity constraints. Moreover, the estimated *SCE* indicates the proportion of total cost that a hospital would recover if practiced marginal cost pricing. It

[27] Our estimates align with the early work by Cowing & Holtmann (1983) finding slight economies of scale (0.14) for New York general hospitals.

may not desirable for the “typical” Tennessee hospital to price at marginal cost because it leads to revenue shortfalls. Estimates of partial scale economies further imply that by expanding the number of patients covered by private insurance, Medicare, and other payers hospitals can decreases unit production costs and increase efficiency. Similarly, marginal cost pricing for these outputs can result in revenue loses.

It is important to note that the method used to measure outputs might affect the magnitude of the estimated scale parameters. Within the aggregated output by payer units, given the structure of the industry, larger hospitals might offer broader range of services and provide more specialized and costly treatments. To the extent that the measurement of output by payer within an aggregated category fails to account for the scope of output which varies positively with the scale of output, and because the marginally added output is likely more costly than average, this effect may work to depress measurements of true scale economies for large hospitals. This implies that the scale estimates might be lower bounds for large hospitals.

Additional policy implications emerge from possibilities of gaining unit cost efficiency through exploiting economies of scope by payment source. We find significant partial scope economies in care provided to uninsured and private patients, Medicaid/Tenncare and private patients, other payers and Medicare patients, and marginally to uninsured and patients covered by others payers (Table 9).

Table 9. Hypothesis tests of the economies of scope estimates for inpatients admissions and outpatient visits by payer type[i]

	Economies of Scope[ii] Estimate	Statistical Hypothesis Test	Chi-square Statistic	Probability of Rejection	Economies of Scope
i.	$\alpha_{12} - \alpha_1\alpha_2 = -.3380$	[ltc]lyselfpriv - [ltc]lyself*[ltc]lypriv = 0	5.39	0.020**	Yes
ii.	$\alpha_{13} - \alpha_1\alpha_3 = .1717$	[ltc]lyselfmcare - [ltc]lyself*[ltc]lymcare = 0	0.35	0.552	
iii.	$\alpha_{14} - \alpha_1\alpha_4 = -.1077$	[ltc]lyselfmcaid - [ltc]lyself*[ltc]lymcaid = 0	0.29	0.591	
iv.	$\alpha_{15} - \alpha_1\alpha_5 = -.1174$	[ltc]lyselfother - [ltc]lyself*[ltc]lyother = 0	2.95	0.086*	Yes
v.	$\alpha_{23} - \alpha_2\alpha_3 = .0587$	[ltc]lyprivmcare - [ltc]lypriv*[ltc]lymcare = 0	0.05	0.820	
vi.	$\alpha_{24} - \alpha_2\alpha_4 = -.5773$	[ltc]lyprivmcaid - [ltc]lypriv*[ltc]lymcaid = 0	7.62	0.006***	Yes
vii.	$\alpha_{25} - \alpha_2\alpha_5 = .1837$	[ltc]lyprivother - [ltc]lypriv*[ltc]lyother = 0	3.29	0.070	
viii.	$\alpha_{34} - \alpha_3\alpha_4 = .6375$	[ltc]lymcaremcaid - [ltc]lymcare*[ltc]lymcaid = 0	3.87	0.049	
ix.	$\alpha_{35} - \alpha_3\alpha_5 = -.3472$	[ltc]lymcareother - [ltc]lymcare*[ltc]lyother = 0	6.70	0.010***	Yes
x.	$\alpha_{45} - \alpha_4\alpha_5 = .1328$	[ltc]lymcaidother - [ltc]lymcaid*[ltc]lyother = 0	1.89	0.169	

[i] The inpatient and outpatient services by source of payment are: 1 = Self-pay, 2 = Private insurance (includes Blue Cross/Blue Shield and Commercial Insurance), 3 = Medicare, 4 = Medicaid/Tenncare (includes Cover TN, Cover Kids, and Access TN), and 5 = Other non-government insurance (includes Workers Compensation).

[ii] The EOS estimates are based on the hybrid flexible translog cost model with Hicks technological trend and controls. Hypothesis testing uses *LR* likelihood tests and bootstrapped errors.

Summary Discussion and Conclusion

Hospital spending is the largest (30%) component of U.S. aggregate health care expenditure. The 2010 ACA implementation is ushering in broader access to health care, major changes to provider reimbursement policies (e.g., based more on value than quantity), and expanding hospital health care services ownership reach through incentives promoting acquisition of private (solo and group) practice physicians, diagnostic test laboratories, and related healthcare facilities. This cost study, using comprehensive 2000-2008 panel data of 117 hospitals in the state of Tennessee, presents baseline estimates against which hospital cost behaviors can be compared following full implementation of the ACA. Knowledge of the shape of hospital technology cost structure is crucial to having a correct understanding of quality and production incentives affecting value-based reimbursements for the health care provided and managerial resource allocation decisions of service providers.

The core contributions of this study include describing long-run hospital cost structure with outputs defined as cases by payer and a large number of controls for quality and patient mix, decomposing the effects of technological advances on costs, assessing cost efficiency possibilities through opportunities for scale and scope economies, and evaluating input substitution possibilities as factor market prices change. Other contributions of this work include evaluating the cost-quality tradeoff (e.g., accreditations by both JACHO and ACSCC, and medical school teaching affiliation, found as significant proxies for hospital care quality, are cost-increasing. Membership in AHA reduces costs perhaps because it is industry-specific, and that it enhances access to wide ranging resources with additional incentives for efficiency improvements). The estimated own-price, Allen-Uzawa, Morishima, and Shadow substitution elasticities indicate inelastic demand for labor and broadly defined supplies. The input factors categories (capital, labor, energy, supplies, and non-operating inputs) are substitutes in the long-run regardless of the conceptual measure of pair-wise factor substitution. The data rejected Hicks-neutrality, and technical progress is supplies-using and marginally worker-saving. The scale-augmenting part of technical change effect is entirely due to diseconomies of scale in the production of patients with private insurance, and regional location affects production cost.

Consistent with the emerging provider reimbursement policy environment, the flexible production cost model incorporates multi-dimensional hospital quality considerations. Second, to our knowledge this study is the first to model the shape of hospital production technology with the outputs defined by payment source. Significant operational scale economies evaluated along the mean expansion path were found, which indicate cost-beneficial scale advantages for the typical hospital. Hospital production occurs in the range of increasing returns suggesting that efficiency gains are achievable by concentrating care in existing hospitals instead of increasing investments in new hospitals with market expansion, or by consolidating hospital departments in Tennessee, given the current demand for hospital care. Finally, there are unexploited scope economies (e.g., hospitals can reduce unit cost by jointly treating commercial insurance and Tenncare/Medicaid patients). The research results presented here are relevant in the context of rising hospital provision of healthcare services as implementation of the 2010 ACA intensifies.

CHAPTER II: CRIME SPILLOVERS AND HURRICANE KATRINA[*]

[*] A version of the research presented in this chapter is under a third revision at the *Journal of Human Resources*. Earlier versions were presented at the 9th Annual Missouri Economics Conference (Columbia, MO, March 2009), and at the 79th annual meeting of the Southern Economic Association (San Antonio, TX, Nov. 2009).

Introduction

On August 29, 2005, Hurricane Katrina made a landfall in New Orleans, severely impacting the city and its inhabitants. In two days, 80% of New Orleans was flooded, with some parts under 15 feet of water. Even though the population loss was minimal because of early warning, Katrina forced more than a million residents to evacuate, causing the largest and most abrupt mass movement of U.S. citizens since the Dust Bowl. Estimates derived from the Current Population Survey (CPS) indicate that approximately 1.5 million individuals age 16 and older evacuated their homes in southeast Louisiana due to Hurricane Katrina (Groen & Polivka, 2007 and 2008). Other studies report that Katrina resulted in an immediate displacement of about 1.3 million people, an estimated 723,000 of whom relocated over 100 miles from their homes (Baen & Dermisi, 2006). While 75% of evacuees were living in Louisiana prior to the storm, 19% in Mississippi, and 6% were living in Alabama, the evacuation was widespread. The demographic composition of evacuees closely echoes the composition of those residing in the Katrina-affected counties in these states prior to the storm (Gabe *et al.*, 2005). Using survey data for Houston, Wilson and Stein (2006) characterizes the evacuees as being poor, overwhelmingly African-American and unemployed. Specifically, a third of the respondents had less than a high school education, more than 98% were African-American and almost half of the respondents reported incomes of less than $15,000 per year prior to Katrina. Moreover, the CPS data shows a remarkable degree of disparity between the evacuees that finally returned to their pre-Katrina address by the time of the survey and the longer term evacuees. Non-returnees are on average five years younger, almost twice as likely to be African-American, 20% less likely to be married with a spouse present in the household, and more likely to be living with children under the age of five (Vigdor, 2007).

For economists, Hurricane Katrina provided a rare opportunity to study the effects of spontaneous immigration on various characteristics of the host regions in a “natural experiment” setting. Most of the existing studies related to Katrina are based on data provided by the CPS, as its questionnaire was modified in October 2005 to include questions that identify the Katrina evacuees, the county (or parish) from which they had evacuated, and if and when they returned to their pre-Katrina residences (Cahoon *et al.*, 2006).

The vast majority of prior studies look at the effects of Katrina on evacuees’ labor outcomes, as well as at the effect of evacuees’ presence on the labor market of host areas. Vigdor (2007) finds that in the short-term, non-returnees lost on average almost ten weeks of work in 2005. Furthermore, persistent evacuees (beyond February 2006) have employment rates 10 to 20 percentage points lower and average 5 to 8 fewer hours worked per week than locals, with no evidence of diminishing effects. Groen and Polivka (2008) support those findings, showing that over the first seven months after Katrina struck, the unemployment rate of evacuees increased by 8.1 percentage points; six months later, the estimated impact was down to 4.6 percentage points, while still remaining positive and significant. McIntosh (2008) looks at the effects of Katrina evacuees on the labor market in the affected areas. She finds that migration due to Katrina was associated with a 1.8% decrease in wages and a 0.5% decrease in the probability of being employed among the local population. DeSilva *et al.* (2010) incorporate changes in the demand for local goods and services caused by the abrupt increase in the Houston-area population due to Katrina and find that average quarterly wages of firms in low skills industries decreased by 0.7% relative to firms in high skill industries when compared with the same group of industries in a control metro before and after the Hurricane. Imberman *et al.* (2009), using data from Houston and Louisiana schools, show that the influx of student evacuees moderately reduced elementary math test scores in Houston and increased absenteeism and disciplinary problems among native students.

While these studies examine the effects of Katrina on labor markets and schooling outcomes, the literature generally overlooks the potential effects of Katrina evacuation on crime rates in host cities, despite highly publicized speculations by the media of an association between Katrina evacuees and large increases in crime. Indeed, about 58% of the evacuees came directly from New Orleans, a city known for its high crime rates. The estimated evacuation rate of the city was 92% (Groen & Polivka, 2008). That led to speculations, especially in the Houston media, that Katrina triggered a huge jump in crime rates, but the existing research has yet to substantiate these claims.[1] One goal of this paper is to address this lack of substantial evidence by carrying out the first thorough investigation of the causal effects that Katrina had in destination areas of evacuees.

Furthermore, the broader literature that attempts to determine the impact of immigration on criminal activity finds no effects or offers inconclusive evidence. For example, Butcher and Piehl (1998) use data from the CPS and the Uniform Crime

[1] According to CNN (February 17, 2006): “Across Houston, there have been a series of high-profile crimes involving Katrina evacuees. Houston police say evacuees have been victims or suspects in about 20% of the city's homicides, more than double their percentage in the population.” However, Sacerdote (2008) looks across different types of crimes (murders, robberies, burglaries, and larcenies) and finds no evidence that crime was differentially higher in zip codes with a higher fraction of Katrina evacuees.

Reports (UCR) from 1981 to 1990 to estimate the effect of immigration on adult arrest rates by city. Grogger (1998) uses 1980 and 1990 Census data and data from the National Longitudinal Survey of Youth to estimate the effects of immigration on African-American crime rates. Even though both papers find no effect of immigrants on city crime rates, they point out that their estimates probably suffer from an endogeneity problem.[2] The primary problem in attempting to estimate a causal relationship in such a context is overcoming the fact that the decision to move is made endogenously. In particular, non-experimental evidence may confound the effects of migration or local characteristics on an individual's criminal activity with unobserved individual or family characteristics related to both their propensity to commit crime and decisions regarding where (and potentially when) to relocate. In this paper, we extend the existing literature by examining the effect of migration on multiple regional (U.S. metro areas) and local (Houston districts) crime rates in the context of a natural experimental setting, the aftermath of Hurricane Katrina. Though specific to an important but unparalleled event in U.S. history, this analysis should thus help to strengthen the general understanding of the causal relationship between migration and crime.

By using a natural experiment, this study augments a small but growing body of evidence of the effects of migration caused by experimental randomization or plausibly exogenous policy shocks. The Moving to Opportunity (MTO) experiment used a lottery to assign housing vouchers to public housing residents in five cities. Early studies investigating the effects of the resulting relocation on family and youth outcomes, suggest that the program led to, among other things, increased safety and reductions in behavior problems and criminal activity among youths (Katz *et al.*, 2001; Ludwig *et al.*,

[2] See Horowitz (2001) for a review of the broader literature.

2001). More recently, Kling *et al.* (2005) focuses on the effects of MTO on youth crime and delinquency, finding positive effects of decreased arrests among females, but conflicting effects on delinquency and types of crime for males, as well as differing effects in the short run versus long run. Other studies have exploited randomized school attendance via lotteries to investigate the effects of school mobility and school characteristics on crime rates among movers. For example, Cullen *et al.* (2006) find that winners of school choice lotteries in Chicago Public Schools report fewer disciplinary incidents and arrests compared to non-winners (though no effects on academic outcomes are observed). Similarly, Deming (2009) finds reductions in the number and seriousness of crimes committed by lottery winners in a large North Carolina school district, seven years after middle or high school attendance.

This research complements these studies involving random assignment in a couple of ways. First, unlike these studies, which focus on the effects of school or neighborhood mobility on individual outcomes of those who move, since we lack data on actual arrests by evacuee status, we attempt to measure the overall impact of immigration on local crime rates. Second, rather than merely causing migration within a city, Hurricane Katrina affected a large geographic area, causing substantial mobility across U.S. cities. Finally, experiments such as Movement to Opportunity involved both specific eligibility requirements, as well as individual families electing to participate in the program. These families, like many Katrina evacuees, tended to be poorer and at greater risk for criminal activity than those in the non-treatment group (Katz *et al.*, 2001; Ludwig, 2001). However, unlike MTO, evacuation due to Hurricane Katrina, for many individuals, was not a choice, but one that was necessitated by circumstances.

The study consists of two parts. First, the effect of Katrina immigrants on crime rate in the host cities (metro areas) is examined by employing a Difference-in-Differences (DID) approach. The CPS data covering years 2003 to 2007 was used taking advantage of the fact that starting in 2005 it allows for identifying Katrina evacuees. To measure crime, data from the Federal Bureau of Investigation (FBI) was employed on two main crime categories, violent and property crime, and the corresponding sub-categories.

Since immigration due to Hurricane Katrina was relatively spontaneous, Katrina is treated as being an exogenous "treatment" shock. Thus, self-selection is likely less of a concern than it is in other studies relating immigration and crime, as it seems unlikely that the decision to evacuate to a certain metropolitan area was made based on crime-related characteristics of that location. Urgency, rather than careful consideration, dictated the move.[3] However, to account for possible remaining endogeneity between the socio-economic characteristics (or their trends) of a host city and evacuees, we instrument the number of evacuees going to a certain city by its distance to New Orleans, LA.

The results show that a 1% increase in the evacuation rate is associated with a 13% increase in the number of murders and non-negligent manslaughters (which is the equivalent of 0.8 additional offenses per 100,000 inhabitants) and an almost 3% increase in robbery (which is the equivalent of 4 additional offenses per 100,000 inhabitants). We also find that immigration due to the Hurricane is associated with a 1% rise in the

[3] According to Wilson and Stein (2006) -- an overview of a study of Katrina evacuees living in Houston -- when asked what was important to them during those first days after Katrina, 50% of the respondents answered "Find a place to live", 23% answered "Find family and friends" and 21% said they would try to get a job.

property crimes (almost 39 additional offenses), primarily via a 4% increase in motor vehicle theft.

In the second part of this study, we examine Houston, a destination city for a large number of Katrina evacuees. By applying DID methodology at the district level, we find dramatic increases in murder (27%) and aggravated assault (28%) coupled with increases in illegal possession of weapons (32%) and arson (41%). Overall, migration to Houston due to Hurricane Katrina is associated with a 4% jump in violent crime, which is equivalent to more than 8 additional offenses per month.

The remainder is organized as follows. Section 2 discusses some of the potential mechanisms through which higher crime rates may be manifested following immigration due to Hurricane Katrina. Section 3 outlines the primary estimation strategy. Section 4 describes the sources of data and characteristics of the sample. Section 5 presents the main results and is followed by several robustness checks that are detailed and presented in Section 6. In Section 7, we analyze the impact of Katrina evacuees living in the greater Houston area on district-level crime followed by a discussion of the results. Given the main findings, Section 8 attempts to shed some light on the source(s) of the observed increases in crime. Finally, Section 9 concludes with a summary of the results and a discussion of their implications.

Possible Mechanisms

In principle, evacuees could affect the crime rates in destination cities for several reasons. As mentioned previously, evacuees tended to come from relatively disadvantaged backgrounds, potentially giving them greater risk of criminal behavior, even prior to Katrina. When the Hurricane hit, the New Orleans' homicide rate was appreciably lower than a decade ago, when the city was considered the country's capital of murder. However, the city was still struggling with violent crime nearly 5 times the national average.[4] Immigration due to Katrina could therefore lead to increases in local crime rates due to an influx of individuals with greater propensities to commit crime, merely moving crime from one area of the country to another. However, according to economic theory, potential criminals weigh the expected rewards from criminal activity with the risks and penalties associated with being caught and the opportunity cost of committing crime (Becker, 1968). In this vein, as Katrina evacuees tended to originate from relatively poor areas, migration of evacuees may lead to their increased propensity to commit crime due to greater income inequality in destination cities. Income inequality was also exacerbated by the lower employment opportunities available to evacuees, negatively affecting their opportunity cost of crime. Several empirical studies support a positive association between earnings inequality and crime rates. Fajnzylber *et al.* (2002), for example, find a robust correlation between income inequality and homicide and robbery rates, both within and across a large number of countries. Freeman (1999), for the case of the United States, and Witt *et al.* (1999), for the case of the United Kingdom, report a positive association between earnings inequality and crime rates for vehicle crime, theft and burglary. Aside from economic motivations for criminal activities, the sudden evacuation and dire aftermath of Hurricane Katrina likely left many victims in an unstable, or at the very least a highly stressed, psychological state. The psychology

[4] Compared with rates in cities of similar size, murder rates in New Orleans were substantially higher since at least 2004, but the disparity worsened after the Hurricane. The comparable national murder rate in 2004 was 13.2 per 100,000 people, compared with 57.1 in New Orleans. Two years later, the calculated murder rate in New Orleans was 96.6 per 100,000 people - more than eight times higher than a projected comparable national average of approximately 11.9 100,000 people (VanLandingham, 2007).

literature has linked crime and delinquency among youths and young adults to stressful life events (Vaux & Ruggiero, 1983).

Beyond the possibility of increased criminal activity committed by evacuees, there are additional reasons why crime rates may have been affected by the Hurricane Katrina immigration. First, due to their housing arrangements, lack of social networks, or discriminatory attitudes among the local population[5], evacuees may have found themselves disproportionately victims of criminal activity. Second, evacuees could crowd out locals from legal sector jobs (McIntosh, 2008) and access to health care or other publicly provided goods, increasing the likelihood of natives being engaged in criminal activities. Third, on the deterrence side, such significant undertakings like the building of emergency shelters and organizing the incoming of hundreds or thousands of evacuees could potentially detract from police patrols in crime-populated areas, increasing the probability of not being caught when committing a crime, even among the local population.[6] Finally, the pool of evacuees could have differential apprehension rates compared to the local residents, causing an increase or decrease in the reported number of arrests (Orrenius & Coronado, 2005).

Public opinion generally favors the view that Katrina evacuees were directly responsible for the increases in crime (Khanna, 2005). Furthermore, based on 2006 statistics, the Harris County correctional facilities processed an estimated 3,600 evacuees through its system (Gelinas, 2006). However, anecdotal evidence suggests that evacuees

[5] Hopkins (2011) utilizes migration following Katrina to test theories of racial threat, showing that natives in destination cities who had contact with evacuees had worsened attitudes toward African Americans and lowered support of public spending aimed at combating poverty.

[6] Levitt (1997) finds that increases in police reduce violent crime, but have a smaller impact on property crime.

were either victims of crime committed by locals, or victims of crime committed by other evacuees.[7]

Part 1. The Effect of Hurricane Katrina on Countrywide Crime Rates

Methodology

Katrina is treated as being an exogenous shock, and initially assume that the ensuing migration is exogenous. A DID approach is employed to evaluate the effects of Katrina-induced migration on crime rates of destination (or host) cities. Specifically, we estimate panel regressions of the following form:

$$Crime_{it} = \beta(Katrina_t \times Evacuation_i) + Z_{it}\Pi + \gamma_t + \mu_i + \varepsilon_{it} \qquad (1)$$

where *i* = {1...N} indexes the host metropolitan statistical areas (N = 85 in this case) and *t* = {2003, 2004, 2006, 2007}.[8] We include fixed effects μ_i to account for unobserved differences between the cities, and time dummies to capture possible country-wide tendencies.

The dependent variable, $Crime_{it}$, is the crime rate for a core-based statistical area i, at time *t*, defined as the number of reported offenses per 100,000 inhabitants. Following McIntosh (2008), $Evacuation_i$ is the share of Katrina evacuees in the total population of the host city, as reported in the September 2005 – August 2006 CPS, and $Katrina_t$ is a

[7] It was reported that on November 1, a New Orleans evacuee was stabbed to death by a Texan who was defending himself from an attempted carjacking at the hands of the evacuee; on November 20, a New Orleans evacuee shot a fellow evacuee to death at a pool hall; on December 29, a gun battle at a motel ended with one young New Orleans evacuee dead (Gelinas, 2006).

[8] As Katrina hit the U.S. in the middle of the year 2005, we exclude it from the estimation. Alternatively, treating it as either a “before” or “after” year does not substantially affect the results. The analysis presented here includes a balanced number of “pre” and “post”-Katrina years, given that adding more “pre”-Katrina years does not qualitatively influence the results.

dummy variable that takes a value of one starting with year 2006, and zero otherwise. Thus, the effect of Katrina evacuation is captured by the interaction effect that is zero before 2005, and positive and constant in time after 2005.

Other factors that are typically considered to affect the crime, such as income, unemployment, and law enforcement officers and civilians, are included in the matrix *Z*. The effect of a metro's *income per capita* on the likelihood of committing a crime is well-grounded in the literature. In Becker's (1968) basic model, individuals rationally decide whether to engage in criminal activities by comparing the expected returns to crime with the returns to legitimate market opportunities. Mocan and Rees (1999) find that higher levels of local poverty increase the probability of juveniles committing a crime.

Unemployment typically enters "the supply of offense" function as it is assumed to influence the opportunity cost of engaging in illegal activities. Indeed, Levitt (1996), Witt *et al.* (1999) show positive associations between unemployment and property crime, while Buonanno (2005) finds large and positive effects of unemployment on crime rates that stand against various robustness checks for model specification, possible endogeneity, changes in the classification of crimes, and alternative measures of unemployment.

The risk of apprehension and the severity of the expected punishment also affect crime. To incorporate a deterrence component, *total law enforcement officers* and *civilian employees* are included in the control vector as measures of a metro's ability to detect crime. Previous empirical work finds ambiguous effects of police force on reported crime (McCormick & Tollison, 1984). This could be due to a simultaneity issue, as law enforcement is a function of the incidence of crime (Ehrlich & Brower, 1987; Levitt, 1997), or, in most studies using cross-sectional data, could be a result of failing to condition on local level unobserved heterogeneity (Cornwell & Trumbull, 1994). The migration effects are obtained from a panel data set, allowing us to control for unobservable region-specific characteristics that may be correlated with the criminal justice variables in the model.

Regional Data Description

The crime data comes from the Federal Bureau of Investigation (FBI).[9] The FBI provides a listing of all core-based statistical areas (CBSA),[10] their populations, actual and estimated offense totals and crime rates per 100,000 inhabitants for different years This analysis uses reported rates for the following offenses: homicide, forcible rape, robbery and assault (classified as violent crimes) and burglary, larceny/theft, motor vehicle theft (classified as property crimes). Law enforcement employment data is reported by the FBI through the Uniform Crime Reporting (UCR) Program and specifies

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[9] Available at http://www.fbi.gov/.

[10] The term refers collectively to metropolitan and micropolitan statistical areas, each of which consists of a substantial nucleus plus the adjacent communities with which that nucleus has a high degree of economic and social integration. Census 2000 standards require that each CBSA must contain at least one urban cluster with a population minimum of 10,000; metropolitan areas must have minimum of 50,000 and micropolitan areas must have at least one urbanized area with a population between 10,000 and 50,000 (U.S. Bureau of Census, 2006). Since our data contains a small number of micropolitan areas, the terms CBSA and Metropolitan Statistical Area (MSA) are used interchangeably in this paper.

law enforcement officers and civilian employees by city and by year. The police data is aggregated for all the cities located in each CBSA.[11]

The migration data is based on the Basic Monthly CPS, which includes a nationally representative sample of more than 60,000 households per month. The questionnaires were modified from September, 2005 to August, 2006 to reflect the impact of Hurricane Katrina. Three questions were added to the basic monthly survey: "Is there anyone living or staying here who had to evacuate, even temporarily, where he or she was living in August because of Hurricane Katrina?" and if the response was affirmative, the evacuees are identified within each household: "Did…have to evacuate, even temporarily, where he or she was living in August because of Hurricane Katrina?" Lastly, respondents were asked about their pre-Katrina residence: "In August, prior to the Hurricane warning, where was…living?" This additional information included in the CPS allows us to identify and characterize Katrina evacuees across the U.S. and by metropolitan area. Following McIntosh (2008), we use estimates of the number of evacuees and their share of total population by core-based statistical area.[12][13]

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[11] The data on full-time law enforcement employees is reported as of October 31 for years 2003 and 2004. Starting in 2005, the data refers to the number of police officers and civilian employees as of December 31.

[12] While respondents commonly appear in up to four consecutive months of the CPS (and another four months following an intermediate eight months not surveyed), care was taken so as to not double count evacuees. See McIntosh (2008) for details.

[13] The evacuation captured in the data is likely underestimated due to the CPS methodologies (U.S. Bureau of the Census, 2006a). Estimates from other sources range from 700,000 evacuees to almost 1.5 million individuals aged 16 and older were forced to evacuate from their homes, even temporarily, because of Hurricane Katrina (Groen & Polivka, 2007).

The initial sample consists of 85 core-based statistical areas that were affected by immigration due to Katrina according to the CPS. The New Orleans-Metairie-Kenner metro area is excluded since the focus is on destination areas affected by immigration, rather than including a confluence of the two effects. Moreover, the area experienced a high degree of flooding and catastrophic structural damage as assessed by the Federal Emergency Management Agency (Gabe *et al.*, 2005). Concentrated efforts of rebuilding the city were initiated by governmental local and national forums, which could have affected the social environment, and in particular, the crime rates, in ways not related to the changing population.

Income per capita is included as a control and is measured as the personal income of the residents of an MSA divided by the resident population of that area (according to the Census Bureau's annual midyear population estimates). The income and Consumer Price Index (CPI) data is from the Bureau of Economic Statistics.[14] The unemployment rates are annual averages for each metropolitan area. Unemployment data comes from the Bureau of Labor Statistics of the Department of Labor.[15] Descriptive statistics for the crime, evacuation variables, and other covariates are shown in Table 1.

[14] CPI data is available at http://www.bls.gov/cpi/home.htm.

[15] The unemployment data can be obtained from http://www.bls.gov/lau/.

Table 1. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Violent crime	279	517.41	193.49	123.40	1,262.70
Murder and non-negligent manslaughter	289	5.96	3.48	0.30	25.40
Forcible rape	287	38.68	14.40	12.30	151.70
Robbery	289	147.05	72.70	15.00	458.50
Aggravated assault	281	326.42	149.28	59.60	925.30
Property crime	284	3,974.67	975.50	1,894.70	6,229.20
Burglary	286	875.74	294.20	339.50	2,084.50
Larceny-theft	286	2,694.16	693.56	1,311.00	4,601.70
Motor vehicle theft	289	404.49	198.65	109.60	1,355.00
Total law enforcement employees	332	1,564.90	2,586.61	71.00	15,422.00
Law enforcement officers	332	1,223.61	2,145.77	42.00	14,161.00
Civilian employees	332	341.26	538.62	5.00	4,049.00
Unemployment	328	4.79	1.12	2.50	10.10
Income per capita	334	34,550.17	7,465.93	23,029.00	80,192.00
Population	289	1,499,454	2,021,515	114,352	13,000,000
Number of evacuees due to Katrina	336	9.80	24.67	1.00	194.00
Non-evacuees according to the CPS	336	2,516.10	3,275.74	271.00	16,937.00

Notes: Crime rates are number of offenses per 100,000 inhabitants. The law enforcement variables are expressed as the number of police employees per 100,000 inhabitants. Number of Katrina evacuees and non-evacuees per core-based statistical area are raw counts as reported by the Current Population Survey (November 2005 – August 2006, Basic Monthly CPS).

Estimation Results for Regional Analysis

The Placebo Experiment

Before estimating the equation (1), the identifying assumption of the model must be verified implying that both the control group (low evacuation rate) and treatment group (high evacuation rate) would have been the same in terms of crime in the absence of the storm. This is accomplished by conducting a falsification experiment in the spirit of Angrist and Krueger (1999) in which the pre-Katrina outcomes are regressed on the post-Katrina number of evacuees relative to the population in the destination areas, as if the evacuation occurred on January 1, 2004. Explicitly, we estimate equation (1) with $t = \{2003, 2004\}$ and (fake) $Katrina_t$ being equal to 0 in 2003 and equal to 1 in 2004. The idea is that if we are simply capturing differences in pre-existing crime trends across CBSAs that experienced a significant versus a more modest influx of the evacuees, then the treatment variable would be significant. The results from Table 2 show that the model passes the test – out of 9 different crime rates, none is significant at the 5% level and only robbery being marginally significant at the 10% level, but with the negative sign. It can be proceeded towards estimating the actual model.

Table 2. Effects of Migration due to Hurricane Katrina: Estimates of the Placebo Experiment, 2003-2004

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina	-659.843	29.389	-75.895	-254.471*	-369.457	-236.886	-815.526	742.860	-173.992
Evacuation	(449.944)	(33.911)	(64.468)	(147.305)	(387.243)	(2404.980)	(734.441)	(1532.908)	(496.684)
Unemployment	26.616	-0.066	0.861	4.536	20.240	-43.602	-28.430	4.887	-19.774
Rate	(19.337)	(0.682)	(2.928)	(6.144)	(17.487)	(137.002)	(44.208)	(89.040)	(31.272)
Law enforcement	0.672	-0.066	-0.069	-0.027	0.893	3.621	0.852	2.413	0.280
officers	(1.014)	(0.082)	(0.161)	(0.316)	(0.801)	(5.297)	(2.956)	(2.835)	(0.882)
Law enforcement	-1.556	0.071	0.241	-0.893	-0.985	-5.020	-5.761*	2.101	-1.145
civilians	(1.929)	(0.117)	(0.222)	(0.857)	(1.341)	(10.441)	(2.932)	(7.368)	(1.856)
Income per Capita	0.001	0.000	0.001	-0.000	0.000	-0.018	-0.022*	0.005	-0.002
	(0.006)	(0.000)	(0.001)	(0.002)	(0.006)	(0.029)	(0.012)	(0.024)	(0.006)
R-squared	0.986	0.885	0.840	0.988	0.984	0.985	0.981	0.986	0.987
Observations	141	143	143	143	141	140	141	141	143

Notes: Regressions are restricted to pre-Katrina data; Falsification tests assume that Katrina stroked at the beginning of 2004. Dependent variable is expressed as number of offenses per 100,000 inhabitants. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level. Evacuation due to Katrina is an interaction term between treatment (a dummy that takes a value of one for the MSAs that experienced an evacuation shock larger than .2% relative to population) and post-Hurricane years.

The OLS Estimations and Results

The DID estimates of the impact of Katrina-related evacuation on various types of violent and property crimes are shown in Table 3. If the logarithm of the crime rate is used as the dependent variable in both these regressions qualitatively similar results are obtained (results shown in the Appendix Table A2).

As implied by the media, we find that Hurricane migration is indeed associated with increases in murder and non-negligent manslaughter, robbery, and motor vehicle theft (columns 1.1, 1.3 and 2.3, respectively). Since the independent variable is defined as the ratio of Katrina evacuees relative to the local population, the coefficient estimate of 72.3 on murder and non-negligent manslaughter, for example, corresponds to an average increase of 0.8 additional offenses per 100,000 people in response to a 1% increase in the local population due to Katrina evacuees. Similarly, estimated increases in robberies and car thefts due to Katrina immigration are 4.1 and 16.6 offenses, respectively. Putting these numbers in perspective, an evacuation shock of 1% relative to the local population is associated with more than a 13.3% increase in murder and non-negligent manslaughter, a significant 3% increase in robbery, and a 4% increase in motor vehicle theft. In terms of actual increases in the number of offenses per 100,000 inhabitants, these results link Katrina to 4.1 additional robberies and 16.6 additional car thefts in the host metro area, for a 1% increase in local population due to evacuees. We do not find statistically significant effects on other types of crime (forcible rape, aggravated assault, burglary and larceny-theft) following the Hurricane.

Table 3. Effects of Migration due to Hurricane Katrina on Violent Crime and Property Crime, 2003-2007

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina	614.898	72.209**	-45.116	380.559**	188.700	3584.897	750.882	1332.653	1530.317**
Evacuation	(776.337)	(29.390)	(97.802)	(150.783)	(638.081)	(2498.240)	(1728.811)	(2223.761)	(616.453)
Unemployment	7.758	0.205	0.553	8.813**	-1.892	209.335***	44.429**	165.186***	-3.238
Rate	(10.157)	(0.398)	(0.891)	(3.615)	(9.053)	(67.323)	(17.707)	(40.716)	(15.815)
Law enforcement	1.325**	-0.019*	0.046	0.084	1.159*	-1.158	-0.690	-0.585	0.127
officers	(0.622)	(0.010)	(0.069)	(0.117)	(0.609)	(1.748)	(0.627)	(1.549)	(0.293)
Law enforcement	-3.585**	0.045	-0.037	-0.428	-3.020**	0.861	-0.514	-0.229	1.116
civilians	(1.333)	(0.035)	(0.089)	(0.342)	(1.155)	(4.276)	(1.068)	(3.301)	(0.859)
Income per Capita	-0.000	0.000	0.000	0.000	-0.001	0.020	-0.000	0.018	0.002
	(0.003)	(0.000)	(0.000)	(0.001)	(0.002)	(0.025)	(0.006)	(0.017)	(0.004)
R-squared	0.936	0.828	0.807	0.957	0.923	0.931	0.938	0.934	0.943
Observations	279	289	287	289	281	284	286	286	289

Notes: Dependent variable is expressed as number of offenses per 100,000 inhabitants; Evacuation due to Katrina is an interaction term between evacuation ratio (defined as number of evacuees divided by population of MSA) and post-Hurricane years 2005-2006. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

Apart from these effects, unemployment appears to be an important determinant of crime. The estimates of the effect of unemployment on robbery, larceny-theft and in general on property crime are positive and statistically significant, which is consistent with previous studies. The deterrence impact of law employment officers and civilians on various types of offenses appears mixed: while more civilians appear to reduce violent crime, law enforcement officers are positively correlated with violent crime and in particular with aggravated assaults. This result is perhaps not surprising, as more police should increase the number of recorded offenses (Levitt, 1997; Orrenius & Coronado, 2005).

To investigate whether these effects were larger or smaller in the immediate aftermath of Katrina, we conducted an additional analysis which only included post-Katrina observations from 2006 (omitting 2007). These results are shown in Table 4. We find positive and significant increases in motor vehicle theft: the estimated coefficient suggests that a 1% increase in the population of a CBSA due to Katrina corresponds to car thefts increasing on average by more than 4% or 17.2 additional offenses per 100,000 inhabitants. We do not find any short-run increase in murder or robbery, which showed increasing tendencies two years after Katrina hit the coast.

Robustness Checks

As discussed previously, one of the main advantages of investigating the effect of Hurricane Katrina on crime in the destination cities of evacuees is the fact that the cause for migration was sudden and can be reasonably viewed as exogenous. Furthermore, the inclusion of metro fixed effects eliminates the possibility of time-invariant unobserved heterogeneity from plaguing the estimates.

Table 4. Short Run Crime Effects of Evacuation due to Hurricane Katrina, 2003-2006

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina	254.081	39.842	111.778	331.186	-237.995	2905.023	489.581	785.929	1584.454**
Evacuation	(694.126)	(32.787)	(117.125)	(219.864)	(616.229)	(3292.211)	(1790.915)	(3589.330)	(708.678)
Unemployment	16.709	0.016	0.456	10.664**	5.209	187.886**	35.781	155.949***	-7.363
Rate	(11.272)	(0.414)	(1.198)	(4.629)	(9.139)	(79.725)	(22.591)	(48.090)	(18.009)
Law enforcement	2.123**	-0.019	0.057	0.164	1.898*	1.741	-0.449	1.711	0.534
officers	(1.009)	(0.022)	(0.037)	(0.240)	(1.013)	(2.784)	(1.147)	(1.955)	(0.548)
Law enforcement	-4.793*	0.031	0.068	-0.820	-4.091	-2.897	-2.430	-2.023	1.256
civilians	(2.760)	(0.064)	(0.073)	(0.770)	(2.501)	(7.159)	(1.613)	(5.804)	(1.197)
Income per Capita	0.002	-0.000	0.000	0.001	0.000	0.028	-0.001	0.029	0.001
	(0.008)	(0.000)	(0.001)	(0.002)	(0.006)	(0.039)	(0.010)	(0.025)	(0.007)
R-squared	0.935	0.840	0.843	0.962	0.923	0.943	0.950	0.945	0.957
Observations	210	216	215	216	211	212	213	214	216

Notes: Regressions are estimated using one year of post-Katrina data, 2006. Dependent variable is expressed as number of offenses per 100,000 inhabitants; Evacuation due to Katrina is an interaction term between evacuation ratio (defined as number of evacuees divided by population of MSA) and post-Hurricane years 2005-2006. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

Nonetheless, the possibility remains that the decision to immigrate to particular areas is endogenous. Unobserved characteristics of the metropolitan areas may be correlated with both migration and trends in local crime rates, making the estimates biased. Furthermore, evacuees identified by the CPS are likely subject to measurement error. Reported crime statistics from the FBI are generally estimates and do not cover the entire area of a jurisdiction. The number of recorded offenses is influenced both by victims' willingness to report crime and by police recording practices and procedures. At the level of individual police department, it is common that both administrative and political changes can lead to abnormalities in reported data or to failures to report actual crimes.

The IV Estimations

These possibilities are accounted for via the use of instrumental variables method by instrumenting the number of evacuees going to a certain city with its distance to New Orleans. Similarly, McKenzie *et. al.* (2006) examine the impact of migration on individuals' "earning potential" abroad using distance from the New Zealand consulate in Tonga as an instrument for Tongan migration. We expect the number of evacuees to decline for locations further away from New Orleans due to increasing transportation costs, decreasing familiarity of the area, and lower likelihood of knowing people currently living in the area. Furthermore, distance from New Orleans is safely exogeneous after accounting for CBSA fixed effects and changes in covariates. To take into account possible non-linearity and the fact the main independent variable is expressed in per capita terms, we include as instruments the squared distance, host city population and population growth rate prior Hurricane Katrina. The first stage regressions (Table 5) indicate that the instruments are jointly significant at the 1% level ($F = 4.55$). In addition to the Two-Stage Least Squares (2SLS), the Limited Information Maximum Likelihood (LIML) was used to obtain instrumental variables estimates. As presented in the Appendix Table A1, the results were similar using both methods, with LIML resulting in slightly higher significance levels (assault becomes significant). Moreover, similar results are obtained if the logarithm of the crime rate is used as the dependent variable in the 2SLS regressions.

The IV estimation results are reported in Table 6. Katrina evacuation is associated with statistically significant increases in violent crimes. In particular, an increase by 1% in the average number of evacuees relative to the total population translated into 1 additional murder per 100,000 inhabitants and about 9 additional robberies. In other words, a 1% immigration shock resulted in estimated 6.1% increase in violent crime via a 15% increase in murder and non-negligent manslaughter and more than a 6% increase in robbery. The estimates for property crime and its subcategories are positive but not statistically significant at the 5% level. The OLS estimates appear to be downward biased, which may suggest that the data is subject to measurement error. Nonetheless, the OLS and the IV estimates are not statistically different from each other. It should be noted that if evacuees are undercounted in the CPS (rather than being subject to classical measurement errors), the estimated magnitudes of effects on crime rates in destination cities will be upward biased.

Table 5. First Stage Instrumental Variables Estimations

	IV Regression in Levels							
	Population Growth	Population 2004	Distance	Distance Squared	Unemployment Rate	Law Officers	Law Civilians	Income per Capita
P-value	0.387	0.711	0.001	0.004	0.163	0.668	0.785	0.981
	F(4, 26) = 4.55, Prob > *F* = 0.0064, *R-squared* = 0.418							
	IV Regression with Evacuation Dummy							
	Population Growth	Population 2004	Distance	Distance Squared	Unemployment Rate	Law Officers	Law Civilians	Income per Capita
P-value	0.388	0.168	0.002	0.038	0.819	0.384	0.434	0.841
	F(4, 26) = 10.01, Prob > *F* = 0.000, *R-squared* = 0.266							

Notes: Population2003 and Population2004 are reported by the FBI through the Uniform Crime Reporting Program; Distance is between each MSA and New Orleans, LA, measured as an average between city centers, using Google Maps software. Included in the first stage regressions are the covariates contained in the IV specification.

Table 6. Effects of Migration due to Hurricane Katrina on Violent and Property Crime Rates: Instrumental Variables Estimates

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina	2892.587*	82.017*	-126.998	808.750*	2015.216	6909.130	-335.575	4894.497	2189.109
Evacuation	(1647.606)	(46.354)	(139.202)	(424.079)	(1512.428)	(6665.091)	(1694.581)	(5461.046)	(1782.408)
Unemployment	9.255	0.222	0.175	10.147**	-1.632	184.265**	32.482*	151.544***	-3.365
Rate	(12.097)	(0.335)	(1.016)	(4.248)	(9.935)	(71.263)	(16.082)	(42.865)	(18.712)
Law enforcement	1.297**	-0.018*	0.054	0.095	1.112*	-0.490	-0.381	-0.156	0.069
officers	(0.603)	(0.010)	(0.075)	(0.112)	(0.586)	(1.850)	(0.592)	(1.592)	(0.302)
Law enforcement	-3.078**	0.045	-0.071	-0.398	-2.510**	2.905	-0.478	1.408	1.459*
civilians	(1.248)	(0.034)	(0.112)	(0.363)	(0.996)	(3.513)	(0.915)	(2.828)	(0.795)
Income per Capita	-0.002	0.000	0.000	0.000	-0.003	0.020	0.001	0.017	0.002
	(0.004)	(0.000)	(0.000)	(0.002)	(0.003)	(0.026)	(0.006)	(0.017)	(0.005)
R-squared	0.948	0.827	0.807	0.957	0.941	0.951	0.951	0.956	0.941
Observations	258	268	266	268	260	263	265	265	268

Notes: Dependent variable is expressed as number of offenses per 100,000 inhabitants; Evacuation due to Katrina is an interaction term between evacuation ratio (defined as number of evacuees divided by population of MSA) and post-Hurricane years 2005-2006. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the.01 level; ** at the .05 level; * at the .10 level. Instruments used to predict the evacuation due to Katrina consist of population 2004, the growth rate of population between 2003 and 2004, distance and distance squared to the downtown New Orleans, LA.

An additional threat to the internal validity of our IV estimates occurs if Katrina evacuees are self-selecting into cities of varying distance from New Orleans according to their proclivity to engage in criminal activities. To examine this possibility, we regressed various individual characteristics of Katrina evacuees on distance they have travelled. The only variable that was correlated with distance is age (at 10% significance) -- younger evacuees tended to travel further. The rest of the variables, including household size, education, income, race and sex, are insignificant. It can be inferred that for these observables available in the CPS, selection does not appear to be substantial. Furthermore, our main results are robust to including only those evacuees that traveled to relatively distant metro areas.

Finally, we focused on possible self-selection of evacuees from New Orleans by utilizing data from the Displace New Orleans Resident Pilot (DNORP). This small telephone survey of pre-Katrina New Orleans residents interviewed 147 households in the fall of 2006, who had since left New Orleans. We found no statistically significant differences in age, race, income levels prior to Katrina, and marital status between evacuees who relocated to Texas (the state with the largest number of evacuees in the sample) and those who relocated to other states. Without claiming to prove the endogeneity of Katrina evacuation, this robustness check suggests that the composition of evacuees by distance did not indeed depend on unobservables.

The IV Estimations with Binomial Treatment

As an additional robustness check, in the context of the IV estimations, we next compare metropolitan areas more severely affected by the Hurricane to those less affected, before and after the storm, creating single treatment and control groups more in line with the traditional DID estimation. We construct an ad-hoc treatment sample that includes metropolitan areas for which the evacuees to total population ratio is higher than the median level (roughly 0.2%). The control group consists of metropolitan areas that, according to the CPS, experienced a migration shock of less than 0.2% relative to the population. By imposing this differencing, we are underestimating the true effects of forced migration due to Katrina on various types of crimes.

The two samples appear to be similar to each other prior to Katrina evacuation (Table 7). Explicitly, for the majority of crime sub-categories, the differences in crime rates are not statistically significant. In addition, the metropolitan areas that experienced high migration versus those less affected are similar with respect to the law enforcement employment and unemployment rates. Even though the cities that attracted more evacuees were less populated, had significantly lower per capita income levels, and were characterized by higher burglary rates, in general, the computed *t*-statistics do not reject the null hypothesis of equal means for most of the variables of interest, meaning that the treatment and the control groups were sufficiently similar before Katrina happened.

The first stage regressions presented in Table 5 indicate that the instruments are strong and jointly significant at the 1% level (F = 10.01). Table 8 shows that the evacuation due to the Hurricane is associated with increases in overall violent crime. Regarding specific sub-categories of offenses, robbery is positively and significantly affected by the Katrina migration. The results are found to be robust to alternative values of the threshold, both above and below the 0.2% increase in local population.

Table 7. Descriptive Statistics for the Treatment and Control Groups before Hurricane Katrina

Variable	Treatment Group before Katrina			Control Group before Katrina			p-value
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	
Violent crime	81	528.463	180.138	60	491.855	180.437	0.235
Murder and non-negligent manslaughter	83	6.247	3.277	60	5.435	3.788	0.173
Forcible rape	83	41.302	17.233	60	39.325	13.961	0.465
Robbery	83	146.819	73.416	60	131.287	55.851	0.171
Aggravated assault	81	334.740	143.074	60	315.808	139.151	0.433
Property crime	81	4,251.123	865.041	59	4,032.192	1,141.629	0.199
Burglary	82	971.888	304.458	59	799.017	266.307	0.001
Theft	82	2,873.566	594.973	59	2,777.797	865.449	0.437
Motor vehicle theft	83	399.789	200.519	60	424.683	201.729	0.083
Law enforcement employees	83	114.935	54.783	60	109.460	48.510	0.117
Unemployment	96	5.210	0.961	68	5.465	1.035	0.108
Income per capita, x 1,000	100	30.048	4.019	68	34.472	7.475	0.000
Population, x 1,000	83	1,059.522	1,439.557	60	2,037.292	2,478.840	0.004

Notes: Crime variables correspond to numbers of offenses per 100,000 inhabitants. The measure of law enforcement is expressed as the number of police employees per 100,000 inhabitants. Corresponding p-values are from the regression of the individual variable on a treatment dummy and refer to statistical significance of the difference of the means.

Table 8. Effects of Migration due to Hurricane Katrina: IV Estimates with a Dummy Variable for Katrina Evacuation

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina	91.971*	2.323	-3.546	28.551**	58.619	155.298	-14.722	98.214	70.472
Evacuation	(49.166)	(1.555)	(4.279)	(11.663)	(45.127)	(180.137)	(44.396)	(137.177)	(48.263)
Unemployment	-3.943	-0.117	0.717	6.539*	-10.187	158.050***	34.074**	133.134***	-12.810
Rate	(15.550)	(0.477)	(0.972)	(3.291)	(13.807)	(55.771)	(14.334)	(33.007)	(16.089)
Law enforcement	1.222*	-0.019	0.056	0.072	1.077	-0.473	-0.364	-0.108	0.023
officers	(0.708)	(0.012)	(0.075)	(0.128)	(0.652)	(1.933)	(0.612)	(1.704)	(0.355)
Law enforcement	-2.764**	0.051	-0.080	-0.288	-2.332**	3.083	-0.548	1.429	1.698*
civilians	(1.248)	(0.037)	(0.127)	(0.358)	(0.997)	(3.253)	(0.952)	(2.701)	(0.847)
Income per Capita	-0.001	0.000	0.000	0.001	-0.002	0.023	0.000	0.019	0.004
	(0.005)	(0.000)	(0.000)	(0.002)	(0.003)	(0.026)	(0.006)	(0.017)	(0.005)
R-squared	0.945	0.810	0.808	0.954	0.941	0.952	0.950	0.957	0.937
Observations	258	268	266	268	260	263	265	265	268

Notes: Dependent variable is expressed as number of offenses per 100,000 inhabitants; Evacuation due to Katrina is an interaction term between evacuation ratio (defined as number of evacuees divided by population of MSA) and post-Hurricane years 2005-2006. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level. Evacuation due to Katrina is an interaction term between treatment (a dummy that takes a value of one for the MSAs that experienced an evacuation shock larger than .2% relative to population) and post-Hurricane years.

Selection by Distance and Other Robustness Checks

To evaluate the hypothesis of selection of evacuees on travelled distance and evaluate the extent of the selection, two exercises are performed. First, the main results are probed by considering only evacuees that traveled to metro areas located further away than one half of the distance to the farthest recorded CPS area of evacuation, which corresponds to Seattle-Tacoma-Bellevue, WA metro area. Based on the prior that those evacuees are better-off than the average Katrina evacuee (better education and higher income), no negative effects of their migration on local crime rates are expected. Using the reduced sample (from 261 to only 61 metro-area/year data points), the same significant increases in crime rates are found as in the full sample: “Violent Crime” and “Robbery” (Appendix Table A3).

Next step was testing whether the evacuees who travelled far are indeed different from those that remained relatively close to New Orleans. The original evacuees-level CPS data was used to regress various individual characteristics of Katrina evacuees on distance they have travelled. In the first set of specifications, a continuous distance variable is used, and in the second – a dummy variable that equals 1 for those evacuees who traveled more than half of the maximum distance. The evacuees who remained in New Orleans are dropped from the analysis. The only variable that seems to be correlated with distance is “Age” (at 10%) – younger evacuees have travelled further. The rest of the variables, including the household size, education, income, race, and sex are insignificant suggesting that at least for these observables, selection does not appear to be substantial (Appendix Table A4).

Part 2. Crime Effects of Hurricane Katrina in Houston

Katrina Evacuation to Houston

The second part of the analysis is focused on Houston, TX, a destination city for numerous Katrina evacuees. In the twenty days following the day of August 31, 2005, over 65,000 residents of New Orleans were transported to Houston, provided food, sheltered in the first-ever mega shelters, given medical treatment, and later assisted in obtaining permanent housing. While the exact number of evacuees is uncertain, unofficial sources maintain that 250,000 evacuees came to Houston and as many as 150,000 remained, which represents more than 7% increase in population. The Community Development Block Grant program identified more than 100,000 individuals displaced by the Hurricane living in Houston housing in July 2006 (Houston City Report, August 2, 2006).

Houston became a place of refuge for the segment of the population hardest hit by the Hurricane: those who did not evacuate in time, had to rely on government help to evacuate, and did not have access to housing on their own. Brodie *et al.* (2006), in a survey conducted in Houston shelters on September 10 through 12, 2005, finds that 93% of evacuees were African American, with more than one third of the Houston shelter residents reported making less than $10,000 in 2004 and only 6% of reported having a college degree. While 30% were married or living as married, nearly half of the shelter residents were single; 51% were childless, but 45% had children younger than 18 years, of which 33% had their children with them in the shelter.

Moreover, in comparison with those who evacuated ahead of the storm, the Houston evacuees experienced more suffering: going without food (60% versus 47%), water (59%

versus 45%), and medicine (37% versus 25%), and suffering injuries (37% versus 26%). Twenty-two percent reported having been threatened with violence, especially the refugees that spent time in the two New Orleans shelters (Brodie *et al.*, 2006).

After facing the destruction of their homes and communities and traumatizing personal experiences, it is not surprising that while in shelters, over two-thirds of the Katrina evacuees indicated that it was likely that they would stay in Houston (Wilson & Stein, 2006). After September 25 when the Harris County Housing Authority ceased to assist the evacuees, the City of Houston had the principal responsibility for transitioning the Katrina survivors from shelters into temporary housing (Harris County Housing Authority, 2005 Annual Report). Sources from FEMA report that 56,865 evacuees applied for housing assistance in the city of Houston alone. The vast majority of evacuees were moved into southwest Houston, an area that was largely comprised of low-income families and ethnic and racial minorities. A "tornado" of news reports and articles followed in the press, accusing or implying that Katrina evacuees were responsible for the violent crimes in those areas.

The objective is to validate or reject the hypothesis that following Hurricane Katrina, crime spiked in the greater Houston area due to the forced migration. In this community-level analysis, we employ local Houston crime data aggregated by district in an effort to evaluate the impact of Katrina evacuees on a large number of types of crime occurring in the neighborhoods surrounding the apartment complexes where they live.

Houston Data Description and Methodology

Crime data provided by the Houston Police Department (HPD) was collected under the Uniform Crime Report Program. The sample contains monthly data from January, 2005 to December, 2007 on 23 Houstonian districts, for the two general categories of offenses according to the FBI classification: violent crime (murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault) and property crime (burglary, theft, and auto theft) that we study in the first part of the paper. The information contained in the HPD reports permits analysis of additional crimes such as arson, forgery and counterfeiting, fraud, embezzlement, stolen property, vandalism (criminal mischief), weapons (carrying, possessing), prostitution and commercialized vice, sex offenses, narcotic drug laws, gambling, offenses against family and children, driving under influence (DUI), liquor laws, drunkenness, disorderly conduct, vagrancy, and a category that includes all other offenses (except traffic). Reported cases of several of other types of offenses were low in number (or consistently zero), making their analysis impossible. In the interest of space, the reporting of results regarding the majority of crimes beyond those in the regional analysis is limited to those found to be significantly affected by Katrina evacuation.

The sample includes the type of crime, exact date and time of occurrence, district and police beat (geographic areas of the city broken down for patrol and statistical purposes), premise code of the location, block numbers and street name. Means of selected crimes for the period under analysis are presented in Table 9. We drop all the observations that did not have any recordings across crime types and aggregate the data to the district level since there is only information at the district level on where the evacuees reside.

Table 9. Descriptive Statistics for Selective Crimes in Houston

Variable	Obs.	Mean	Std. Dev.
Violent Crime:			
Murder and non-negligent manslaughter	816	1.263	1.458
Forcible rape	816	2.795	2.586
Robbery	816	39.353	28.565
Aggravated assault	816	40.978	27.874
Property Crime:			
Burglary	816	95.977	56.164
Larceny-theft	816	256.201	151.846
Motor vehicle theft	816	70.436	44.392
Additional Crimes:			
Arson	816	0.714	1.002
Forgery and counterfeiting	816	22.368	15.69
Fraud	816	9.786	7.303
Stolen property	816	0.123	0.443
Vandalism (criminal mischief)	816	90.493	52.415
Weapons – carrying, possessing	816	6.447	4.872
Prostitution and commercialized vice	816	7.674	11.166
Sex offenses	816	5.555	4.997
Narcotic drug laws	816	45.701	35.564
Gambling	816	0.168	0.473
Offenses against family and children	816	5.093	3.837
Driving under influence	816	8.225	12.863
Liquor laws	816	0.35	0.659
Drunkenness	816	5.022	4.568
Disorderly conduct	816	36.02	21.373
Vagrancy	816	0.027	0.196
All other offenses (except traffic)	816	27.14	27.985

Note: Crimes are expressed in number of offenses by district and by month.

Out of 23 Houstonian districts, the HPD identified apartment complexes in divisions Fondren (includes district 17), Southwest (includes districts 15 and 16), West (includes districts 19 and 20), and Greenspoint (corresponds to district 18), as complexes where a high concentration of evacuees reside. The variable that describes the locations impacted by the evacuees and the surrounding areas, $Apartments_i$, includes police districts 15 to 20, located in the southwest quadrant of the city. Using this variable interacted with a post-Katrina time dummy as our treatment variable we estimate the following regression specification for the two main categories of crime and by specific type of offense:

$$Crime_{it} = \beta_1(Apartments_i \times Katrina_t) + \beta_2 Katrina_t + \gamma_i + month_t + \varepsilon_{it} \qquad (2)$$

where $Crime_{it}$ indicates the number of various crimes recorded by the HPD in district i, in the month t; $Apartments_i$ is a dummy that takes a value of one for the districts where apartment complexes are located and their immediate surroundings, and zero for all other districts; $Katrina_t$ is a dummy that takes the value of one after September, 2005, and zero otherwise. The months of September and October 2005 are dropped from the regressions. Unfortunately, we do not have any other district-specific data available. However, we include γ_i (district) and $month_t$ (month) effects to account for some degree of heterogeneity.

Estimation Results for Houston Analysis

Confirming the results from the regional analysis, we find evidence that migration due to Hurricane Katrina affected crime in the greater Houston area. Violent crime is 4% higher following Katrina in the areas resided by evacuees relative to the mean for the whole period (Table 10). In particular, significant increases in murder and non-negligent manslaughter are found following Katrina in this evacuation area, though the differences in the control groups between the regional analysis and the local Houston analysis make direct comparisons of magnitudes difficult.

Table 10. Crime Effects of Hurricane Katrina Evacuees Living in Apartment Complexes in Houston

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft	(3.1) Arson	(3.2) Weapons - caring, possessing
Katrina Apartments in Houston	8.023**	0.342**	-0.444	-3.523	11.648***	-14.899	-0.542	-11.570	-2.787	0.290*	2.092***
	(3.730)	(0.137)	(0.284)	(2.729)	(2.560)	(14.730)	(2.811)	(11.523)	(5.891)	(0.156)	(0.663)
After Katrina	-3.649	0.125	-0.353**	2.602***	-6.024**	14.707**	2.971	7.210	4.525**	-0.148	1.665***
	(2.451)	(0.111)	(0.140)	(0.778)	(2.336)	(6.712)	(2.429)	(5.561)	(1.976)	(0.116)	(0.453)
R-squared	0.941	0.364	0.454	0.914	0.918	0.965	0.913	0.956	0.896	0.249	0.644
Observations	816	816	816	816	816	816	816	816	816	816	816

Notes: Dependent variable is the number of offenses by district, by month. Katrina Apartments in Houston is defined as an interaction term between the post Hurricane months (including November, 2005) and a dummy that takes a value of one if the district is identified as an area of Houston where evacuees have settled and zero otherwise. Monthly dummies and fixed effects by district are included. Standard errors are clustered by district and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

On average, murder increased by 0.34 offenses (27%) in the targeted districts of Houston relative to the other districts. Moreover, Houston witnessed 11.6 additional cases of aggravated assaults in the districts intensively lived by the evacuees relative to other areas, corresponding to an increase of 28%.

Looking across additional types of crimes, we find evidence that arson and carrying and possession of weapons were crimes committed differentially more in districts where the Katrina evacuees reside and surroundings. The estimated coefficient for arson is 0.29 and for weapons is 2.09, which represent increases of 41% and a 32%, respectively (Table 10). The effects of Katrina evacuation on other crime types within the Houston dataset were found to be insignificant (not shown in the table). In particular, it is notable that crimes that are not expect to be affected by recent immigrants, such as embezzlement, fraud and forgery, were found statistically unchanged. The results from a falsification experiment, in which pre-Katrina data is used and (fake) Katrina is assumed to have occurred on May 1, 2005, are shown in Table 11. As seen in the table, the estimated coefficients on the treatment variable are statistically insignificant for all crimes, suggesting that trends in crime rates did not vary prior to Katrina across areas more and less affected by immigration due to the Hurricane.

To verify and substantiate the Houston results, the impact of treatment intensity was investigated with the use of a continuous measure of evacuee presence obtained from the third wave of Wilson and Stein (2006), rather than employing a discrete variable representing areas known to be inhabited by a large number of Katrina evacuees.

Table 11. Crime Effects of Hurricane Katrina Evacuees Living in Apartment Complexes in Houston: Estimates of the Placebo Experiment

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft	(3.1) Arson	(3.2) Weapons - caring, possessing
Katrina Apartments in Houston	-2.394	-0.245	-0.662	2.208	-3.694	0.185	-7.315	14.352	-6.852	-0.106	1.190
	(8.976)	(0.358)	(0.423)	(2.656)	(7.334)	(9.253)	(5.213)	(9.799)	(7.641)	(0.255)	(1.096)
After Katrina	15.473***	0.103	-0.793**	-4.135	20.299***	8.620	4.079	-1.755	6.296	0.360	-1.006
	(4.987)	(0.333)	(0.315)	(2.835)	(4.407)	(12.463)	(4.274)	(7.646)	(5.094)	(0.314)	(0.799)
R-squared	0.983	0.444	0.674	0.921	0.981	0.980	0.942	0.977	0.915	0.388	0.655
Observations	168	168	168	168	168	168	168	168	168	168	168

Notes: Regressions are restricted to pre-Katrina data; Falsification tests assume that Katrina happened on May 1st, 2005; Dependent variable is the number of offenses by district, by month. Monthly dummies and fixed effects by district are included. Standard errors are clustered by district and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

The evacuees' survey data was collected as part of a year-long project involving 1,081 Katrina evacuees living in Houston. The final wave of the study took place in July 2006 in apartment complexes and included 362 evacuees. The vast majority (74.3%) of respondents reported living in the districts identified in the Houston analysis by the Apartments variable, which represents approximately 27% of the police beats in Houston. The number of survey respondents who reported living in a given zip code was converted to the number of respondents in corresponding police beats. There was imperfect matching between zip codes and police beats. Zip code boundaries may overlap beat boundaries and there may be several beats within several zip codes and vice versa. We assumed a uniform distribution of the evacuees residing within a zip across all the beats located (partially) in the particular zip code boundaries.

These results corroborate the main findings, and provide strong evidence of a positive association between evacuee presence and increased crime rates. In particular, the relationship between evacuees and violent crimes were, as before, positive and statistically significant. Unlike the main findings, positive and significant effects were found for property crimes. Similar to the findings at the country-level, other crimes, such as sex offenses, forgery, embezzlement, gambling and liquor law violations, were not affected by Katrina evacuation.

Sources of Increased Crime

While this investigations brings strong evidence of increases in certain types of crime at both the national and city levels due to migration caused by Hurricane Katrina, the channel through which crime rates increased remains uncertain. In particular, with the available data, it is difficult to determine whether the additional crimes were committed by evacuees themselves, whether they were the victims of crimes, or whether the increased crime was otherwise triggered by the evacuees' presence.

In an attempt to address the question of whether increases in crime rates were due to criminal activity of immigrants themselves, we utilized data from the American Community Survey (ACS). Beginning in 2006, the survey includes individuals who were institutionalized (either in correctional institutions or mental institutions). Unfortunately, the survey does not provide Katrina evacuee status, but it does provide information regarding migration status and location of residence in the previous year. Due to the relatively heavy influx of Katrina evacuees into Texas, we first compared frequencies of individuals in Texas who were institutionalized in 2006 by their state of residence in the previous year. Despite not being able to specifically identify evacuees due to Hurricane Katrina, we do observe significantly higher rates of institutionalization for individuals who immigrated from Louisiana and Mississippi, the two states (in addition to Texas) that were most affected by the storm. These statistics are displayed in Table 12.

Specifically, of individuals between the ages of 18 and 50, 5.1% and 4.6% who came from Louisiana and Mississippi, respectively, were in institutions. In comparison, only 3.5% were institutionalized among those who emigrated from other states, a statistically significant difference (at the 10% level) from the mean institutionalization rate of immigrants from Louisiana. Further, only 2.1% were institutionalized among those who lived in Texas (either in the same location, or elsewhere) in the previous year, significantly different from both immigrants from Louisiana and from other states.

Table 12. Institutionalization Rates by Migration Status

Panel A. Living in Texas in Current Year (2006)				
Migrated within last year from:	Institutionalized	Obs.	p-value (vs. Texas)	p-value (vs. Other)
Louisiana	0.0506	514	0.000	0.079
Mississippi	0.0455	66	0.159	0.064
Other states	0.0349	3,327	0.000	
Living in Texas in previous year	0.0207	129,611		
Panel B. Living in Houston in Current Year (2006)				
Migrated within last year from:	Institutionalized	Obs.	p-value (vs. Texas)	p-value (vs. Other)
Louisiana	0.0622	225	0.000	0.851
Mississippi	0.0714	14	0.037	0.841
Other states	0.0585	427	0.000	
Living in Texas in previous year	0.0116	18,793		
Panel C. Living in Houston in Current Year (2006 or 2007)				
Migrated within last year from:	Institutionalized	Obs.	p-value (vs. Texas)	p-value (vs. Unaffected)
LA affected areas	0.0712	281	0.000	0.684
LA unaffected areas	0.0476	21	0.130	
MS affected areas	0.0625	16	0.062	0.553
MS unaffected areas	0.0000	6	0.789	
Living in Texas in previous year	0.0119	38,293		

Notes: Includes respondents to the American Community Survey (ACS), year 2006, or years 2006 and 2007, who were between 18 and 50 years old. Institutionalized includes correctional and mental institutions. LA (or MS) affected areas include counties or parishes where individuals were eligible for FEMA assistance due to Hurricane Katrina. Unaffected areas are other counties or parishes in the same state. Reported p-values correspond to two sided t-tests of differences in group mean institutionalization.

To isolate a group of potential Katrina evacuees among the institutionalized population, we focused on the percentage of individuals in institutions in the Houston area, by state of residence the previous year (Table 12, Panel B). About 6.2 and 7.1% from Louisiana and Mississippi, respectively, were in institutions in 2006. Somewhat fewer were institutionalized among those from other states (5.8%), though, with small sample sizes, these differences are not statistically significant. However, only 1.2% from Texas (either Houston or elsewhere in the state) were in institutions, a statistically significant difference from those from other states.

Finally, we indentify the counties (or parishes) from which immigrants to Houston originated (Table 12, Panel C). In particular, we compare those areas that were hit the hardest by Hurricane Katrina to those areas within the same state that were less affected, according to whether or not individuals in the county (or parish) were eligible for assistance from FEMA. Because of the small sample sizes of these groups, we include data from 2006 and 2007. While the differences are not statistically significant, Houston observed greater rates of institutionalization among those who lived in the more affected areas of both Louisiana and Mississippi in the previous year, compared to those from other areas of the same state.

Taken as a whole, we view this analysis as weak evidence that at least some of the observed increases in reported crimes were due to crimes committed by Katrina evacuees themselves. Stronger support of this hypothesis would involve a comparison of rates of institutionalization prior to Hurricane Katrina among immigrants from the same areas. Unfortunately, a Difference-in-Differences analysis of this sort is not possible due to the lack of institutionalization data in the ACS prior to 2006.

While the ACS offers too small of a sample to provide any meaningful information for those individuals who left New Orleans around the time of Katrina, it is worth noting the pattern of crime observed in that city prior to and following the storm. FBI crime data show immediate decreases across several types of crime in the year following Katrina, then dramatic jumps between 2006 and the end of 2007. Specifically, murder dropped by

13.6% with reference to the average between 2002 and 2004, but climbed by almost 30% from 2006 to 2007. While determining crime effects in New Orleans is complicated due to a confluence of population movements into and out of the city coupled with increased police presence and other recovery efforts, it is observed that by the end of 2007, most types of crime hiked higher than their pre-Katrina levels. Robbery and car theft show substantial increases without reaching their pre-Katrina average levels, whole murder showed an attenuated increase by only 12.2%. Robbery and auto theft decreased by 6.6% and 20.9% respectively compared to the three-year average before the Hurricane, which is contrary to the statistically significant increases observed in these crime types following Katrina in areas inhabited by evacuees throughout the country.

Summary Discussion and Conclusion

This study brings evidence to substantiate the multitude of reports and speculations that have circulated in the local and national media, according to which Hurricane Katrina could have caused crime to propagate from New Orleans and its surroundings to the destination areas of evacuees. At the regional level, Katrina is associated with higher violent crime due to increases in murder and non-negligent manslaughter and robbery, and higher property crime due to increases in motor vehicle theft.

The analysis on Houston uncovers in depth insights on the connection between Katrina evacuation and crime, as Houston welcomed the most disadvantaged individuals who were left behind. Not only did the City witness more murders, but also significantly more aggravated assaults, more illegal possessions of weapons, and more incidences of arson. According to federal guidelines, FEMA normally pays for emergency protective measures, such as police and fire overtime, for the first 72 hours of a disaster. These results suggest that the federal provision might not be enough to adequately keep criminal behavior under control in areas where evacuees are being relocated.

The federal and local governments provided shelters, housing and meal vouchers for the evacuees. While this should certainly remain a priority following natural disasters, there were no initial actions taken to protect the local residents of the areas that welcomed the evacuees, and longer-term responses proved inadequate to prevent a significant rise in certain types of crime. The results uncovered by this study raise questions not only about how best to protect vulnerable populations in future disasters, but also about the appropriate policies designed to protect the populations welcoming the evacuees. Moreover, the Houston analysis warns that concentrating the low-income, low-educated, disadvantaged evacuees in poor subsidized neighborhoods was possibly responsible for generating disruptions and criminal activities in the destination areas. Previous research indicates that crime rates tend to be higher in lower class communities as compared to middle and upper class communities. The factors that have been identified as contributing to the higher levels of crime among the lower class communities are poverty and unemployment.

While the regional and local analyses bring strong evidence of the relationship between Katrina migration and increases in local crime, we offer no strong evidence suggesting whether these crimes were committed by the evacuees themselves or triggered by their presence, as we lack arrest or incarceration data on Katrina evacuees. Furthermore, we are unable to determine whether migration had a positive or negative effect (in terms of likelihood of engaging in criminal activity) on the evacuees themselves.

More generally, this study has provided a rare opportunity to study the impact of immigration on crime in a situation where many individuals did not choose to migrate, but where this occurrence was necessitated by a catastrophic event. The traditional literature investigating the relationship between immigration and local crime rates has resulted in a wide range of estimates possibly due to endogeneity issues. This study suggests that there are significant effects of immigration on several types of local crime rates, a result that is robust to both national and local (Houston) settings and the use of Two-Stage Least Squares and other estimation methods (Limited Information Maximum Likelihood) to overcome remaining endogeneity. Further, existing studies that exploit policy experiments to investigate outcomes resulting from migration (usually between neighborhoods and/or schools within the same metropolitan area) necessarily focus on a specific population and track outcomes among those who have moved, rather than focusing on the effects of migration on those living in destination areas. The study's findings underscore the importance of not overlooking negative spillover effects on the local environment by focusing on crime, another important determinant of economic viability.

Appendix Chapter II

Table A1. Effects of Migration due to Hurricane Katrina on Violent and Property Crime Rates: LIML Estimates

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina	3135.140*	82.083**	-127.000	854.901**	2302.896*	6983.080	-385.500	5066.140	2353.368
Evacuation	(1427.209)	(37.995)	(113.233)	(375.494)	(1344.204)	(5499.704)	(1423.680)	(4610.147)	(1699.353)
Unemployment	9.930	0.222	0.175	10.276***	-0.818	184.470***	32.344**	152.021***	-2.906
Rate	(9.882)	(0.273)	(0.826)	(3.536)	(8.044)	(57.999)	(13.097)	(35.108)	(15.686)
Law enforcement	1.281***	-0.018*	0.054	0.092	1.093**	-0.494	-0.378	-0.167	0.059
officers	(0.482)	(0.008)	(0.061)	(0.092)	(0.469)	(1.502)	(0.481)	(1.294)	(0.252)
Law enforcement	-3.039**	0.045	-0.071	-0.390	-2.464***	2.917	-0.486	1.435	1.485**
civilians	(1.012)	(0.028)	(0.091)	(0.295)	(0.810)	(2.859)	(0.742)	(2.318)	(0.652)
Income per Capita	-0.002	0.000	0.000	0.000	-0.003	0.020	0.001	0.017	0.002
	(0.004)	(0.000)	(0.000)	(0.001)	(0.003)	(0.021)	(0.005)	(0.014)	(0.004)
R-squared	0.947	0.827	0.807	0.956	0.940	0.951	0.951	0.956	0.941
Observations	258	268	266	268	260	263	265	265	268

Notes: Dependent variable is expressed as number of offenses per 100,000 inhabitants; Evacuation due to Katrina is an interaction term between evacuation ratio (defined as number of evacuees divided by population of MSA) and post-Hurricane years 2005-2006. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level. Instruments used to predict the evacuation due to Katrina consist of population 2004, the growth rate of population between 2003 and 2004, distance and distance squared to the downtown New Orleans.

Table A2. Effects of Migration due to Hurricane Katrina on (Log) Violent Crime and Property Crime, 2003-2007

	(1) Violent Crime	(1.1) Murder and Non-negligent Manslaughter	(1.2) Forcible Rape	(1.3) Robbery	(1.4) Aggravated Assault	(2) Property Crime	(2.1) Burglary	(2.2) Larceny-Theft	(2.3) Motor Vehicle Theft
Katrina Evacuation	1.142	7.626*	-2.209	3.598***	0.067	0.982	0.814	0.640	4.287***
	(1.231)	(3.775)	(2.740)	(0.861)	(2.187)	(0.704)	(1.575)	(0.755)	(1.420)
Unemployment Rate	0.028	0.068	0.021	0.073**	0.015	0.046**	0.052**	0.051***	(0.007)
	(0.019)	(0.048)	(0.024)	(0.029)	(0.023)	(0.019)	(0.025)	(0.016)	(0.036)
Law enforcement officers	0.001	-0.002*	0.001	-0.001	0.002	0.000	0.000	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	0.000	(0.001)	(0.001)	(0.001)
Law enforcement civilians	-0.004**	0.005	0.000	-0.001	-0.006***	0.000	-0.001	0.000	0.001
	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Income per Capita	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.94	0.867	0.887	0.966	0.941	0.929	0.937	0.934	0.948
Observations	279	289	287	289	281	284	286	286	289

Notes: Dependent variable is the logarithm of the number of offenses per 100,000 inhabitants; Evacuation due to Katrina is an interaction term between evacuation ratio (defined as number of evacuees divided by population of MSA) and post-Hurricane years 2005-2006. Each regression include MSA fixed effects and yearly dummies. The standard errors are clustered by state and presented in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

Table A3. Effects of Migration due to Hurricane Katrina; Estimates with a Dummy Variable for Katrina Evacuation

	Larceny-Theft	Violent Crime	Robbery	Motor Vehicle Theft	Forcible Rape	Aggravated Assault	Burglary	Murder and Non-negligent Manslaughter	Property Crime
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Katrina Evacuation	-209.558	206.082*	61.735*	265.123	5.579	140.188	-10.733	0.519	44.714
	(178.962)	(102.166)	(31.808)	(160.352)	(5.983)	(81.920)	(87.036)	(0.716)	(240.265)
Unemployment Rate	140.942**	17.977	8.507*	-3.864	0.754	7.983	34.991#	0.189	172.062#
	(58.900)	(13.197)	(4.552)	(38.043)	(1.013)	(10.026)	(21.693)	(0.218)	(106.364)
Law enforcement officers	5.644**	-0.381	-0.094	0.669	-0.005	-0.286	1.516*	-0.014	7.830*
	(2.112)	(0.665)	(0.176)	(0.997)	(0.048)	(0.650)	(0.749)	(0.010)	(3.600)
Law enforcement civilians	5.212#	-0.884	0.042	5.042**	-0.020	-0.954	0.228	0.031***	10.481**
	(2.940)	(0.829)	(0.423)	(1.902)	(0.066)	(0.557)	(1.348)	(0.008)	(4.174)
Income per Capita	0.044	0.007	0.004**	0.018*	0.001**	0.003	0.010	0.000	0.072#
	(0.032)	(0.005)	(0.001)	(0.010)	(0.000)	(0.004)	(0.009)	(0.000)	(0.046)
R-squared	0.969	0.959	0.977	0.956	0.925	0.931	0.956	0.957	0.971
Observations	61	60	61	61	61	60	61	61	61

Notes: Distance dummy equals 1 if $Distance > {}^{1}/_{2}\, Distance^{max}$, and 0 otherwise. $Distance^{max}$ = 2,724 miles (Seattle-Tacoma-Bellevue, WA). Half-distance cut-off point = 1,279 miles (Sioux Falls, SC). The robust standard errors are in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

Table A4. The Dependency of Various Evacuees' Characteristics on their Distance to New Orleans, LA

Dependent variable(s)	Independent variable: Distance to New Orleans, 1,000 miles	Independent variable: Distance Dummy
Age, years	-3.28*	-4.80*
	(1.67)	(2.85)
Household size, # of people	-0.04	-0.05
	(0.17)	(0.32)
Log (Income), $	-0.06	-0.14
	(0.10)	(0.21)
Education (1 if High school graduate diploma GED or better, 0 otherwise)	0. 03	0.03
	(0.04)	(0.08)
White (1 if race=white, 0 otherwise)	-0. 03	-0.02
	(0.04)	(0.07)
Black (1 if race=black, 0 otherwise)	0.04	0.05
	(0.04)	(0.07)
Male (1 if sex=male, 0 otherwise)	0.01	0.07
	(0.46)	(0.46)

Notes: The table shows the slope coefficients from regressing various dependent variables (left column) on distance to New Orleans, LA. Distance dummy equals 1 if $Distance > {}^{1}/_{2}\, Distance^{max}$ and 0 otherwise. $Distance^{max}$ = 2,724 miles (Seattle-Tacoma-Bellevue, WA). Half-distance cut-off point = 1,279 miles (Sioux Falls, SC). The robust standard errors are in parentheses. *** indicates statistical significance at the .01 level; ** at the .05 level; * at the .10 level.

CONCLUSION

The chapters included examined, separately, the effects of changes due to the recent implementation of the 2010 Patient Protection and Affordable Care Act on hospital industry and the consequences of forced population migration caused by the Hurricane Katrina on various crime types in the areas of destination for evacuees.

Using a rich 2000-2008 panel data set of 117 hospitals in Tennessee, the study of hospital industry presented in the first chapter produced baseline estimates against which hospital cost behaviors can be compared following full implementation of the Obama's health care reform. Knowledge of the shape of hospital technology cost structure is crucial to having a correct understanding of quality and production incentives affecting value-based reimbursements for the health care provided and managerial resource allocation decisions of service providers.

The core contributions of this study include describing long-run hospital cost structure with outputs defined as cases by payer and a large number of controls for quality and patient mix, decomposing the effects of technological advances on costs, assessing cost efficiency possibilities through opportunities for scale and scope economies, and evaluating input substitution possibilities as factor market prices change. Other contributions of this work include evaluating the cost-quality tradeoff (e.g., accreditations by both JACHO and ACSCC, and medical school teaching affiliation, found as significant proxies for hospital care quality, are cost-increasing. Membership in AHA reduces costs perhaps because it is industry-specific, and that it enhances access to wide ranging resources with additional incentives for efficiency improvements). The estimated own-price, Allen-Uzawa, Morishima, and Shadow substitution elasticities indicate inelastic demand for labor and broadly defined supplies. The input factors categories (capital, labor, energy, supplies, and non-operating inputs) are substitutes in the long-run regardless of the conceptual measure of pair-wise factor substitution. The data rejected Hicks-neutrality, and technical progress is supplies-using and marginally worker-saving. The scale-augmenting part of technical change effect is entirely due to diseconomies of scale in the production of patients with private insurance, and regional location affects production cost.

Moreover, consistent with the emerging provider reimbursement policy environment, the flexible production cost model incorporates multi-dimensional hospital quality considerations. To the present knowledge, this study is the first to model the shape of hospital production technology with the outputs defined by payment source. Significant operational scale economies evaluated along the mean expansion path were found, which indicate cost-beneficial scale advantages for the typical hospital. Hospital production occurs in the range of increasing returns suggesting that efficiency gains are achievable by concentrating care in existing hospitals instead of increasing investments in new hospitals with market expansion, or by consolidating hospital departments in Tennessee, given the current demand for hospital care. Finally, there are unexploited scope economies (e.g., hospitals can reduce unit cost by jointly treating commercial insurance and Tenncare/Medicaid patients). The research results unveiled here are relevant in the context of rising hospital provision of healthcare services as implementation of the 2010 ACA intensifies.

The research presented in the second chapter provided the first empirical evaluation of the link between the Hurricane Katrina and crime rates in the U.S. and shows that at the regional level, Katrina is associated with higher violent crime due to increases in murder and non-negligent manslaughter and robbery, and higher property crime due to increases in motor vehicle theft.

The analysis on Houston uncovered in depth insights on the connection between Katrina evacuation and crime, as Houston welcomed the most disadvantaged individuals who were left behind. Not only did the City witnessed more murders, but also significantly more aggravated assaults, more illegal possessions of weapons, and more incidences of arson. According to federal guidelines, FEMA pays for emergency protective measures, such as police and fire overtime, for the first 72 hours of a disaster. These results suggested that the federal provision might not be enough to adequately keep criminal behavior under control in areas where evacuees are being relocated.

The federal and local governments provided shelters, housing and meal vouchers for the evacuees. However, following the natural disaster, no initial actions were taken to protect the local residents living in the areas that welcomed the evacuees, and longer-term responses proved inadequate to prevent a significant rise in certain types of crime. This study raises questions not only about how best to protect vulnerable populations in future disasters, but also about the appropriate policies designed to protect the populations welcoming the evacuees. Moreover, the Houston analysis warns that concentrating the low-income, low-educated, disadvantaged evacuees in poor subsidized neighborhoods was possibly responsible for generating disruptions and criminal activities in the destination areas. Previous research indicates that crime rates tend to be higher in lower class communities as compared to middle and upper class communities. The factors that have been identified as contributing to the higher levels of crime among the lower class communities are poverty and unemployment.

While the regional and local analyses bring strong evidence of the relationship between Katrina migration and increases in local crime, they offer insufficient evidence indicating whether these crimes were committed by the evacuees or triggered by their presence, due to lack of arrest or incarceration data on Katrina evacuees. Furthermore, the study is unable to determine whether migration had a positive or negative effect (in terms of likelihood of engaging in criminal activity) on the evacuees themselves.

More generally, Hurricane Katrina has provided a rare opportunity to study the impact of immigration on crime in a situation where individuals did not choose to migrate, but where this occurrence was necessitated by a catastrophic event. The traditional literature investigating the relationship between immigration and local crime rates has resulted in a wide range of estimates possibly due to endogeneity issues. This study suggests that there are significant effects of immigration on several types of local crime rates, a result that is robust to both national and local (Houston) settings and the use of 2SLS for calculation of instrumental variable estimates and other estimation methods (LIML) to overcome remaining endogeneity. Furthermore, existing studies that exploit policy experiments to investigate outcomes resulting from migration (usually between neighborhoods and/or schools within a metropolitan area) necessarily focus on a specific population and track outcomes among those who have moved, rather than focusing on the effects of migration on those living in destination areas. The study's findings underscore the importance of not overlooking negative spillover effects on the local environment by focusing on crime, another important determinant of economic viability.

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