THE SUPPLY AND DEMAND OF PHYSICIAN ASSISTANTS IN THE UNITED STATES: A TREND ANALYSIS

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The supply of non-physician clinicians (NPCs), such as physician assistant (PAs), could significantly influence demand requirements in medical workforce projections. This study predicts supply of and demand for PAs from 2006 to 2020. The PA supply model utilized the number of certified PAs, the educational capacity (at 10% and 25% expansion) with assumed attrition rates, and retirement assumptions. Gross domestic product (GDP) chained in 2000 dollar and US population were utilized in a transfer function trend analyses with the number of PAs as the dependent variable for the PA demand model.

Historical analyses revealed strong correlations between GDP and US population with the number of PAs. The number of currently certified PAs represents approximately 75% of the projected demand. At 10% growth, the supply and demand equilibrium for PAs will be reached in 2012. A 25% increase in new entrants causes equilibrium to be met one year earlier.

Robust application trends in PA education enrollment (2.2 applicants per seat for PAs is the same as for allopathic medical school applicants) support predicted increases. However, other implications for the PA educational institutions include recruitment and retention of qualified faculty, clinical site maintenance and diversity of matriculates. Further research on factors affecting the supply and demand for PAs is needed in the areas of retirement age rates, gender, and lifestyle influences. Specialization trends and visit intensity levels are potential variables.

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LIST OF ABBREVIATIONS

AAPA	American Academy of Physician Assistants
ACGME	American Council on Graduate Medical Education
AMA	American Medical Association
APAP	Association of Physician Assistant Programs
CDS	Chronic Disease Score
CNM	Certified Nurse Midwives
CNS	Certified Nurse Specialist
COGME	Council on Graduate Medical Education
COTH	Council of Teaching Hospitals
CPT	Current Procedural Terminology
ED	Emergency Department
EPSDT	Early/Periodic Screening and Diagnostic Testing
HMO	Health Maintenance Organization
ICD-9	International Classification of Diseases: 9th Revision
IPMUS	Integrated Public Use Microdata Series
ISS	Injury Severity Score
LOS	Length of Stay
MEPS	Medical Expenditure Panel Survey
MCO	Managed Care Organization
MSC	Multispecialty Clinic
NAMCS	National Ambulatory Medical Care Survey
NCCPA	National Commission on the Certification of Physician Assistants
NHAMCS	National Hospital Ambulatory Medical Care Survey
NHSC	National Health Service Corps
NIA	National Institute on Aging
NMES	National Medical Expenditure Survey
NP	Nurse Practitioner
NPC	Non-physician clinician

OTA	Office of Technology Assessment
PA	Physician Assistant
PAEA	Physician Assistant Education Association
PPRC	Physician Payment Review Commission
PT	Physical Therapist

CHAPTER I

INTRODUCTION TO THE STUDY PROBLEM

Introduction

The physician assistant (PA) profession and its role in the delivery of care in the US continues to expand as the debate of the physician workforce flourishes. As of 2006, 70,612 individuals were ever eligible to practice as PAs according to the American Academy of Physician Assistants (AAPA) and approximately 65,000 were clinically active (American Academy of Physician Assistants, 2006a). While the majority of healthcare workforce researchers concentrate on physician components, attention to nonphysician clinicians (NPCs) such as PAs remains an area poorly studied in terms of supply and demand. Calls for a more detailed look at the PA profession have yet to be answered (Cooper, 1995; Cooper, 2004; Council on Graduate Medical Education, 2005; Mullan, Rivo, & Politzer, 1993). This dissertation is an analysis of the supply of and demand for PAs, as it relates to the healthcare workforce of the US. Factors affecting these dynamics are examined and utilized to develop forecast models to comparatively assess their implications over the next fifteen years.

Background

The establishment of the PA profession in the US occurred in 1967 with the graduation of 3 PAs from the first program to formally train PAs in primary care. This event followed the convergence of a number of social, political, and medical policy shifts that included the return of former medics and corpsmen from the Viet Nam War, a social zeal for correcting the inequities of poverty during the Great Depression, the period of the sixties and its social revolution, and a belief that technology could solve many problems. Over the ensuing decades the emergence of the PA has met with varying levels of acceptance and integration as the profession moved from its infancy to its attainment of "professional" status (Cawley, 1996). Envisioned as new generalist providers of healthcare, the first PA students were recruited from the ranks of veterans. Following a suggestion by Hudson, then the President of the National Board of Medical Examiners, the first students were trained in a condensed educational program paralleling that of their future physician employers. Noting changes in medical labor/hospital staffing demands and advancing technology, he fostered the idea that has ultimately become the PA of today (Hudson, 1961). Following the development of the first program at Duke University School of Medicine, other programs were established to train providers that would enhance access to basic medical care service, fill gaps resulting from geographic and specialty maldistribution of physicians, and to control healthcare costs (Jones & Cawley, 1994).

PA scope of practice, governed by state legislation, prohibits PAs from the unlicensed practice of medicine and stipulates that they function under the supervision of a licensed physician. This dependent role and its continued affirmation across the profession is one of the significant differences between PAs and all other types of NPCs. Because of the similarities in physician and PA training, the PA profession reflects its commitment to practice under the supervision of a licensed physician in its definition. This commitment has resulted in wider support from medicine as evidenced by the American Medical Association (AMA) Guidelines for Physician/Physician Assistant Practice, American Academy of Family Physician policies, and the Pew Health Professions Commission recommendations. Each of these documents support the continuation of the traditional physician-PA team in which PAs regularly consult with, refer to and are supervised by their physician colleague.(American Academy of Family Physicians, 1997; American Medical Association, 1998; The Pew Health Professions Commission, 1998)

The sociocultural shifts that gave rise to the PA profession in the 1960's are paralleled in scope and tumult in today's healthcare environment. Despite multiple reports of physician surpluses, what has emerged is a shortage of both primary care and specialty physicians (Cooper, 2004; Cooper, Getzen, McKee, & Laud, 2002; Council on Graduate Medical Education, 2005). Continued escalation of healthcare expenditures and recognition of growing health disparity in this country contribute to the shaping of the healthcare workforce of the 21st century. A number of factors can be implicated; the changing demographics of the nation's population, the unprecedented pace of biomedical breakthroughs, and productivity in the delivery of healthcare represent the major contributors to overall cost escalations. The potential of PAs to reduce the impending shortages and their ability to contribute cost effective healthcare has led to increased interest in the supply of and demand for these providers. This work contributes the first known analysis of the PA workforce as it exists in 2006 and projects its possible evolution over the next fifteen years.

In an attempt to clarify the issues in healthcare workforce policy development and reform, McLaughlin suggested dividing the discussion into three thematic issues: demand for healthcare services, the supply of healthcare professionals, and the roles/responsibilities of policy makers in regard to supply and demand. The demand side of the equation is influenced by both micro and macro-level factors. On the micro level, patient real or perceived need for services is a major driving force of healthcare demand. Age, socioeconomic status, health status, and prevalence of disease contribute to a significant degree. The demand for healthcare service is also influenced by a person's access to services and their degree of insurance coverage. Other factors include the patient's personal understanding of the medical condition and its available treatment, medical advances in technology, and practitioner preferences (McLaughlin, 1994).

The aging of American society represents the single most significant macro-level factor affecting the demand for healthcare services. Representing eight percent of the US population in 1950, the elderly are projected to account for over 17% by the year 2020. The rising levels of sustained chronic diseases such as hypertension, diabetes, and obesity will amplify the impact of this aged cohort. Other important macro level factors that influence heath care service demand include the organization of the healthcare market and its financial structure, roles that various health professionals play within the delivery system, and the level of health technology advances (McLaughlin, 1994).

The supply side determinants of the health workforce encompass the geographic location of providers, the number and type of students in health education programs, the number and capacity of such programs, retention rates, retirement rates and level of productivity of various providers. Despite a variety of attempts to correct the geographic maldistribution of physicians, many rural and urban Americans lack sufficient access to healthcare services (McLaughlin, 1994). Since the turn of the 21st century the majority of workforce researchers suggest that shortages of both primary care and specialist physicians will occur by 2015. While medical school enrollment has been expanded since the late 1990's, other health profession schools are varied in terms of enrollment and capacity. Retention and retirement rates for other professions such as PAs need further examination as do productivity levels (Cooper, 2001; Cooper, 2004; Council on Graduate Medical Education, 2005; Goodman, 2004; Sox, 2004).

Several interested parties have roles and responsibilities in the development of healthcare policy. The federal and state governments actively participate through initiatives such as Titles VII and VIII of the Public Health Service Act, grants, scholarships, loans and loan repayment programs to influence and support the educational institutions training future healthcare providers including PAs. Federal legislative initiatives, such as the National Health Service Corps, addresses geographic maldistribution. The Council on Graduate Medical Education (COGME) continually assesses the state of the US health workforce. State governments' oversight of Medicaid expenditures and reimbursement, licensing and creditentialing of providers and regulation of scope of practice issues provides the basis of its role. Academic institutions and professional organizations provide the necessary information to inform policy maker decisions on the various supply dimensions, anticipated changes in demographics, and evolution of roles within the healthcare delivery system (McLaughlin, 1994).

The analysis herein applies a similar approach to the examination of the PA workforce. It examines factors contributing to the demand for these healthcare professionals, the supply capacity of its educational programs, and provides interested parties much needed information for policy determinations.

Problem Statement

One of COGME's central charges is to make policy recommendations with respect to the adequacy of the supply and distribution of physicians in the US. Utilizing existing models to forecast physician supply and demand, COGME's reassessment seeks to guide decisions by the medical education community, policy makers, and others concerned with the health of Americans. This report acknowledges its inability to consider the contributions of PAs and other NPCs in healthcare delivery. It further recognizes that these contributions have the potential to reduce the projected shortages (Council on Graduate Medical Education, 2005).

While the PA educational and professional organizations provide ongoing support and information to assist in the development of national health workforce policy, to date no attempts have been made to provide projections of the demand for or supply of PAs. While individual research efforts have encompassed several of the leading factors influencing the supply of and demand for physicians in the US, no single effort has extended these findings to investigate the impact on the future of the PA workforce. This lack effectively causes national recommendations, such as those suggested by COGME, to exclude the effect of PA practice on the Nation's delivery of healthcare.

Attempts to forecast the future US medical workforce encompass a variety of methodologies and assumptions including needs-based models, demand or utilization-based models, and benchmarking or requirements models. These models focus their predictions on the premise that specific components of the workforce (primarily its physician component) could be quantified, associated with full time equivalents and that this greater detail would lead to greater medical workforce predictive accuracy. While each of these methodologies differs in design, all represent micro-analytic approaches that focus on what *ought* to occur in the workforce and have extensive data requirements (more fully delineated in Chapter II). Of note, each of these methodologies arrived at similar predictions of physician workforce oversupply by 15% to 30% by the year 2000, predictions which never manifested (Cooper et al., 2002; Council on Graduate Medical Education, 2005). Equally important, the most often used national databases required by these methodologies do not accurately account for PA utilization, thus making them unsuitable for the examination of PA workforce issues (Morgan, Strand, Ostbye, & Albanese, 2007).

In contrast, Cooper adopted a macro-analytic approach that attempts to define what is *most likely* to occur in the workforce. Based on historical long-term economic and demographic trends, this methodology links the demand for healthcare services to the growth of the economy expressed in terms of economic well-being using gross domestic product (GDP) with number of physicians per 100,000 population. The results are then compared to supply projections based on the number of new entrants into the profession, work effort, retirement, mortality, and attrition rates. Even with significantly fewer data requirements, Cooper's predictions have demonstrated a higher level of accuracy than the micro-analytic approaches discussed above. Given the constraints of available data sources reflective of PA practice, the approach to healthcare workforce supply and demand championed by Cooper and colleagues is considered applicable to this endeavor.

In addition, Cooper's trend model provides the most parsimonious approach to health workforce forecasting. Through the elimination of "dissecting and reconstituting the healthcare system . . .to the metric of time," the errors associated with predictions of utilization rates, diseases rates, and derivation of full time equivalents is minimized (Cooper, 2000), page 88). This simplicity coupled with its noted accuracy makes it an appropriate approach for this initial effort in PA workforce forecasting.

Research Question and Objectives

No research currently exists that examines the demand for PA services and the relationship to its supply. With the growing number of studies suggesting shortages of their physician colleagues in both primary care and specialty practice, PAs have an increasing role in the solution to providing adequate levels of healthcare delivery. Given the increased utilization of PAs in the US and the need for more accurate estimation of the US health workforce as a whole, the research question posed is:

> "Will the projected supply of PAs in the US meet the projected demand over the next fifteen years?"

The following objectives were established as the focus of this dissertation:

1) Describe the current status of PA practice in the US to include:
    a) demographic composition and distribution trends
    b) practice selection by specialty and practice setting trends
    c) scope of practice prerogatives effecting PA utilization
2) Delineate a demand model for the utilization of PAs that utilizes:
    a) the past and future estimates of gross domestic product as chained in 2000 dollar
    b) the past and future estimates of US population growth
3) Delineate a supply model for the PA profession that utilizes:

a) the current pool of certified PAs

b) educational institution capacity and assumed attrition rates

c) assumptions for retirement rates

4) Utilize the developed models to consider whether the demand for PA services would be met by supply based on *status quo*, a 10% increase and a 25% increase in institutional capacity as alternative scenarios.

5) Discuss the implications posed by the results of the developed PA supply and demand prediction models given the alternative scenarios examined.

Professional Significance

The development of PA Supply and Demand Models begins to answer the calls from other healthcare workforce researchers for better understanding of the potential for PAs to reduce the projected physician shortages.(Cooper, 2004; Council on Graduate Medical Education, 2005; Mullan et al., 1993). These projections will enhance discussions concerning workforce issues of a nation faced with rising numbers of elderly, immigrants, and underinsured. This expansion on what is likely to occur in the demand for PAs and considering supply projections provides the PA educational community information as they develop strategic plans for enrollment initiatives.

Consideration of this study's implications will provide a much needed plank in the discussion platform of healthcare delivery in the US. A forecast offers interested parties a more detailed examination of a portion of the healthcare workforce that has previously been acknowledged as part of the solution to the anticipated shortages in primary and specialty healthcare. As workforce researchers, medical professional organizations, and policy makers continue to assess the ability of the US to meet the healthcare needs of its residents, this study contributes to the understanding of how PAs will fit into the equation. This forecast serves as a catalyst for the PA community of researchers to consider efforts that would further extend the understanding of the factors that affect the supply of and demand for PA services.

Overview of Data Sources and Methodologies

Data Sources

The American Academy of Physician Assistants (AAPA) is the national professional organization for PAs. The Academy's Research Division conducts a variety of annual surveys to include clinically active PA census, membership census, and student census. The Academy is recognized for its maintenance of a remarkably complete and highly reliable master file and series of databases. Results provided in the annual census survey were extracted to describe the current status of the PA profession. Historical values required for the development of the demand model were also extracted.

The Physician Assistant Education Association (PAEA) is the national organization representing PA educational programs. Its *Annual Report on Physician Assistant Educational Programs in the US* provides comprehensive analyses of institutional, faculty, and student characteristics to include annual attrition rates. The *Directory of Physician Assistant Programs* is a resource on institutional capacity. These PAEA publications were utilized to obtain the required variable values in the development of the PA Supply Model.

The National Commission on the Certification of Physician Assistants (NCCPA) is the only credentialing organization for PAs in the US. As all states require NCCPA certification of PAs for licensure and the right to prescribe medications, the database maintained by the organization contains information on all PAs eligible to practice medicine. Data on gender, birth date, geographic location, and self-reported practice specialty for each currently certified PA were obtained. The total number of certified PAs and birth date provide the base year values for the supply model. The other data points contributed to the description of the current status of the PA profession.

The Bureau of Economic Analysis (BEA) provides annual estimates of national income and product accounts (NIPAs) that include estimates of current-dollar gross domestic product (GDP) and real (inflation-adjusted) GDP. These estimates are made available for public use on the BEA website in *Excel* spreadsheets that can easily be transferred to other statistical software databases for the purposes of analyses. The real GDP estimates were utilized to examine the long term trends in relation to PA demand.

The Integrated Public Use Microdata Series (IPUMS) is a coherent national database that combines census microdata files produced by the US Census Bureau for the period since 1960 with new historical census files produced at the University of Minnesota and elsewhere. The IPUMS is designed to facilitate the use of the census samples as a time series and provides both the database and the documentation through an on-line data access system. Population estimates required to consider the ratio of PAs to population occurring over the last decade and for future projections were obtained from this source.

Methodologies

To describe the current status of the PA profession, secondary data analyses of the preceding ten years of the AAPA census survey data were conducted. Descriptive statistics and frequency tables were analyzed to provide the demographic composition, distribution trends, and practice selection trends by specialty and practice setting.

Representing a modification of Cooper's "Trend Model," the PA Demand Model considered the number of PAs per 100,000 population as the dependent variable (PA-Demand) with GDP and US population trends as the predictor variables. Values for PA-Demand were derived utilizing historical numbers reported by AAPA divided by the US population as reported by the IPUMS. The predictor variable values were obtained from public use data files of the IPUMS and the BEA. Time series analysis techniques were performed and 15-year forecasts obtained using SAS/ETS® Version 9.1.

The future supply of PAs is a function of the number of currently eligible PAs, the number of PAs that will be produced by educational institutions minus those lost to attrition, and losses due to the retirement or mortality of the overall eligible PA pool. The PA Supply Model base year 2006 began with the number of PAs eligible to practice in the US as represented by the number currently maintaining national certification, as reported by the NCCPA. This baseline number of PAs was adjusted to reflect the estimated number of PAs entering and exiting the workforce for each year of the forecast. Using the PAEA annual report and program directory, the anticipated annual number of new graduates (by age and gender), with attrition rates applied, was added to the pool of PAs eligible to practice. For each forecast year, the pool was aged and assumed retirement rates applied. As no data exists on retirement of PAs, an assumed retirement age of 68 was utilized. Final values were expressed as number of PAs per 100,000 population. These processes provided the estimated number of PAs eligible to practice and thus deliver healthcare services for each forecast year. Three supply scenarios were developed using these methods to reflect no change (*status quo*) in PA education institution capacity, a 10% increase and a 25% increase.

Consideration of the implications of these analyses began with the comparison of the projected supply scenarios to that of the projected demand for PA services. The current status of PA demographic composition, distribution, practice selection by specialty and practice setting were extrapolated to future time points at 5 year intervals. The impact of the various predictions to the overall delivery of healthcare in the US is discussed with recommendations for future research suggested.

Limitations

A number of factors regarding PA practice remain to be elucidated in regard to the predictions of overall supply of PAs eligible to deliver healthcare services in the US, thereby limiting the scope of the current study. These factors include activity rates of currently certified PAs, work effort trends of the current and future generation of PAs, the affect of the feminization of the profession, retirement and mortality rates.

Like their physician colleagues, PAs are involved in a variety of activities outside that of patient care including PA education, research, and administration. This activity rate affects the number of available PAs to provide direct patient care. Furthermore, changes in the distribution of activities will have an effect on the overall supply of PAs. The use of the number of currently certified PAs as a proxy for those available to provide direct healthcare services likely overestimates the supply of PAs, however, no studies examining the activity of PAs have been conducted to account for these effects.

Studies on the physician workforce suggest a trend in changing lifestyles of the newest entrants with a predilection towards decreased work effort and plans for retirement at an earlier age in comparison to their predecessors. In addition, female physicians tend to work fewer hours over the course of their professional careers than men (Council on Graduate Medical Education, 2005). Whether or not female PAs work fewer hours has not yet been researched. While the AAPA has begun collection of work effort in terms of number of hours per week and number of patients seen, trend analyses based on age, gender, and year of entry into the profession have not been conducted or published. In addition, the currently available databases maintained by the three major professional organizations (AAPA, PAEA, and NCCPA) do not collect data regarding age at retirement or future retirement plans. This lack of available data constrained the scope of considerations in the present study.

Modeling demand using a time-series analytic approach requires historical data to produce future forecasts or projections. It would be desirable to test the developed PA Demand Model accuracy by taking early historical data points and project over a period that has already occurred. The relative youth of the PA profession and its early slow growth precluded the ability to assess PA Demand Model's accuracy retrospectively at different points in time over the past decades.

Delimitations

Various assumptions serve as the delimitations of this study. These include retirement rates of PAs from active practice, attrition rate of matriculated PA students, and productivity factors.

As retirement rate trends have not been adequately documented in the PA literature, the proposed trend analyses will assume retirement of PAs to be at the age of 67. This assumption is made without regard to gender or age at entry into the profession and is based on Social Security data that most individuals will retire by age 67.

As actual graduation numbers of PAs are not reported in aggregate form, it was necessary to use anticipated matriculation capacity to add to the pool of PA supply for each forecast year. To more accurately reflect measures of PA supply, the attrition rate of matriculated PA students was assumed to be 7%. This level reflects a compromise between the twenty year trend in PA education and a lower rate seen in the last two years.

Although physician workforce models consider that productivity levels vary by gender, age, life-style, employment status, and efficiency, little research has been conducted in this area for the PA profession. While physician levels may be reflected in PA practice, no assumptions were applied in this regard.

Key Term Definitions

The following alphabetical listing of key terms is provided to ensure consistency of interpretation.

Demand: a term used to describe the projected size of labor force that will be required in order to deliver the quantity of service that is predicted, expressed relative to the number of active PAs per 100,000 population.

Modeling: finding a suitable statistical model to describe the data-generating process used to forecast future values. A *univariate* model is based only on the past values of the variable of interest while *multivariate* models are based on the past values of the interest variable and also on past values of other predicator or explanatory variables.

Nonphysician clinicians: a term applied to a group of licensed professionals who have in common the authority to be the point of first contact for patients, to take the principal responsibility for the care of patients and to provide elements of care that fall within the "practice of medicine." Professionals included in this aggregate term include PAs, NPs, certified nurse-midwives, clinical nurse specialists, nurse anesthetists, optometrists, podiatrists, and the alternative disciplines of chiropractic, acupuncture and naturopathy.

Physician assistant: healthcare professionals licensed to practice medicine with physician supervision. PAs conduct physical exams, diagnose and treat illnesses, order and interpret tests, counsel on preventive healthcare, assist in surgery, and in virtually all states can write prescriptions.

Primary care: the group of medical practices encompassed by family/general medicine, general internal medicine, pediatrics, and obstetrics/gynecology.

Supply: the number of active PAs who will be in the labor forces relative to the base year of 2006, extrapolated based on the number who are currently certified, the number of PA graduates, and the number who leave the profession due to retirement.

Substitution rate: the amount of healthcare services a nonphysician clinician provides relative to physician delivery of the same service.

Time-series: a set of observations measured sequentially through time, taken at discrete set of time points or continuously.

Trend: The type of variation present in a time-series that exhibits steady upward growth or downward declines over several successive time periods.

Summary

Research about the supply of and demand for PAs in the US has not been undertaken. Having provided an overview for the need of such an examination, a brief introduction to the PA profession and a limited review of healthcare workforce approaches, an outline of the research question and objectives was delineated. Chapter II extends these concepts through the review of relevant literature.

CHAPTER II

LITERATURE REVIEW

Introduction

A historical perspective of physician workforce investigation and the development of various approaches used to project its adequacy to meet the healthcare needs of Americans set the stage for the explicit examination and projection of the supply of and demand for PAs in the US. Following a justification for the selection of the Cooper trend model and its conceptual framework, this literature review focuses on its application to this physician assistant (PA) workforce analysis. Understanding the current thinking on the utilization of nonphysician clinicians (NPCs) and their adequacy of service provides the background required to support the establishment of PA workforce projections. Expounding on the trends affecting the supply and demand of healthcare professionals provides the underpinnings for the proposed workforce projection variables. In particular the trends of provider productivity, attrition from the profession, the US economy and the changing US population demographics are examined. Constraints on the training of PAs are delineated through the discussion of the PA educational system as the provider of new PAs and the effect of attrition rates on future projections. Discussion of the fiscal constraints on healthcare spending such as Medicare and Medicaid expenditures completes the review.

Physician Workforce Studies in the US

The interest in physician workforce studies in the US gained considerable momentum during the mid-1900's and has continued into the 21st century. Historically, the projected shortage of physicians in primary care and the geographic maldistribution of physicians gave rise to the “initial demand” for PAs. In response to this demand, the PA profession became a reality. Because PAs are dependent practitioners required to work under the supervision of physicians, the demand for PAs is closely linked to that of their physician colleagues. A clear understanding of the past and current physician workforce projections is required in order to extend the discussion to that of the PA workforce. In addition, the following historical perspective on physician workforce analysis illustrates the various approaches undertaken in these efforts.

Prior to the early twentieth century, the US healthcare system was more or less a traditional free market for physician services, largely devoid of third-party payment systems with patients incurring most of the healthcare costs. The publication of the Flexner report *Medical Education in the US and Canada* in 1910 marked the first distinct shift in physician workforce policy. In the decade following its release, over 30 medical schools were closed, resulting in a drop from 175 physicians per 100,000 population to 125 per 100,000 by 1930. While geographic maldistribution of the physician supply was documented particularly in rural America, Grumbach suggested that planners of the era “conveniently sidestepped complicated computations of physician requirements involving interactions among supply, productivity, service delivery, and health outcomes” (Grumbach, 2002), page 17).

Following World War II, pressures from society at large pushed for increases in the supply of physicians, not only from swelling enrollments at the undergraduate level demanding more opportunities for medical school seats but also from rural and medically underserved communities in need of more physician coverage. While little growth in the number of medical schools or graduation rates resulted in the near term, the publication of the “Bane report” in 1959 shocked the public and the medical community by projecting a nationwide shortfall of nearly 40,000 physicians by 1975. Advocating the increase of the number of medical school graduates from the existing 7,400 per year to 11,000 over the next twenty-years, the report became the catalyst for passage of the Health Professions Educational Assistance Act of 1963 and marked the beginnings of intense focus on health workforce projections in the US As a result of federal assistance, the number of medical schools grew from 87 to 126 from 1963 to 1980. The number of graduates correspondingly increased from 7,264 to near 16,000 (Ludmerer, 1999).

During this post-war period, the broader cultural change in which medical care became viewed as a basic right was realized in the establishment of the Social Security Act. An abundant supply of well-trained physicians was deemed necessary to meet the needs of the public health. Noted economist, Eli Ginzberg cautioned at the time, that the demand for medical care might be limitless and that producing more physicians might increase the costs of medical care without appreciably improving the nation’s health, a warning still much ignored in today’s healthcare delivery system. He went on to criticize the lack of scientific basis of supply and demand for physician services in either the pre- or post- WWII efforts in this regard (Blumenthal, 2004; Ginzberg, 1989; Ludmerer, 1999).

The 1963-1990 era of increased physician supply was also supported by Medicare funding of graduate medical education. This, coupled with prior legislative support, marked the first time the US federal government became heavily invested in medical education and physician supply. During the Carter administration, the Graduate

Medical Education National Advisory Committee (GMENAC) made dramatic efforts to analyze in detail the expected healthcare needs for the US The resultant needs-based workforce policy attempted to forecast supply and demand for physicians for the years 1990 and 2000. Its detailed projections of the required supply by individual specialty concluded that excesses in physician supply were fast approaching. GMENAC recommended curtailment of medical school enrollments and the numbers of international medical graduates (IMGs) utilized within the system. The Reagan administration that followed more narrowly defined government's role in physician supply issues and focused on the continued maldistribution of the supply with its introduction of the National Health Service Corps (Grumbach, 2002). The "promarket, antiplanning mentality" led to no Congressional requests for federal support for health professions programs nor projection of workforce needs. This mentality virtually eliminated scholarly interest in the field (Mullan et al., 1993). Congress responded by discontinuing of federal funding for new physician training; however, it also inadvertently provided teaching hospitals with greater incentives to utilize IMGs in the 1983 Medicare hospital reimbursement reforms. The net result of these reforms was the growth in the number of graduate medical education trainees in the form of IMGs while numbers of US medical school graduates only moderately increased (Blumenthal, 2004).

In 1986, Congress authorized the establishment of the Council on Graduate Medical Education (COGME). Title VII of the Public Health Service Act requires the Council to provide advice and recommendations to the Secretary of the Department of Health and Human Services and to Congress on issues related to the physician workforce. These issues include the supply and distribution of physicians in the US, current and future shortages/excess of physicians by specialty, international medical school graduates, financing of undergraduate and graduate medical education, appropriate efforts to be carried out by hospitals, medical schools and accrediting bodies in light of physician supply as well as deficiencies and needs for improvement in databases concerning physician demand and supply. Since its inception, the Council has produced and released sixteen reports (Council on Graduate Medical Education, 2005).

The COGME Reports of the early 1990s predicted a surplus of about 80,000 physicians by the year 2000, particularly in specialty areas. Over the same period, the number of generalists or primary care physician ranks would remain stable. To stem these problems, the Council recommended policies to ensure that a 50/50 split into generalist and specialty practice occur for all new physician entry. In addition, the Council recommended decreasing the available residency slots from 140% of the number of US medical graduates to 110%, thus limiting the utilization of IMGs. These recommendations, known as the 110/50/50 rule became widely accepted and the basis for much of the response to the physician supply debates of the 1990's (Blumenthal, 2004).

The surplus projections gained further support when reexamined by Weiner's work contracted by the Bureau of Health Professions (BHPr), and COGME's fourth report. Using health maintenance organization staffing models, Weiner projected a 28% surplus or 165,000 physicians by the year 2000. He subsequently revised the predictions raising the percentage to 38% of all practicing physicians by the year 2020 (Weiner, 1994; Weiner, 1995). COGME's fourth report suggested lower values with projected surpluses of 15% or 80,000 physicians by 2000 and 18% by 2020. (Council on Graduate Medical Education, 1994). While using different approaches, each of these studies employed demand-based models rather the needs-based approach of GMENAC. Of note, however, all arrived at similar results. By the mid-1990's, the projections began to trickle down without further federal interventions. This was evidenced by the decreased number of medical students seeking residencies in specialty areas such as anesthesiology and radiology while the number seeking family medicine increased (Grumbach, 2002).

In 1995, Cooper's seminal work "Perspectives on the Physician Workforce to the Year 2020", reevaluated the various reports of physician surpluses of 15% to 30% predicted in the early 1990's in light of his own projections of 10%. The assessments were conducted from three perspectives, that of physician utilization in group and staff-model HMOs, physician distribution and the future supply of NPCs. Using trend analyses and a carefully outlined series of assumptions that included corrections for current population estimates, Cooper recalculated the reports of GMENAC, COGME, Weiner, and the BHPr. The results of these analyses found significantly less surplus in each of the previous reports. The GMENAC surplus projection of 145,000 physicians reduced to 4200, COGME from 80,000 to 60,000, Weiner from 165,000 to 6000, and BHPr from 73,000 to 5000. His own projections remained at 31,000. Accounting for the discrepancies among the various studies were variations in the estimates of physician work efforts, underreporting of physician utilization, the increased demand for beneficial services over time, population reports and the utilization of resident physicians. Cooper furthered the debate on supply and demand of physicians by including geographic distribution analyses that demonstrated significant surpluses in the Boston-Washington corridor, normative values for much of the East-West states, and significantly lower per capita rates in the central zone of the US. He concluded that while differences existed, the solutions would be local rather than national in scope.

Finally, the author turned attention to the growing number of NPCs and their potential impact on the debate. Noting the differences in the three broad categories of these types of providers, [a) advanced practice nurses (APNs) and PAs, b) other traditional clinicians such as certified nurse anesthetists, midwives, psychologists and several others, and c) alternative clinicians such as chiropractors, naturopaths, and oriental medicine doctors)], projections of future supply of these providers were formulated. Cooper believed four general conclusions could be made from the exercise he had undertaken. First, HMO analyses allowed the derivation of national norms for physician demand, and suggested an 18% increase over the time frame examined. Second, the supply of physicians expressed in per capita terms would increase faster than national norms for the first 15 years creating a bulge effect around 2000 with the gap narrowing thereafter. Third, distributional shortages (in some areas of the country as much as two fold) continued to exist and could have significant impact on future supply and demand issues. And finally, the impact of the rapid rise in the number of NPCs needed intense examination. Ultimately, he supported the previous suggestions that any future policy needed to incorporate the universe of providers and not just physicians (Cooper, 1995; Mullan et al., 1993). To date no attempts have been conducted to intensely examine the impact of the rising numbers of NPCs. While focused on the PA profession, this dissertation begins this examination.

The Physician Workforce Policy Guidelines for the US, 2000 – 2020 published in January 2005 provides the basis for current thought on the subject at hand (Council on Graduate Medical Education, 2005). Given the current production and practice patterns, the Report noted an expected 24 percent increase in full-time equivalent (FTE) physicians from 781,200 in 2000 to 971,800 in 2020. Two factors, separation due to aging of the physician cohort and the relatively level number of new entrants, will contribute to a considerable slowing of growth after 2010. As population growth is expected to exceed physician growth by 2015, the per capita number of physicians will rise to 301 per 100,000 Americans by 2015, then drop to 298 by the year 2020. The total cohort of physicians in active practice was predicted to be around 1.02 million FTEs in 2020.

The COGME Report noted three major factors as driving forces behind the demand for physicians: 1) the projected 18 percent growth in the US population between 2000 and 2020; b) the aging of the population; and c) the change age-specific per capita physician utilizations rates. In addition, the need for services is projected to grow between 1.09 and 1.17 million physicians by 2020. This need reflects use of service under universal insurance and increased utilization review process. It then examined the projected range of supply against demand and against need. Given the demand assumptions and using midpoints of projections, a shortage of approximately 85,000 physicians would occur by 2020. When considering the projected need for the US, a projected shortage of 96,000 is evident. Additional scenarios were included, many of which will add to the projected shortages above. These included the changing lifestyles of younger physicians who will possibly work fewer hours than their predecessors; the increased use of services by individuals over the age of 45, and economic expansion that contributes to increased utilization. Other factors may limit the shortages such as improved productivity due to advanced technologies and information systems, and decreased amounts of inappropriate or unnecessary services due to more effective utilization review and quality assurance efforts. Finally, a number of factors that could potentially reduce the shortages projected were not included within the Report's scenarios. Specifically, the impact of increases in the supply and utilization of PAs, NPs, and other non-physician clinicians was not considered (Council on Graduate Medical Education, 2005).

Based on the projection of a significant shortage of active physicians, COGME recommended a multi-pronged strategy to overcome its affects. These recommendations included the increase in total enrollment in US medical schools by 15% from the 2002 levels over the next decade coupled with a phased increase in the number of residency/fellowship positions eligible for Medicare funding. The development of a system to track the supply, demand, need and distribution of physicians was called for with a comprehensive reassessment within the next four years. Specialty-specific studies were deemed important to better understand the needs and to inform the educational and policy makers (Council on Graduate Medical Education, 2005). As previously stated, COGME recognized that the growing number of NPCs could reduce the projected shortages. The lack of a coordinated effort focused on factors affecting the supply and demand of these potential contributors effectively stopped COGME from giving due consideration to their potential contribution. The current endeavor will provide much needed information to national organizations charged with projecting the adequacy of healthcare delivery in the US, physician and nonphysician alike.

Health Workforce Forecasting Approaches

Since the early twentieth century, a variety of forecasting models for healthcare personnel have been utilized: simple extrapolation or supply forecasting; needs-based models; demand or utilization-based models; benchmarking models, and econometric (time series or trend) models (Canadian Policy Research Networks, 2002; Dall, 2006; Kolehmainen-Aitken, 1993; O'Brien-Pallas et al., 2001). Within each of these approaches, variations occur as researchers select particular variables of interest for inclusion. A review of these approaches provides justification for the selection of a trend (time-series) approach for the purposes of this dissertation.

Supply forecasting considers the number of personnel at baseline and projects future supply on maintaining the same level of resources. The underlying assumption that the baseline ratio of personnel to population supplied an adequate amount of healthcare services limits the usefulness of this approach. Discouraging further analyses of productivity, the selected ratios are often inappropriate or unrealistic. The supply forecasting methodology, while simple to implement, fails to consider the complexity of relationships inherent to healthcare service demand either at the current or future time period under consideration. Historically, this method provided the basis for the initial projections of physician supply in the US in the early twentieth century but has fallen from favor due to these serious limitations.

Needs-based models, a micro-analytic approach, utilize epidemiologic estimates of disease characteristics and rates as indicators of current and future healthcare needs of the population under consideration. Through the examination of such data as mortality and morbidity rates, norms for the adequate delivery of services to address the disease characteristics, and expert opinion of staffing requirements, service is converted into time requirements. Based on the time requirements, the demand for healthcare providers are modeled based on the age, sex and anticipated need (Canadian Policy Research Networks, 2002; Kolehmainen-Aitken, 1993; O'Brien-Pallas et al., 2001). The requirement of needs-based modeling for substantial data systems, survey capabilities and a wide range of expert opinion to reach consensus effectively limits its utility for specialty focused inquiries. The Graduate Medical Education National Advisory Committee (GMENAC) utilized this type of analysis, projecting a surplus of generalist and specialist physicians by 2000 that failed to occur which has called this methodology into question. While the needs-based approach continues to be utilized, the successors of GMENAC have incorporated other types of methodology to overcome the perceived weaknesses of this approach. In regard to the present project, a recent study that examined the strengths and weakness of existing national healthcare surveys concluded PA practice was frequently under-represented and would required revision to allow accurate estimations (Morgan, Strand, & Ostbye, 2006). Given the previously stated limitations coupled with the lack of robust data sources required for this type of analysis, the needs-based approach to forecast future requirements of PAs was deemed inappropriate.

The most common type of forecasting methodology, utilization or demand-based, considers patterns of service delivery and utilization of health services in determining requirements for future numbers of providers (Dall, 2006; Greenberg & Cultice, 1997;

Goodman & Committee on Pediatric Workforce, 2005). Minimum data requirements for a demand-based model include population projections, trends in healthcare utilization, and trends in delivery patterns. This model assumes that the current trends reflect desirable patterns of delivery and that future population will follow similar trends in utilization rates. Criticisms of this methodology include its neglect of the geographic maldistribution of providers, its normative approach to utilization patterns, and its micro-analytic perspective. The Bureau of Health Professions Physician Requirements Model (Greenberg et al., 1997) incorporates additional data sources representing trends in medical insurance coverage, copays and other economic factors. While population projections and the additional data sources could be utilized for the present investigation, current national databases provide little information concerning trends in the utilization or delivery patterns of PAs. The inherent focus on physicians as providers of care has limited the utility of these databases in examining other types of providers such as PAs. These shortcomings led to the exclusion of this approach for the purposes of this study.

Benchmarking methodologies involve the identification of “best practices” in which relatively low levels of healthcare provider utilization occurs without apparent compromise to the health status of the population. Adjustments for variation in patient characteristics, disease prevalence/severity, practice location, and other key health and socio-economic factors can be made and used in the development of requirement for providers. Rather than assuming stability in the healthcare system, this methodology targets specific geographic areas or health systems such as managed care to representing the future environment. As considerable disagreement can arise from such selections, this methodology is currently utilized as one alternative in the COGME forecasting efforts for the US physician workforce. While “benchmarking” studies have included the utilization of PAs, they are dated and/or practice setting specific, making this choice of methodology less than optimal (Dial, Palsbo, Bergsten, Gabel, & Weiner, 1995; Jacobson, Parker, & Coulter, 1998).

Forecasting with trend analyses seeks to estimate the relationship over time between health personnel demand and its determining factors through the use of various statistical techniques such as time-series regression. Proposed by Cooper for use in estimation of the US physician workforce, this methodology has been utilized by researchers considering workforce requirements by several physician specialty groups (Freed, Nahra, & Wheeler, 2003; Rizza et al., 2003; Shipman, Lurie, & Goodman, 2004). In addition, COGME incorporated this methodology as one of the alternative scenarios in its most recent report on physician requirements (Council on Graduate Medical Education, 2005). This macro-analytic model of long-term trends underlying the supply and utilization of physician services differs from the previously described methods in a number of ways that make this approach suitable for the present endeavor. By assuming historical trends in provider supply reflects the historical demand for healthcare services; it conceptually links supply and demand. Future demand projections based on past trends are compared to separate supply projections for the determination of shortages or surpluses. Because of its macro level perspective, fewer data requirements exist and an aggregate (more parsimonious) model is generated. Such a model appears to be more effective and reproducible, key characteristics desired in any new model developed for the PA profession. Data sources are available that have captured the PA practice characteristics that allow historical trend analysis utilized in this approach. This avoids the use of national surveys that are known to under-represent PA practice productivity, geographic distribution, and utilization patterns (Cooper et al., 2002; Cooper, 2004). Given these differences, a trend model approach was selected for the purposes of this dissertation.

The conceptual framework of the trend model proposed by Cooper (Figure 1) is constructed by the assessment of trends affecting the supply of and demand for physician services.

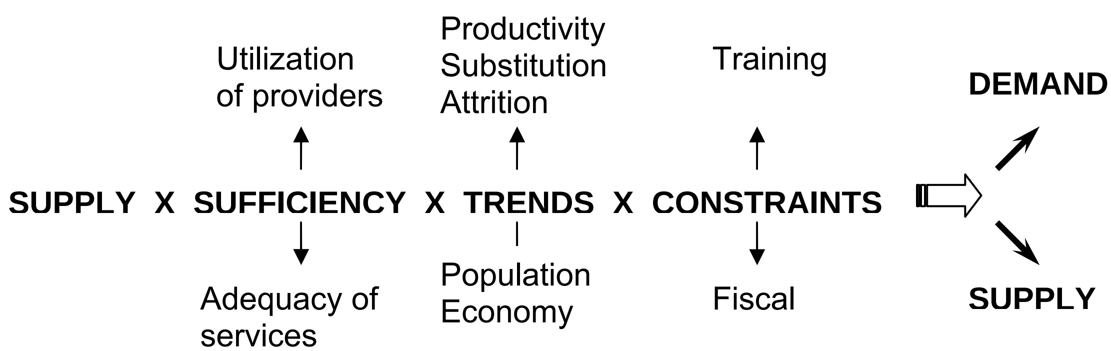

Figure 1. Graphic representation of the Cooper trend model.

Each of the model's elements can be readily applied to the PA profession, with the exception of "substitution." Currently, there are no other professions that are recognized as alternative providers of services considered to be the "sole" realm of PAs; thus, the term has little meaning in the assessment of the PA workforce being undertaken. The remaining sections of this chapter are organized in accordance with these conceptual elements and their application to the PA profession. Supply: The PA Workforce

Adapting the Cooper trend model to the PA profession requires an assessment of the PA workforce in terms of the number of active PAs. To provide context for the discussion of this study's results and implications thereof, baseline characteristics of the

PA workforce were compiled using the most recent census data from the national professional organization, the AAPA. The resultant review provides insight into the profession's demographic composition, geographic distribution, practice settings, specialty selections, and work effort.

The AAPA has undertaken annual census surveys of its membership since 1990. Recognizing that not all practicing PAs were active members of the association, in 1996 the AAPA expanded its reach to include non-members believed to be eligible to practice in the US The most recent results were compiled and released in October 2006. Paper forms or email invitations to participate were sent to 93% of the 70,612 individuals eligible to practice as PAs with a 35.7% response rate (33.2 percent of those eligible to practice). As the data were not weighted or adjusted for non-response, the number of useable response for each item varies. Data results from the previous years beginning with 1996 will be examined and presented in Chapter IV.

PA Demographics and Geographic Distribution

The 2006 AAPA Census Report indicates that the majority of PAs are female (62%). Eighty-eight percent of practicing PAs are white. The respondents were 41 years of age (median = 40), graduated from professional education at age 31 (median = 29), and had been in practice for 11 years (median = 7). Ninety-one percent of respondents reported practicing clinically, with 4% working as PA educators.

The AAPA defines five geographic regions of the US: Northeast, Southeast, North Central, South Central and West. PAs are fairly evenly distributed across regions (19 -24%), the exception being the South Central region at 13%. The states with the largest number of clinically practicing respondents included New York (8%), California

(8%), Texas (6%), Pennsylvania (6%), Florida (5%), North Carolina (5%) and Michigan (5%). In addition, the substantial majority of PAs practice in metropolitan status areas (84%). Utilizing the number of currently certified PAs (as reported by NCCPA) and the 2006 population estimates of the US Census Bureau, a geographic distribution of PAs per 100,000 population was developed to facilitate comparisons with physician workforce studies (Figure 1).

PA Practice Characteristics

The majority of PAs are found either in single/multi-specialty physician group practices (44%) with many employed by hospitals (22%) or in solo physician offices (13%). With over 60 different specialty fields reported, 38% of PAs practice in one of the primary care fields: family/general medicine (27%), general internal medicine (7%), general pediatrics (3%), and obstetrics gynecology (2%). General surgery and surgical subspecialty practices accounted for 25% of respondents. Other prevalent specialties for PAs include various subspecialties of internal medicine (11%), emergency medicine (10%), and dermatology (3%).

Eighty-five percent of respondents work full-time defined as greater than or equal to 32 hours per week. The average number of hours worked per week reported an average of 44.3 hours worked per week. However when considering types of settings (exclusively outpatient versus inpatient), the average number of hours spent in direct patient care were 39.0 and 43.2 hours per week, respectively. Self-reported outpatient visit encounters per week averaged 94.6 in 2006 compared to 67.3 visit encounters reported by those exclusively providing inpatient care.

Utilization Trends of Physician Assistants

Both the NP and PA professions began in response to an uneven geographic distribution of physician and primary care services, particularly in rural and inner city areas. A comparison of the practice specialties conducted during the late 1970's found 67.3% of PAs (n=3416) and 83.4% of NPs (n=1101) in the primary care areas of family practice, general internal medicine and general pediatrics. Family practice was a dominate choice for PAs (52%) while general pediatrics was favored by NPs (31.9%). PAs were more likely than NPs to locate in smaller communities defined as county population under 50,000, while both groups appeared concentrated in central rather than suburban settings when based in urban areas. Private practice settings were more common for PAs than for NPs (34.7% vs. 18.2%), but equal percentages of these two groups selected in hospital-based (23.7% vs. 27.4%) or community-based settings (22.8% and 23.2%)(Perry & Breitner, 1982).

As NPs and PAs gained further acceptance within the healthcare delivery systems, more attention has been brought to further describe their utilization with various practice settings (American College of Emergency Physicians, 1997; Cawley & Hooker, 2006; Committee on Hospital Care, 1999; Hooker, Cipher, Melson, Cawley, & Herrman, 2006; Kelvin et al., 1999; Leshin & Hauser, 1999; Montague, 1994; Oliveria, Altman, Christos, & Halpern, 2002; Wolman & Madden, 1996; Anonymous, 1995; Anonymous, 1997b; Anonymous, 1997a). In general, this literature focused on definitions of NPs and PAs, their respective educational backgrounds, regulation and prescriptive authority, reimbursement, and considerations on how to implement these clinicians into specific practice types. A natural outgrowth of these studies has occurred over the past decade to document defining characteristics in NPCs' scope of practice, extent of substitution, patterns of practice style, and other issues. This has resulted in extensive literature which is encapsulated in the remainder of this section.

Over the fifteen year period 1976 - 1992, utilization patterns for PAs revealed a steady trend toward practice in non-primary care specialties and urban settings. By 1992, only 43% worked in primary care settings (compared to 57% in 1980) with just 32% in family practice. Work in acute care settings, specialties, and subspecialties rose as did the percentage of PAs employed in hospital settings. The latter most likely reflects residency program cutbacks, the curtailment of international medical graduates, and cost considerations (Cawley et al., 2006). While 27% of PAs were in practice in communities of less than 10,000 population in 1981, only 16% maintained a rural focus by 1992. This downward trend was attributed to the feminization of the PA profession coupled with the retirement of older male PAs, who generally were more likely to enter practice in underserved areas, and to the strong demand with higher remuneration in specialty and hospital practice (Cawley, 1993). In comparison, NPs practice continued to be dominated by primary care settings and heavily skewed in favor of metropolitan counties of greater than 50,000 population (92%) (Fowkes, 1993).

With support from the Robert Wood Johnson Foundation, Riportella-Muller, Libby and Kindig (1995) documented various characteristics of clinical departments within teaching hospitals that utilized NPs and PAs to perform tasks routinely done by medical or surgical residents. Results of their national survey of all member institutions of the Council of Teaching Hospitals (COTH) revealed a majority (62%) of responders reported “substitution” occurring in 463 clinical departments. The researchers contacted the individual departments to assess the specific characteristics of interest. Of the 325 responses (70% return), only 255 were eligible for inclusion due to the extent of substitution reported. PAs only were used in 116 departments, NPs only in 77, and both by 62. Of the 178 departments (70% of total), PAs were most likely to be found in surgical departments (42%), followed by primary care (25%) and medical subspecialties (24%). Of the 139 departments employing NPs (54% of total), primary care departments represented 39%, specialty medicine 24% and surgery 23%. In addition, the study noted the increased likelihood of PAs to be found in emergency rooms while pediatric and neonatal care departments were more likely to utilize NPs. Trends in the utilization of PAs and NPs over the two year study period indicated increases of 8 and 11% respectively, with an estimated aggregate increase between 20 and 24%. The authors further assessed reasons for hiring NPCs and their productivity relative to that of resident physicians in a subsample of twenty participating departments. Changes in the number of residency slots and improved quality of care with full-time workers were commonly cited as reasons for hiring NPs and PAs. This further supported the mail survey data that suggested the utilization of these providers to cope with declines in residency program size. Barriers to utilization included administrative and legal problems including county, state, and other legislative requirements, third party reimbursement issues, and scope of practice rules and regulations. Despite these barriers, almost every respondent reported satisfaction with the experience of NP and PA substitution. While noting previous studies had suggested the cost effectiveness of utilizing NPCs in hospital setting, the authors expressed concern over the costs associated with the employment of these providers yet suggested that national policies "consider the overall impact and find innovative ways to support hospitals in using non-physician providers" (Riportella-Muller, Libby, & Kindig, 1995).

An exploratory study of how NPs and PAs are utilized as primary care providers in the managed care environment, specifically in health maintenance organizations (HMOs) and multispecialty clinics (MSCs) was conducted from late 1993 to early 1994. This qualitative endeavor relied on purposeful sampling technique to select institutions that had experience in utilizing PAs and NPs over a number of years, that were geographically diverse, and that were not private practices, community-based clinics or hospitals that were not part of an HMO or MSC. Interview guides served to enhance consistency of data collection and all recorded transcripts were read and coded independently for thematic analysis. For the nine institutions sampled, NPs and PAs were found to be "interchangeable" for primary care, meaning that each group was not only capable of but also expected to perform the range of primary care services provided by the organization. The self-reported range of services coincided with the usual tasks of history acquisition, physical examination, diagnostic test ordering and interpretation, and therapeutic management to include the use of prescriptions. Few distinctions were noted among institutions regarding actual NP or PA prescriptive behaviors and with the authority to order tests. Three limitations to the scope of practice consistently appeared at all institutions:

(1) Elderly patients with complicated illness and multi-system disease were most often referred to the physicians

(2) NPs and PAs lacked the authority to directly admit patients for inpatient care

(3) Accountability for patients was different among the providers with the physicians being ultimately responsible

Admittedly, the sample size limited the generalizability of these findings; however, the authors suggested that the "issue is the extent of the independent primary care role now being performed by NPs and PAs or ways in which they share primary care in teams with physicians . . .". rather than whether or not these providers will become substitutes for their physician colleagues (Jacobson et al., 1998, page 444).

Around the same time, a study designed to further describe HMO staffing ratios utilized a much larger sample than previous literature and also described the utilization of NPCs within this setting. Staffing surveys were received from 58 large group practices belonging to the Group Health Association of America (54.7 % response rate). Unweighted and enrollment-weighted means, standard deviations, medians, and cross-tabulations were used to describe variations in staffing patterns by type of provider, model type and size, geographic location and patient (member) characteristics. The majority of responders indicated use of APNs (65.4%) or PAs (63.4%). Median enrollment weight ratios of FTE per 100,000 members revealed 19.7 APNs and 8.1 PAs. When these ratios were then compared to primary care physician to member ratios, an inverse relationship was revealed. APNs were more likely to care for obstetric gynecology and pediatric patients than PAs (94.7% vs. 51.5%; 89.2% vs. 71.4%) with similar percentages for well adults, chronically ill adults, and urgent care. Target ratios for staffing were documented across the sample of organizations. The single most common ratio used for targeted staffing was 2,000 members per primary care physician with ranges between 1500 and 2000, with a median of 1800. While only one HMO reported modification of target ratios for Medicare patients, the majority of responders indicated ratios from 250 to 1000 members per primary care physician for the Medicare patient population. Most HMOs did not report specific target ratios for NPCs based on member numbers basing staffing estimates on the non-physician to physician ratios instead. A ratio of one NPC per one to two physicians was most commonly utilized. The authors noted that trends of increasing Medicare enrollments could be important factors for future staffing requirements but may be partly offset by the increased use of NPCs. Limitations of generalizability were also noted due to the absence of data from network-model HMOs and IPAs (Dial et al., 1995).

The extent of the independent or autonomous provision of care by nonphysician clinicians provided the focus for analyses undertaken by Cooper and his colleagues (Cooper, Henderson, & Dietrich, 1998). Analyses of 10 distinct provider groups, divided into two groups as either “traditional disciplines” or “alternative/complementary disciplines” were conducted and examined by practice prerogatives. The traditional disciplines encompassed three distinct provider groups, PAs, NPs, and certified nurse midwives (CNMs) while the alternative disciplines included chiropractors, naturopaths, acupuncturists, herbalists, optometrists, podiatrists, certified registered nurse anesthetists and clinical nurse specialists. The practice prerogatives that were examined included state licensure, autonomy and scope of practice, prescriptive authority, and reimbursement. Five trends emerged:

(1) The range of the prerogatives correlated with the numbers of nonphysician providers in each of the states and was noted to vary substantially from state to state

(2) In states with the most extensive prerogatives, NPCs as a total group had broad authority and high degree of autonomy

(3) Considered as an aggregate, NPCs practice prerogatives overlapped with a subset of service provided by physicians, that of “simple licensed general care” and “routine licensed specialty care

(4) NPC provided care was noted to be increasing as task delineation became more distinct and market dynamics of the medical care system delivery changed

(5) Growth in the supply of NPCs paralleled the growth in the range of prerogatives and the utilization of NPCs

Several implications materialized from this examination beginning with redefinition of physicians’ and NPCs’ roles and responsibilities in light of the diversity of clinical practice seen. The overlapping skills and prerogatives noted by the authors necessitates an assessment of each disciplines’ future magnitude in relation to each other. Finally, the authors’ suggested the need for a regulatory environment within the healthcare system that would assure the delivery of quality healthcare by such a diverse workforce (Cooper et al., 1998).

Cooper (2001) identified three significant changes occurring during the 1990’s that allowed for increased utilization of NPCs: the increased number of NPCs trained, state laws and regulations enhancing NPC practice prerogatives, and increased access to reimbursement. Following descriptions of seven disciplines considered in the NPC category (nurse practitioners (NPs), clinical nurse specialists (CNSs), PAs, certified nurse midwifes (CNMs), acupuncturist, chiropractic, and naturopathy), he outlined possible challenges and opportunities facing physicians as they “forge new relationships with NPCs and as their own spectrum of responsibilities evolve.” In addition, Cooper noted:

> . . the practices of primary care NPCs do not fully overlap those of primary care physicians. Rather, they are largely limited to wellness care and the treatment of uncomplicated acute and chronic conditions, and they generally exclude complex or multisystem care. (page 59)

Other research, delineated later, contradicts this suggestion however.

Expounding upon the variation among the various disciplines regarding their ability to substitute or complement physician services Cooper concludes that it is extremely difficult to predict the full impact of such providers on the future demand for physician services. Finally, he suggested that the actual success of any of the non-physician clinician disciplines would be judged by their ability to effectively participate in the continuum of care meeting patient needs and the healthcare system. Since the publication of this study, no additional examination of this type has been undertaken; however, analyses considering role delineations have occurred.

An analysis of primary care physician office encounter data from the 1995 -1999 National Ambulatory Medical Care Surveys (NAMCS) revealed utilization of either NPs or PAs by approximately 25% of primary care office-based physicians. Characteristics of the office encounters were considered by physician only visits, PA only, NP only, PA or NP with a physician and PA or NP without a physician. Analysis by provider category showed that physicians saw a slightly older patient (37.9 years) when compared to PAs (31.8 years) and NPs (28 years). In addition a greater proportion of visits for those aged >65 were seen by a physician only (19.6%) than by a PA or NP without a physician (11.2%). When consider primary diagnoses as specified by the *International Classification of Diseases,* Ninth Revision, Clinical Modification (ICD-9-CM), no statistically significant differences were found by provider category including examination of specific leading diagnoses such as diabetes and hypertension. Further examination of the intensity of services delivered by provider category revealed no statistically significant differences in the mean number of diagnostic/screening services or number of medications ordered. While a higher proportion of therapeutic and preventive services that included counseling/education and other non-medication therapy were noted for the NP-only category, no statistically significant differences were found among the categories. Limited by survey instructions, the mean duration of visit could only be calculated for visits that included a physician. For a physician-only visit the duration averaged 17.3 minutes while the visit in which a physician and either a PA or NP were seen averaged 21.3 minutes. The authors noted that the results most likely underestimated the full degree of primary care services provided by PAs and NPs nationally due to the design of NAMCS to represent the amount of care delivered by non-federally employed physicians (Hooker & McCaig, 2001).

Noting that the focus of much of the previous literature had focused on the differences between NPs and PAs in terms of educational preparation, philosophy of care, scope of legal authority to practice and their working relationships with physicians, Lin, Hooker, Lenz and Hopkins examined NP and PA practice styles employing encounter data from the National Hospital Ambulatory Medical Care Survey (NHAMCS). To ensure sufficient sample size, three years (1997-1999) of data collected annually by the National Center for Health Statistics were combined as a general pool. Results of the analysis revealed that an estimated 237 million visits were made to non-federal hospital outpatient departments with 13 million of these involving NPs and 9.8 million involving PAs over the three year period. Increased participation was documented for both groups, with NP visits increasing from 4.5% in 1997 to 5.9% in 1999 and an average of 5.6% of all visits across the period. In comparison, PA visits increased from 2.1% in 1997 to 5.1% by period end for an average of 4.1% yearly. Patient visits were categorized as sole provider, key provider with assistance from a nurse, nurse assistant or medical assistant, or as a co-provider with physicians. For both NPs and PAs, the majority of care fell into the sole provider or key provider designation, 81.8% for NPs and 76.2% for PAs. When considering geographic distribution of practice as a sole provider of care, no statistically significant differences between the two groups were found in terms of urbanity (metropolitan area versus nonmetropolitan areas) or the four major geographic regions of the US Differences were evident, however, when considering the category of key provider. Here, more PA visits occurred in nonmetropolitan areas, in the Midwest and West while NPs were concentrated in the Northeast and South regions. Expected source of payment (private versus Medicare/Medicaid) was similar between the groups when consider as sole providers, yet a larger percentage of NPs as key providers received Medicaid/Medicare payment, possibly reflecting the greater percentage of pediatric clinic visits seen by NPs.

Statistically significant differences were found in type of practice setting with more PA vs. NP visits occurring in general medicine clinics (sole provider - 81.9% vs. 65.1%, $p<0.0001$; key provider – 92.2% vs.64.7%, $p<0.001$) and more NP vs. PA sole provider visits occurring in obstetric/gynecology clinics (19.8% vs. 8.3%, $p<0.036$) and key provider visits occurring in pediatric clinics (22.2% vs. 3%, $p<0.001$). Whether as a sole provider or a key provider, acute care visits dominated the PA practice while more routine exams and preventive/therapeutic visits prevailed for NPs. The authors expressed that a predictable rising trend in the volume of outpatient department visits for NPs and PAs can now be seen, up 8% over a previous study using earlier years from NHAMCS data. They speculated the reasons for such a trend may be a result of an increased supply of these providers, an increased demand by hospital outpatient departments and by the Balanced Budget Act of 1997 that standardized reimbursement rates for NPCs (Lin, Hooker, Lenz, & Hopkins, 2002).

Victorino and Organ (2003) hypothesized that PAs decrease surgery resident work hours and improve resident work outlook. Spurred by the results of the 2001 surgical residency match that initially left 68 unfilled categorical first-level positions and 425 preliminary first-level positions unfilled and the realization of a 30% decrease in the number of medical students applying to general surgery over the previous nine year period, the authors sought to document the utilization of PAs to “make up the workload that would have been completed by the residents” (page 973). The results of the resident survey (n=61, response rate=91%) conducted monthly for six months following the introduction of PAs onto the service demonstrated significant reductions in the mean number of hours worked per week by residents (from 102.2/week to 87.3/week). The 15 hour per week reduction equated to a near 1:1 ratio of resident work hour decrease to PA work completed. Additional advantages were seen in the decrease of surgical residents' perceptions of work-associated stress, improvement in morale and decreased time spent in the hospital. While recognizing the inherent problems and biases associated with survey research, the short study length, and the complexities involved with perceptions of stress and morale, the authors concluded that the introduction of PAs had been "a tremendously positive experience" (Victorino & Organ, 2003).

Oswanski, Sharma and Raj (2004) examined the effects of using PAs in a Level I trauma center. Their retrospective analysis was prompted by the September 2002 proposal by the Accreditation Council for Graduate Medical Education (ACGME) limiting resident duty hours to 80 per week over a 4-week period. Data were collected from the Toledo Hospital and Toledo Children's Hospital trauma registry for two six-month periods; in 1998 (residents only) and again one year later following the replacement of residents by PAs supervised by trauma attending physicians. All patients evaluated and/or admitted by the trauma services were included. Study variables included injury severity score (ISS), transfer time, length of stay (LOS) and mortality rates. A series of hierarchical linear regressions were conducted to assess the effect of year controlling for age, gender, race and severity of illness on LOS and transfer times. A retrospective analysis of participation (involvement) rates was also conducted. Results revealed a single statistically significant outcome, a decrease by one day in the LOS for patients transferred directly to the floor from the emergency center. The introduction of PAs had had no negative impact on patient outcomes, were seen has a positive experience, and contributed significantly to the trauma centers operations (Oswanski, Sharma, & Rai, 2004).

The Center for Health Workforce Studies at the University at Albany, State University of New York, reported the use of NPCs in the allergy/Immunology physician marketplace and provided an update on the allergist/immunologist marketplace. Conducted in late fall of 2003, the survey received 168 responses for a rate of 56%. All responses were weighted to account for gender, age, and geographic region in attempts to standardize characteristics of the allergist/immunologist population. Of the 27% of panel members who indicated working directly with NPCs, those in group practices were more likely to utilize these providers than those in solo practices. In addition, younger physicians (< 55 years) and female physicians were noted to be more likely to work directly with NPCs; however, statistical significance was not reached. On average, these physicians worked with 1.4 NPs and 0.6 PAs, figures that did not vary when gender, age or practice setting of the physician were considered. The most common use of NPCs was to see routine follow-up patients (94%) with half reporting the inclusion of new patient visits (52%), yet less than a third (29%) reported that NPCs had their own panel of patients, suggesting a complementary focused practice rather than substitution. In terms of satisfaction and practice efficiency, 71% of respondents were very satisfied with the NPCs in their practice, 89% reported that the utilization of these providers increased the number of patients seen in the practice with 66% reporting that practice efficiency was increased and 53% reported increased income to the practice as a result. While plans to hire additional NPs or PAs were considered, no specific results were reported other than the suggestion that growth in the utilization of these providers is likely to be steady but slow (Forte & Salsberg, 2004).

The most recent probe into utilization trends comparing physicians to NPCs as a group is the 1987 National Medical Expenditure Survey and the 1997 Medical Expenditure Panel Survey (Druss, Marcus, Olfson, Tanielian, & Pincus, 2003). This two-stage analysis considered the trends of ten groups of NPCs and concluded that there was a “degree of differentiation” among various provider groups in regard to the services provided but not the type of patient treated. The inclusion of provider groups such as podiatrists, social workers, psychologists and alternative providers hampered the ability of this study to clearly compare provision of services against that of physicians given the often unique and focused services of their respective professions. While certain services may be within the realm of primary care and specialist physicians, their inclusion limits the ability to closely compare providers that provide a broad range of services that are typically (and previously) the sole realm of physicians. As an example of the confounding inherent to the inclusion of such a variety of providers was the finding of decreasing number of acute care visits between 1987 and 1997 provided by the non-physician clinician group. This decrease could have been greatly affected as most services provided by the majority of the providers within the non-physician clinician grouping are non-urgent in nature.

Variable selection for analysis also precluded the ability to develop an accurate comparison of services provided among the various types of clinicians. This study chose broad categories of general checkup, acute care, psychotherapy, preventative care, maternity care or other. While this provided insight into the type of care provided, generalizations are again difficult to make given the vast diversity of provider included in the non-physician clinician group. Furthermore, these more general categories do not provide the level of discrimination needed to more adequately assess similarities or differences among more like providers, such as PAs, to their physician counterparts.

The analysis of medical condition seen is also likely skewed by the diversity of providers examined. The top ten disorders investigated included back problems, acute respiratory infection, arthropathy, eye disorder, mood disorder, normal pregnancy, essential hypertension, and diabetes. It would be rather uncommon for a podiatrist, psychologist, social worker, or midwife to treat the majority of these conditions while rather common for either a PA or an NP to do so. Admittedly, the authors noted that the “amalgamation of providers” was problematic and that the study more likely “useful for understanding the care provided by physicians than care provided by NPCs” (Druss et al., 2003).

Clearly, the literature to date suggests a number of roles have increased the utilization of NPCs within the American healthcare system. However, in terms of “utilization” rates required in demand-based workforce approaches, the data remains to be fully elucidated. This deficiency in existing data sources hampers a more complete examination of PA supply and demand by a variety of workforce approaches.

Adequacy of PA Services

As noted by Cooper (2000), supply must be interpreted in the context of both the utilization of and the adequacy of services provided by clinicians. Analyses of the later focus on such variables as waiting times, unmet needs and excessive services with data gathered through surveys, consensus panels, or that are provided by group practices and other institutions that employ the clinician. Anecdotally, the national PA organizations insist that a significant unmet need exists as “evidenced” by the number of jobs available for new graduates. To date only two published studies exist that focus on this aspect of PA practice, both conducted in the late 1990’s. The results indicated between 2 to 3 jobs per graduate (Cawley, Simon, Blessing, & Link, 1998; Cawley, Simon, Blessing, Pedersen, & Link, 2000). The literature search revealed no studies concerning the “waiting times” to see a PA. Despite the lack of empiric evidence, it can be reasoned that PA services in the US are currently insufficient as there is evidence of physician shortages in both primary care and specialty settings.

In the 2006-2007 edition of its Occupational Outlook Handbook, the US Department of Labor, Bureau of Labor Statistics ranked the PA profession among one of the fastest growing occupations in the US Citing anticipated expansion of the healthcare industry and an emphasis on cost containment, the Bureau expects “much faster than average” growth for PAs through 2014. Their findings suggested additional utilization of PAs will occur in a variety of practices from primary care to medical/surgical specialties, and a variety of settings from solo practices to institutions. The outlook further suggested that additional PAs may be needed to augment medical staffing in inpatient teaching hospital settings as the number of hours physician residents are permitted to work is reduced.

It should be anticipated that the future holds unmet needs for PA services. The examination of the trends influencing the PA workforce undertaken by this study is timely, relevant and will provide much needed information required to assist the nation in responding to these needs.

Trends Influencing Workforce Projections

Productivity Trends of PAs and Other Nonphysician Clinicians

Influences of productivity in relation to workforce projections can be characterized through the examination of the differences in professional time or work output given factors such as gender, age, life-style, employment status and efficiency. For the PA profession much work remains to be done in many of these areas as the majority of the “productivity” studies to date have focused on the PAs versus that of their physician colleagues rather than between subgroups of PAs. With this in mind, the following section provides an overview of the productivity of PAs.

Productivity investigations conducted in the first decade following the emergence of the PA and NP professions revealed differences in the number of patients seen per day, median number of hours of direct patient care, and total median hours at work. PAs saw twice as many patients per day than NPs (25 vs. 12) and averaged 8 more hours per week in direct patient care (System Sciences Inc., 1976). The Congressional Budget Office Report of 1979 compared minutes per visit for physicians, PAs, and NPs and found a 1.13 PA/MD ratio (13.2 to 11.7 minutes) compared to a 1.65 NP/MD ratio (19.4 to 11.7 minutes). In considering reasons to explain these productivity differences, Perry et al. suggested the predominance of female NPs may have accounted for shorter work weeks while their practice orientation may have fostered a less hurried approach during patient visits. They further suggested that longer working hours for PAs may have reflected their greater concentration in fee-for-service practice settings where call and longer work weeks were required and their greater involvement in the management of acute, self-limited conditions (Perry et al., 1982).

The Office of Technology Assessment Case Study (OTA 1986), prepared in response to a request by the US Senate Committee on Appropriations, provided a comprehensive analysis of the potential contributions PAs, NPs and CNMs might make to the management of medical technology and healthcare cost and quality. In reviewing the productivity literature, the report noted that three approaches were taken:

(1) Time per visit (comparing how much time physicians, PAs or NPs take to complete an office visit)

(2) Average number of visits per unit of time (comparing how many visits different providers handled for a given time period)

(3) Marginal product (assessing the effect of adding an NP or PA to a practice by total number of patient visits)

The report concluded that most studies indicated that NPs and PAs spent more time per office visit than did physicians. One study showed an average of 19.4 minutes/visit for NPs, 13.3 minutes/visit for PAs and slightly over 11 minutes/visit for physicians. A similar study conducted in an HMO setting showed PAs used an average of 7.1 minutes/visit while physicians used 8.9 minutes/visit; however, chart review indicated physicians were more likely to see older patients with higher levels of comorbidity. Other studies supported findings that, in general, NPs varied more from physicians in average time spent with patients than did PAs.

The OTA study (U.S.Congress Office of Technology Assessment, 1986).made three summary points:

(1) Physicians can substantially increase practice output by employing NPs or PAs who operate under their supervision

(2) Although PA and, especially, NPs see fewer patients per hour than physicians see, these practitioners are capable of carrying substantial proportions of the workloads of primary care physicians

(3) Practice setting may be an important factor in the productivity of NPs and PAs, as evidenced by the differences in the use and productivity of NPs and PAs in HMOs and traditional settings.

The productivity of PAs is linked to the economic considerations given to their employment. Kaissi, Kralewski, and Dowd (2003) examined financial and organizational factors influencing the employment of NPs and PAs in medical group settings using survey data of 128 such practices in Minnesota (72% response rate). The model utilized was based on the expected influence of restrictive health insurance payment and proposed that practices that had more experience in financial risk sharing and those that had more revenue from such contracts were more likely to employ NPCs. Independent variables included the size (FTE physician numbers), type (single vs. multispecialty), location (urban vs. rural), profit status, and ownership (hospital, plan, or physician) of the practices surveyed as well as the cohesiveness, defined on a 1 to 10 scale. Noting the philosophic differences between PAs and NPs in regard to dependent or independent practice, the authors choose to consider their respective employment rates separately. Results revealed PA/MD and NP/MD ratios the same at 0.25 or one for every four physicians. Larger group practices were more likely to employ PAs, NPs, or both and supported the authors' hypothesis that organization capacity is an important factor influencing NP/PA utilization. Contrary to the authors' beliefs, the presence of specialist physicians in the practice had no positive or negative effect on non-physician clinician employment. Neither the number of years of experience in financial risk sharing nor the amount of revenue from capitation contracts related to employment of PAs or NPs. Noting the geographic limitations of this study, further research continues to be needed at the national level about organizational characteristics that direct group practices towards the hiring of NPCs (Kaissi, Kralewshi, & Dowd, 2003).

To estimate the savings in labor costs associated with primary care visits in a managed care organization (MCO), a study examined primary care practices within Kaiser Permanente Georgia. Data on near two million visits were extracted from computerized visits, representing 206 practitioners with labor costs extracted from payroll ledgers. Overall, PAs/NPs attended 32.4% of adult medicine visits and 18.5% of pediatric visits. Visits for acute minor illness were significantly more likely and chronic conditions less likely to be in the PA/NP realm. In addition, the likelihood that a visit was attended by a PA/NP declined with patient age, controlling for present condition. Relative to the19 to 29 year old group, adjusted odds ratios for 2000 data for 55 to 64 year olds, 65 to 74 year olds and those greater than 75 years were reported as 0.392, 0.237, and 0.177 respectively. Average labor costs per visit were found to vary by the extent to which PAs/NPs were utilized. Those at the seventy-fifth percentile of PA/NP use realized 6.1% lowering of labor costs per visit and 3.1% decrease in total annual labor costs when compared to practices in the twenty-fifth percentile of use. The authors noted that the generalizability of these results may be limited as it focused on a single MCO and was observational in nature rather than suggesting what should or could be realized with varying PA/NP ratios, visit capacities and changes in the PA/NP to doctor salary differential. The authors concluded that since the pressure to manage cost inflation, to improve patient outcomes, and to address physician workload/stress was unlikely to abate, the integration of NPCs represents one strategy which could contribute to the resolution of such issues (Roblin, Howeard, Becker, Adams, & Roberts, 2004).

In addition to a labor benefit, Hooker demonstrated the use of PAs for some episodes of care decreased the use of resources. Examining four common acute medical conditions seen by physicians and by PAs in an HMO setting, the author found the total cost of the visit for each of the conditions managed by PAs was less than of a physician. No statistically differences were found when comparing the use of laboratory and imaging costs between the two types of providers nor were differences found in the rate of return visits for a diagnosis. Further, PAs on average saw ten to fifteen percent more patients per year than doctors in the same department (Hooker 2002).

High levels of PA productivity is evidenced by the research to date; however, there is a lack of research available to ascertain the differences in productivity due to gender, age, or employment status. It remains unknown if female PAs are similar to female physicians who generally work 15% fewer hours and see 15% fewer patients than male physicians. Similarly, the effects of age and lifestyle on PA productivity have not been researched. As a result, the current analysis is unable to consider such factors within the structure of the model. Despite this shortcoming however, the development of baseline projections that can be refined as additional information becomes available is of paramount importance.

Attrition of PAs from the Workforce

Future workforce projections must be cognizant of the loss in the labor force. Attrition comes in various forms and includes retirement, mortality, and change of occupation. In general, trends in attrition are assessed through examination of actuarial tables (mortality) and surveys conducted (retirement, change of occupation). Assumptions concerning the attrition trends of the PA profession are discussed next.

Little is known about the actual retirement rates among PAs. The youth of the profession, 40 years as of 2007, suggests that this factor maybe increasingly important as the first PAs to graduate are at retirement age. As the number of graduates during those early years was considerably smaller than the numbers produced by PA programs today, the impact may not be felt for an additional decade. Recent surveys of their physician colleagues reveal they are leaving their profession at earlier ages and are likely to do so in the future. Whether PAs will follow this pattern is unknown and in need of investigation. The Social Security Administration reports that most American workers will retire between the ages of 65 to 67. For the purposes of this study, an assumption of retirement at age 68 was applied.

PAs appear to be well satisfied with their career choice with little change in occupation evident (Freeborn & Hooker, 1995; Marvell & Kraditor, 1999). While some have pursued physician education, the majority continue to practice as PAs. Thus, this trend was not considered in the workforce projections herein.

The Economy of the US: Gross Domestic Product

In keeping with the conceptual framework outlined by Cooper, it is assumed that the dominant factor in the growth of demand for PA services is the overall growth of the economy as measured by GDP. This domination has been shown in physician workforce studies from the US at the state and national level. In addition, specialty physician studies have also documented the link between GDP and the demand for their services. As will be delineated in Chapter III, correlations between past levels of PA supply and GDP will be conducted to demonstrate this relationship.

US Projections of Population and Demographic Changes

The changing demographics of the US population exerts pressure on the demand for healthcare services including that provided by PAs. Recently clearing the "300 million" mark, its consideration must be included in any workforce projection endeavor. This section provides an overview of expected changes in and delineates how these are incorporated into the projections of the PA workforce.

Commissioned by the National Institute on Aging (NIA), the "65+ in the US: 2005" provides insight into the implications for healthcare provision over the next twenty-five years particularly for the elderly. By the year 2030, the US population aged 65 and over is expected to double in size resulting in 1 out of every 5 Americans belonging to this group. Already in 2006, the fasting growing segment of the US population is the 85 and over group. The anticipated rapid growth is fueled by US Baby Boomers who will turn 65 in the year 2011. Following the incorporation of this generation, the growth of the older population will slow after 2030. As of 2000, the older population accounted for 35 million, with 72 million predicted by 2030, and an additional 15 million by 2050. When put in context with the total population, there is a projected 18% total growth between 2010 and 2030 compared to a 78% growth rate for the elderly during this time frame.

Growth in the diversity of this older population is anticipated shifting from 83% non-Hispanic white, 8% black, 6% Hispanic and 3% Asian in 2003 to 72% non-Hispanic white, 11% Hispanic, 10% black, and 5% Asian by 2030. While the health of older Americans continues to improve, a significant number (14 million in 2000) reported some level of disability mostly linked to high prevalence of chronic conditions such as heart disease and arthritis. The impact of increased prevalence of these chronic diseases, particularly in blacks and Hispanics, will most likely increase the number of people reporting disability. On a more positive side, the proportion of Americans with higher levels of education and its link to better health, higher income and a higher standard of living in retirement demonstrated a five fold increase between 1950 and 2003. By 2030, more than one-fourth of the older population is expected to have an undergraduate degree. Ultimately, this aging of the population represents a clear increase in the demand for medical services. Yet how much demand is generated is linked to the resources available represented by the state of the economy. As such, aging was not considered separately in the PA Demand Model but rather is reflected in the use of GDP as a proxy for the state of the economy.

Similarly, population trends are significantly affected by birth rate and immigrations trends. The ongoing debate over immigration in the U.S creates more uncertainty on what this portends for healthcare demand. In addition, birth rates vary appreciably between ethnic groups. The impact of these trends on demand for healthcare services is difficult to ascertain but like aging it can be reflected by considering the state of economy as its proxy.

While Cooper provides clear arguments to support the upward modification of US Census Bureau population projections, no modifications were made for the purposes of this initial effort in modeling the PA workforce. The most current population projections were utilized for application to the PA Trend Model. This application allows the quantification of demand in terms of PAs per 100,000 population.

Constraints Influencing Workforce Projections

Training Factors: PA Education and its Graduates

The first four PA programs were established between 1965 and 1968. Following the passage by Congress of the Comprehensive Health Manpower Act in 1971, forty-four additional programs were established over the next eight years with only three programs added in the subsequent twelve year period. Significant growth in the number of programs occurred during the 1990's with the development of an additional 69 programs. This trend may reflect the additional support from Title VII grant support that targeted increased enrollment as well as new program development. Since that time, growth has once again diminished with few new programs being established annually (Hooker & Cawley, 2003). Figure 2 graphically depicts this trend, below. As of October 2006, one hundred thirty-five PA programs actively enrolled students.

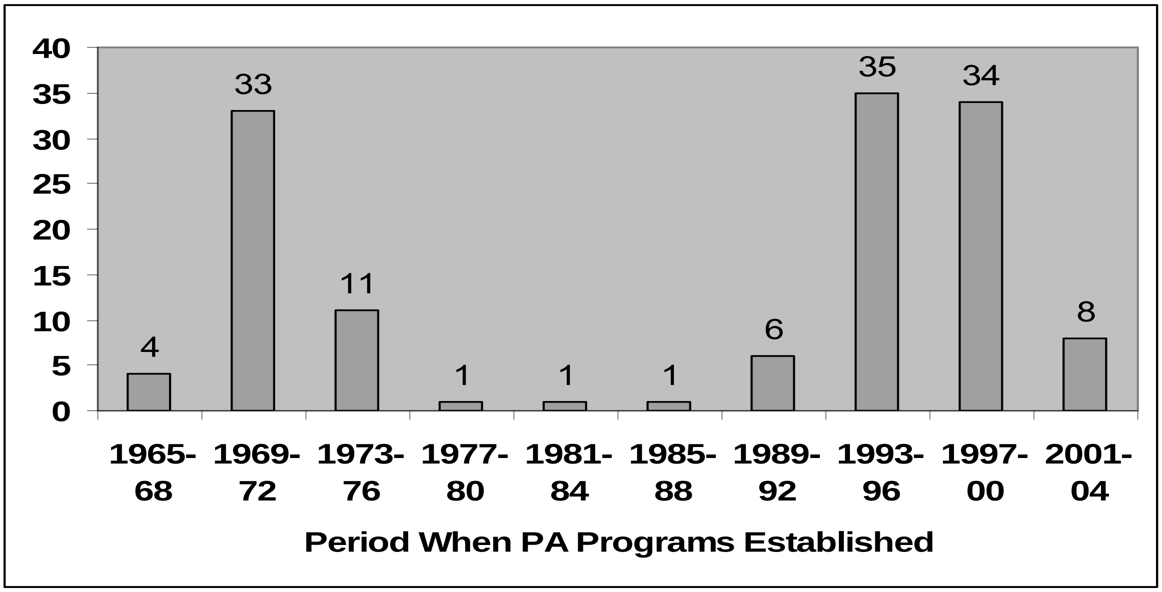

Figure 2. Number of new PA programs by year of first entering class.

Characteristics of PA programs, their students and subsequent graduates are documented within the annual report of the Physician Assistant Education Association (PAEA). The annual survey report covers general program characteristics, program personnel, and PA student characteristics. The trends in graduate information provide the most relevant information in considering workforce issues (Simon & Link, 2005).

The mean number of graduates during the academic year 2004-2005 was 33.9 per program, representing 90.9% of those originally enrolled for this class. Attrition accounted for 6.2% of the loss with 2.9% due to deceleration. While attrition was higher than the previous year, it was lower than the twenty year average of 7.5%.

Attrition rates during the 2004-2005 academic period were notably higher for certain ethnicities, Black/African-American (16.7%) and Hispanic (8.3%), and for students older than 33 years of age (10.3%). The annual rate of attrition for non-white students was reported as 8.9% with fluctuations over the past twenty years ranging from a high of 25% in 1990 to a low of 6% in 2002. When considering age at enrollment, a downward trend has been noted over the past ten years for those in the > 29 years group, although this group still accounted for 27.8% of students enrolled in the Class of 2004-2005.The final estimation of number of graduates was 33.9 X132 or 4,475 as two programs were yet to confer degrees. The graduation rate correlates to NCCPA records of first time candidates for the national certification examination administered during 2005.

Fiscal Constraints: Medicare/Medicaid Coverage

Additional constraints should be considered as workforce projections are interpreted. The utilization of PAs continues to be influenced by fiscal constraints such as reimbursement for services. The single largest payer for medical services in the US is the Center for Medicare and Medicaid Services (CMS). A brief overview of these systems and rates applied to PA services is provided to enhance the understanding of this particular fiscal constraint.

While interest in the provision of health insurance coverage in the US dates back to the early twentieth century, few initiatives beyond the limited support of state activities related to public health and the care of mothers and children provided by the Social Security Act were realized by the 1930's. Following WWII, private health insurance grew rapidly as a means to expand employee fringe benefits given the government-limited direct-wage increases. As a nation, Congress considered various proposals for national health coverage during the 1940's, but instead acted in 1950 to improve the access to healthcare for those receiving public assistance. This represented the first federal government participation in the provision of reimbursement made directly to medical providers. In a similar fashion, the need of the aged population for improved access to medical care resulted in the passage of “Medical Assistance to the Aged” in 1960. In 1965, the Medicare and Medicaid programs (Title XVIII and XIX) of the Social Security Act were established and continue today (Folland, Goodman, & Stano, 2004; Hoffman, Jr., Klees, & Curtis, 2005).

For the consideration of the impact on projections of the PA workforce the following baseline 2004 Medicare expenditures and provider participation rates are provided.

(1) Part A payments totaled $167.6 billion covering 41 million people

(2) Part B payments totaled $135.4 billion covering 33 million people

(3) Total number of Part B practitioners as of February 2004 was 906,422 with 23.3% non-physician providers (211,047)

Medicare reimbursement for services provided by PAs dates back to 1977 and the passage of the Rural Health Clinic Services Act. Since that time, incremental yet significant expansions were realized by the profession to include coverage in hospitals, nursing facilities, rural Health Professional Shortage Areas, and first assisting at surgery. With the Balanced Budget Act of 1997, coverage was extended to all practice settings at one uniform rate. Currently, Medicare pays the employer for medical services provided by PAs at 85% of the physician’s fee schedule. Outpatient services provided in offices and clinics may be billed under “incident to” provisions that allow payment at 100% of the physician fee schedule if the following conditions are met:

(1) The physician is physically on site when the PA delivered the service

(2) The physician treats all new Medicare patients with subsequent care by PAs allowable

(3) The physician treats all established Medicare patients with new medical problems with subsequent care by PAs allowable (American Academy of Physician Assistants, 2006b).

Title XIX of the Social Security Act (Medicaid) is a cooperative venture between the federal and state governments to provide medical assistances to low income/resources individuals and families. Although the benefits of Medicaid are administered by each state, benefits received may vary considerably. Currently, all fifty states cover services provided by PAs under their respective Medicaid programs. As with Medicare, the reimbursement is made directly to the PAs' employer at either the same or slightly lower than physician rates (Folland et al., 2004; Hoffman, Jr. et al., 2005).

The changes to the reimbursement policies of the major payers in the US system may account for the increased utilization of PAs in a variety of practice settings. With uniform rates in Medicare for PA services, the ability to effectively employ PAs has been enhanced. Changes to the state-run Medicaid system could well impact the utilization and subsequent demand for PAs into the future. While important to the considerations, this type of fiscal constraint is not directly added to the PA workforce model *per se*; rather, these influences will be more fully discussed as the implications of the model are delineated in Chapter V.

Summary

This chapter provided a literature review of the historical perspective of physician workforce investigations, the various approaches used, and a justification for the application of Cooper's trend model to PA workforce analyses. Using the framework of the trend model, relevant PA literature was reviewed in regard to trends affecting the supply and demand for PAs. These trends included PA utilization, productivity, and attrition from the profession. Both economic trends measured as GDP and US population changes were described and justified as variables within the proposed demand model for the PA profession. Finally, constraints due to training and fiscal considerations were presented. The following chapter addresses the methodologies that were utilized to answer the research question and objectives of this endeavor.

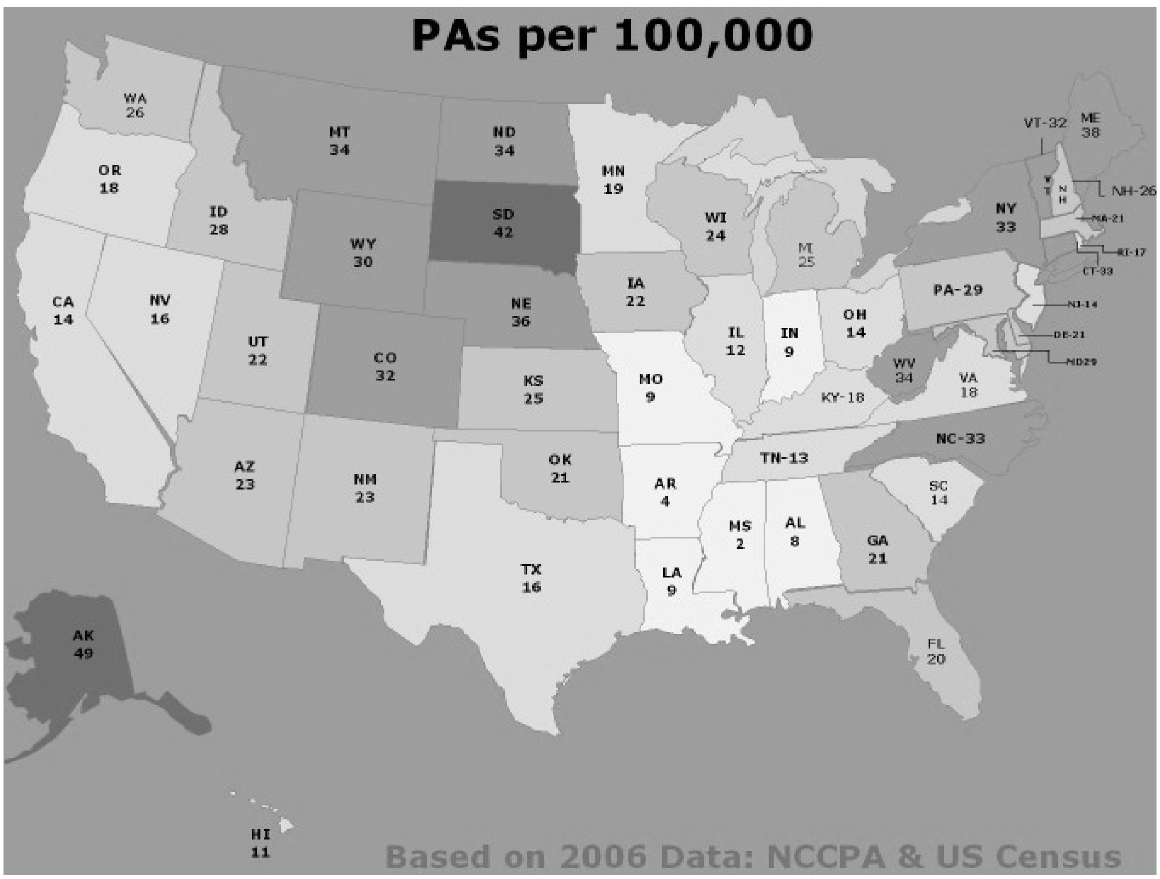

Figure 3: Geographic distribution of PAs in the US per 100,000 population.

CHAPTER III

METHODOLOGY

Introduction

Recognition of the physician assistant (PA) contribution in the delivery of healthcare has lead to calls for its inclusion in estimates of physician workforce supply and demand. To answer these calls, several research objectives were established (Chapter I). The approach and methodology for each of these objectives is described and range from simple descriptive statistics to that of time-series forecasting using an autoregressive integrated moving average (ARIMA) procedure. Various methodologies utilized in health workforce personnel estimates were previously reviewed in Chapter II and substantiated the selection of a trend or time series forecasting approach for the development of the proposed PA supply and demand model. Variable selection and data sources for their representation are also reviewed.

Research Objective 1 Methods

Describe the current status of PA practice in the US to include:

a) demographic composition and distribution trends
b) practice selection by specialty and practice setting trends
c) scope of practice prerogatives effecting PA utilization

The first research objective focuses on the description of PA practice in the US. Variables of interest include its demographic composition and trends of its distribution, practice selection, and practice setting. PA data includes current age, self-reported practice specialty, and state of residence of all certified PAs as of October 2006. Frequency counts establish the current demographic composition of PAs in the US

Each variable is assessed annually by the PA national professional organization, the American Academy of Physician Assistants (AAPA). Data from the 1996-2005 AAPA Census Reports will be accumulated in a single database and examined for trends with descriptive statistics analyzed.

Practice prerogatives or regulations governing PA practice will be reviewed by accessing each state's medical board website and retrieving relevant information. Specifically, the rules and regulations were examined for scope of practice limitations, prescriptive privileges, and the number of PAs a physician can supervise at one time. Each of these elements exerts significantly impact on the utilization of PAs, currently and into the future.

Research Objective 2 Methods

Delineate a demand model for the utilization of PA that utilizes:

a) the past and future estimates of gross domestic product as chained in 2000 dollar
b) the past and future estimates of US population growth

The second objective requires the delineation of a demand model for the utilization of PAs. The notion that the US economy and population growth trends are "causally" linked to physician supply was extrapolated to that of PA supply as was the trend model framework (Cooper et al., 2002). GDP estimates as published by the US Bureau of Economic Analysis were utilized as the proxy for the economy status. Published estimates of the population of the US were used directly without modification.

The selection of a specific quantitative forecasting methodology was based on several factors. First, all conditions required of a quantitative forecast were met.

Information about the past was readily available that could be quantified in numerical data, and it is assumed that past patterns will continue into the future. The next decision was to consider whether an explanatory model or that of time series model was most appropriate. As the objective of the study was to use the pattern of the historical data and extrapolate the patterns into the future, a time series model suitable for the examination of trend data was selected. In addition, this was in keeping with Cooper's trend model methodology. As a variety of time-series approaches are available, further consideration of the data relationships and approach assumptions was required.

Initial considerations of the dominant trends in workforce demand, GDP and population growth, and their relationship to each other suggested a number of factors that influence the specific type of forecasting methodology that would be most effective. Most importantly, because GDP and population are closely linked with correlation approaching 1, it could be anticipated that a significant amount of collinearity would exist. As collinearity increases, the regression coefficients computed become more unstable as measured by their standard errors and unreliable (Makridakis, Wheelwright, & Hyndman, 1998). As a result, the class of ARIMA models was next to be considered.

Given the desire to include both GDP and population trends in a single model, an advanced autoregressive forecasting methodology that allowed the inclusion of other information in one model was required. With GDP and population growth as explanatory variables and PA demand as the forecast variable, a regression with ARIMA errors or a dynamic regression model was considered. Both of these methods are appropriate when no feedback between variables exist, meaning that while the explanatory variables exert affects on the forecast variable, they are not affected by the forecast variable. In addition, these models are capable of handling the autocorrelation inherent in trends.

Finally, it was anticipated that the effect of a change in either GDP or population would precede a change in PA demand by more than one time period. By definition, when explanatory variables exert their influence over several future time periods, a dynamic system exists (Makridakis et al., 1998). Thus, a dynamic regression model (aka, transfer function model) was selected as the approach to forecast PA demand.

The dynamic regression model can be written in the following form.

$$Y_t = a + v(B)X_t + N_t$$

where Y_t is the forecast variable or output series; X_t is the explanatory variable or input series; N_t is the "noise" or combined effects of all other factors influencing the forecast variable; and $v(B)$ or transfer function equals ($v_o + v_1B + v_2B^2 + \cdots + v_kB^k$) where k is the order of the function. Because k is the longest lag of X utilized, a less than desirable level of parsimony exists as k increases. As a result the model can be rewritten to reduce the number of parameters to be estimated, reducing the number of degrees of freedom, thereby increasing the accuracy of forecasts. The more parsimonious form extended to include multiple explanatory variables is:

$$Y_t = a + \sum_{i=1}^{m} \frac{B^{bi}\omega_i(B)}{\delta_i(B)} X_{i,t} + N_t$$

where Y_t is the forecast variable; X_t is the explanatory variable; $\omega_i(B)$ equals ($\omega_{i,0} - \omega_{i,1}B - \omega_{i,2}B^2 -\!- \cdots \omega_{i,si}B^{si}$); $\delta_i(B)$ equals ($1 - \delta_{i,1}B - \delta_{i,2}B^2 - \cdots \delta_{ri}B^{ri}$); N_t is an ARIMA process; and r, s, and b are constants (Makridakis et al., 1998).This form is based on mathematical theorems that demonstrate that the ratio of two lower order finite polynomials ($\omega_i(B)$, $\delta_i(B)$) can accurately approximate an infinite-order power series ($v(B)$.

The procedure used followed the suggested series of steps that began by fitting the appropriate dynamic regression model to the multiple regression model where k was sufficiently large to ensure capture of the longest time lagged response likely to be important (Chatfield, 2001; Makridakis et al., 1998). Given previous workforce studies a lag of 3 was anticipated thus for the initial delineation of the model a lag of 7 was employed. A low-order AR model was used for N_t as the noise level is unimportant at this initial stage. Errors were subsequently inspected to assess stationarity and the need for differencing was assessed. Given the trend nature of this data, differencing was likely to be required thus Dickey Fuller Unit Root testing was performed on the time series prior to the model delineation. Once the errors appear to be stationary, an appropriate transfer function of $v(B)$ was identified. This required the selection of values of b, r, and s. The b value is the number of periods before the explanatory variable influences the forecast variable. The s value, or the order of $\omega(B)$, controls the number of transfer function coefficients before they begin to decay and is determined by the number of non-zero v weights (transfer function coefficients) before decay. The r value, or the order of $\delta(B)$, controls the decay pattern. Visual inspection of the transfer function coefficients against lag determines the decay pattern and subsequent assignment of 0 in the case of no decay pattern, 1 if simple exponential decay is evident, and 2 if a more complex pattern is seen. This process is corresponds to the selection of the number of numerator and denominator factors during the model development stage utilizing the SAS analytic program.

Once the constant values were determined, errors from the regression model were calculated and an appropriate ARIMA model for the error series was identified. Next the entire model was refit using the identified ARIMA for the errors and the transfer function model for *X.* The newly fitted model was submitted to diagnostic tests to determine if the residuals are significantly different from white noise. This was accomplished through the visual inspection of autocorrelation/partial autocorrelation function plots (ACF/PACF) and portmanteau tests (*Q*- and S-statistics). Significant spikes in the ACF/PACF or a significant portmanteau tests require re-identification of the model. Once residual testing met these stated criteria, the model was then used to forecast future demand.

The basic equation for the demand of PAs is:

$$PADt = \int (GDP, POP)$$

where PAD_t is the demand for PA services, *GDP* is the level of gross domestic product in 2000 dollars and *POP* is the population in the US. Data for these variables were obtained from the Bureau of Economic Analyses and the US Census Bureau.

Research Objective 3 Methods

Delineate a supply model for the PA profession that utilizes:

a) the current pool of certified PAs

b) educational institution capacity and assumed attrition rates

c) assumptions for retirement rates

The third objective related to the supply of PAs as it existed in 2006 and to project it fifteen years into the future. Baseline estimates of currently certified PAs were obtained from the national certification organization (NCCPA) as were pass rates on the certification examination over the last ten years. To provide a more accurate assessment of future supply, the pool of PAs was aged across the projection periods with PAs dropped as they reached "retirement." As previously discussed, the retirement age was arbitrarily set at 67.

The basic equation for the PA Supply Model is

$$PA_t = \sum_{a=25}^{67} PA_{a,\,t-1}(1 - r_{a,\,t-1}) + E_t$$

where PA_t is the number of PAs in period *t*;

$PA_{a,\,t-1}$ is the number of PAs who were *a* years old in period *t*-1

$r_{a,\,t-1}$ is the retirement rate for PAs who were age *a* in period *t* – 1.

E_t is the number of new certified PAs entering practice in period *t* estimated by the following equation,

$$E_t = \sum S_{t-2}(1 - l_t)(1 - pr_t)$$

where S_{t-2} is the number of PA students accepted annually by programs;

l_t is the annual attrition rate for period *t*; and

pr_t is the national certification examination annual pass rate.

Data for these variables were obtained from the Physician Assistant Education Association (PAEA) and the National Commission on the Certification of Physician Assistants. Specific methodologies for the establishment of the required database that allowed the supply pool to be aged and assumptions applied are further described under Data Sources and Assumptions.

Research Objective 4 Methods

Utilize the developed models to consider whether the demand for PA services would be met by supply based on *status quo*, a 10% increase and a 25% increase in institutional capacity as alternative scenarios.

The fourth objective required the manipulation of the basic PA supply equation delineated above to simulate increases in the institutional capacity of PA programs. The methodology remained unchanged with the exception of these changes in institutional capacity.

The *status quo* capacity or number of PAs available was derived from published information from each of the accredited PA programs as of October 2006. The 10% level represents a minimal and relatively attainable increase for the majority of programs while the 25% level may require significant alteration to programs. These alternative levels were instituted at year 2009 to represent increases beginning in 2007 and no further adjustment across the forecast periods. As it is unknown how well current institutional capacity leads to supply matching demand, this type of scenario building provides insight for strategic planning. Results of these manipulations were compared to the previously derived demand to assess the adequacy of the supply of PAs into the future.

Data Sources and Assumptions

The AAPA has conducted annual census surveys of its membership since 1990. Recognizing that not all practicing PAs were active members of the association, in 1996 the AAPA expanded its reach to include non-members believed to be eligible to practice in the US The most recent results were compiled and released in October 2006. Forms were mailed to 94.3% of the 66,483 individuals eligible to practice as PAs with a 35.9% response rate (33.8 percent of those considered eligible to practice). As the data were not weighted or adjusted for non-response, the number of useable response for each item varies. Data results from the previous years beginning with 1996 were examined in the elements of interest to this dissertation. Reported data points were extracted to generate the data set used to examine trends in the areas of demographic composition, geographic distribution, practice selection by specialty, and practice setting. Response rates for each year's survey are provided in the Appendix.

The Bureau of Economic Analysis (BEA) provides annual estimates of national income and product accounts (NIPAs) that include estimates of current-dollar gross domestic product (GDP) and real (inflation-adjusted) GDP. These estimates are made available for public use on the BEA website in Excel spreadsheets that can easily be transferred to other statistical software databases for the purposes of analyses. The real GDP estimates were utilized to examine the long term trends in relation to PA supply as derived above.

The Integrated Public Use Microdata Series (IPUMS) is a coherent national database that combines census microdata files produced by the Census Bureau for the period since 1960 with new historical census files produced at the University of Minnesota and elsewhere. The IPUMS is designed to facilitate the use of the census samples as a time series. Funded by the National Science Foundation and the National Institutes of Health, both the database and the documentation are distributed through an on-line data access system at http://www.ipums.umn.edu. Population estimates required to consider the ratio of PAs to population occurring over the last decade and for future projections were obtained from this source.

The National Commission on the Certification of Physician Assistants (NCCPA) develops and administers initial and ongoing certification maintenance for the PA profession. Graduates of PA programs accredited by the Accreditation Review Commission on Education for the Physician Assistant (ARC-PA) are eligible to seek certification by taking the Physician Assistant National Certification Examination (PANCE). Upon successful passage of this initial exam, a certificate is issued and entitles the graduate to use the PA-C designation. Continued certification requires documentation of continuing education activities every two years with recertification by examination every six years. NCCPA certification is a requirement for initial medical practice licensure and/or registration by all fifty states and the District of Columbia. The database maintained by NCCPA represents the most accurate accounting of the number of PAs that are eligible to practice in the United States. This accounting must be considered conservative as certain practice settings such as federally employed PAs may not be required to maintain certification to continue to deliver healthcare services following initial licensure and/or registration. The age variable was obtained from this source and utilized for the baseline figures within the supply model.

The Physician Assistant Education Association (PAEA) collects and disseminates data about its member programs. Through its annual report, the organization provides comprehensive information concerning various characteristics that depict the “typical” PA educational endeavor. The student information reports the number, gender, age, and ethnicity of enrolled students. In addition, attrition rates or students failing to complete the educational program are reported by student age. The Annual Report on Physician Assistant Education Programs in the United States, 2004-2005 provided twenty-year trend data that was employed to establish an appropriate attrition rate for utilization within the supply model. During this period of time, attrition rates ranged from a low of 3.9% in 1999 to a high of 14% in 1988 with an average rate reported as 7.5%. Notably in the previous five years, attrition rates were lower ranging from 4% to 6.2%. For purposes of this study, the attrition rate was set at 7.0% as a compromise between the long and short term trend figures.

In addition, PAEA annual reports provide the percentage of students enrolled by age using intervals of 3 years, beginning with those under the age of 20 and ending with those over the age of 33. As raw data was unavailable for use in this study, the 2004-2005 percentages were evenly divided across the interval to arrive at a percentage for each year of age between 20 and 50. The derived percentages were applied to the number of students accepted into programs as reflected by their published institutional capacity as of October 2006. This process was repeated to establish similar databases used to assess scenarios reflecting either a 10% or 25% increase in capacity over the base year (2006).

Previous analyses of physician work effort suggest declines in the number of hours worked due to a variety of factors. These factors include the aging of the physician cohort, early retirement, the feminization of the profession, a greater emphasis on personal time, and the decreased number of hours residents are allowed to work. No studies to date have assessed whether similar differences are seen in PA work effort forcing the use of assumptions in this regard. To limit the error associated with the application of several assumptions, a single assumption of retirement at the age of 67 was applied to the model projections.

Summary

This chapter has provided an overview of the methodologies that were utilized to meet the listed research objectives. Descriptive statistic analyses provided the tools to describe the PA profession. ARIMA procedures were utilized to develop the PA supply and demand models and forecasts. Variable selection and data sources were described and are summarized in the table below. The following chapter presents the results of these various analyses.

Table 1

Summary of Variables and Data Sources by Research Objective

Research Objective	*Variable*	*Data Source*
Objective 1: PA Practice	*Age*	*AAPA Census Data*
	Gender	*AAPA Census Data*
	Practice Selection	*AAPA Census Data*
	Practice Setting	*AAPA Census Data*
Objective 2: Demand	*PAs in Practice*	*AAPA Census Data*
	Gross Domestic Product	*Bureau of Economic Analysis*
	US Population Estimates	*US Census Bureau (IPUMS)*
Objective 3: Supply	*PAs Currently Certified*	*NCCPA Certification Data*
	PA Matriculates	*PAEA DATA*
	Attrition Rate	*Assumed 7%*
	Retirement Rate	*Assumed Age 67*
	Certification Pass Rate	*NCCPA Certification Data*

CHAPTER IV

RESULTS

This chapter reviews the results from the analyses described in the Methods section (Chapter III). Arranged by research objective outlined in the Introduction section (Chapter I), the results cover a) the historical trends and current status of PA practice in the United States, b) the delineation of the PA Demand Model, c) the delineation of the PA Supply Model, and d) the comparisons of the PA demand versus supply in three scenarios. The scenarios assumed included no growth in PA supply or the *status quo*, a 10% increase in PA supply and finally, a 25% increase in the PA supply.

PA Practice in the United States: Historical Trends and Current Status

Demographic and Distribution Characteristics

The historical demographic and distribution characteristics were derived through the analyses of the annual AAPA Physician Assistant Census Reports from 1996 to present. The number of PAs eligible to practice, gender, age, and geographic distribution for the year 2006 were compared with data obtained from NCCPA that reflects PAs currently certified by the organization. As of October 2006, there were 70,612 PA graduates since the profession's inception (American Academy of Physician Assistants, 2006a). In general, eighty-five percent of PAs remain in clinical practice resulting in 60,020 PAs eligible to practice according to AAPA data. Review of the NCCPA data in October 2006, identified 59,776 PAs maintaining current certification.

While the first Duke class included only men, the male predominance began to shift during the mid eighties with equal percentages realized by the mid nineties (Hooker et al., 2003). The continued feminization of the profession is graphically represented in

Figure 3. Currently the majority of PAs (62%) are female representing a 13% increase over 1996 levels. This increasing trend is likely to continue given that PAEA enrollment statistics indicate a female to male matriculate ratio of 70:30 (Simon et al., 2005). When compared to the available NCCPA data of 2006, a slight difference in gender distribution was noted (female = 59.9%, male = 40.1%).

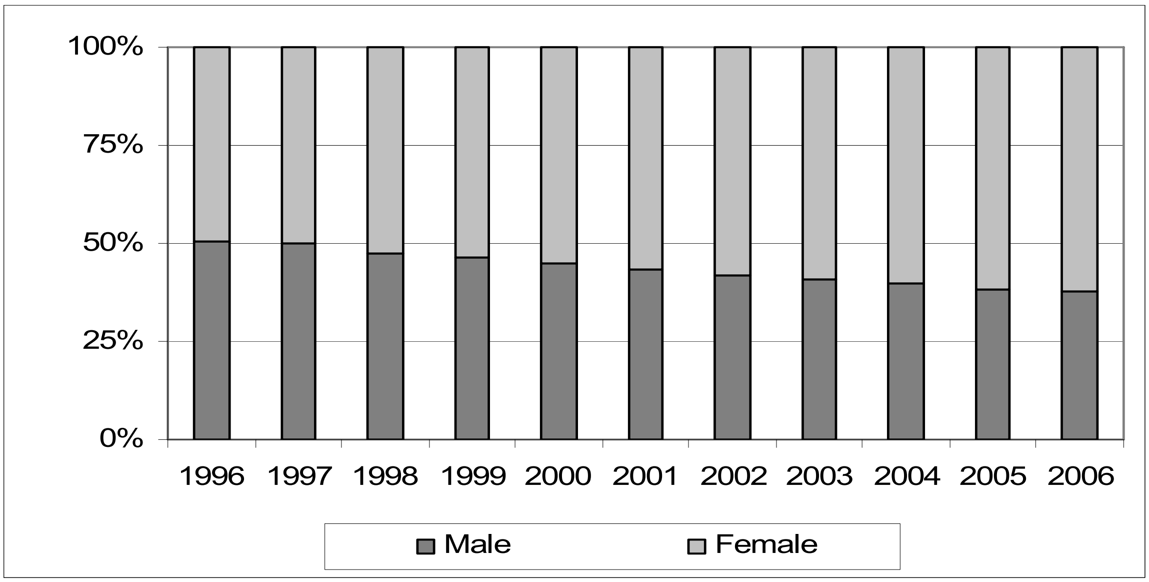

Figure 4. PA gender distribution trend (AAPA Census Reports).

The 2006 AAPA PA Census Report states that the mean age of census respondents was 41 years (median: 40). This corresponds to the mean age of PAs that are NCCPA certified as of 2006 (mean age = 40.4). In 2002, it was noted that female PAs were an average of 10 years younger than males (Hooker et al., 2003). However, examination of the NCCPA certified PA database revealed that the average age of female PAs is 5 years younger than male PAs as of 2006.

Ethnicity of the PA profession has undergone little change over the last decade. In 2006, the profession remains predominantly white (88%), with minimal gains noted in the percentage of Hispanics and African Americans. The Asian/Pacific Islander group gained the largest percentage over the past decade, yet this only represents a 1.5% increase (Figure 5). Ethnicity data was not provided by NCCPA for comparative purposes.

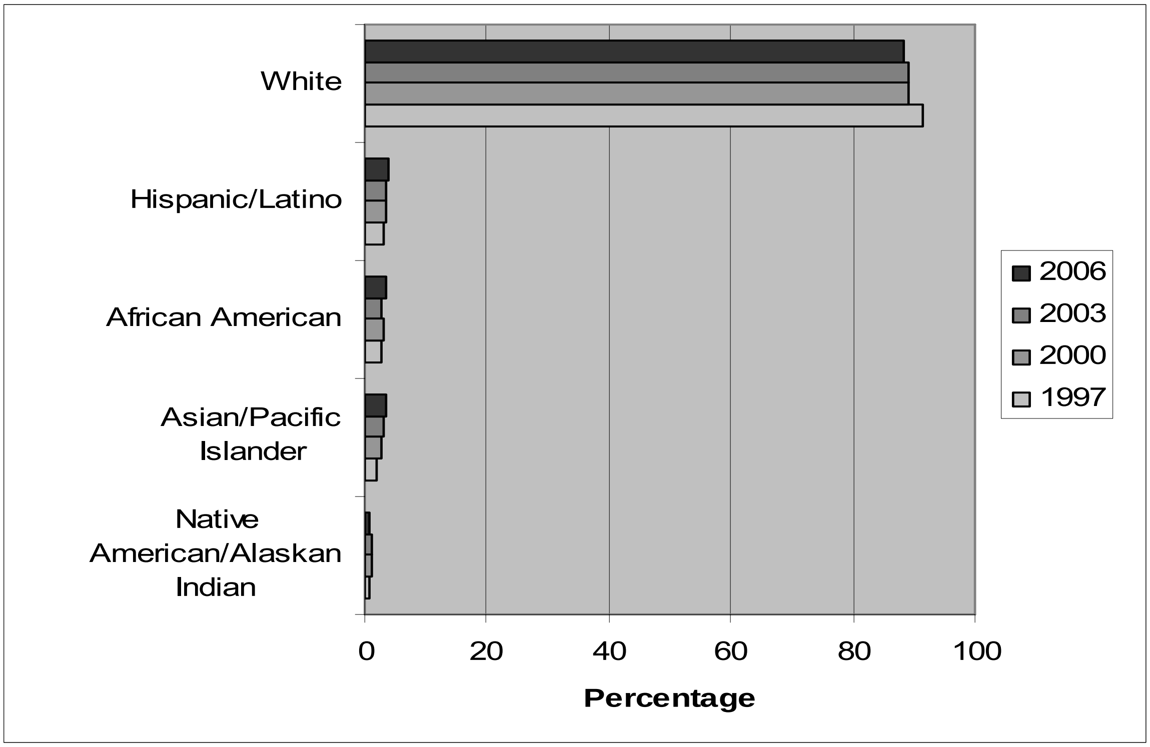

Figure 5. PA ethnicity distribution trend (AAPA Census Reports).

The AAPA defines five geographic regions of the United States, Northeast, Southeast, North Central, South Central and West. PAs are fairly evenly distributed across regions (19 -24%), the exception being the South Central region at 13%. The states with the largest number of clinically practicing respondents included New York (9%), California (8%), Texas (6%), Pennsylvania (6%), Florida (6%) and North Carolina (5%). In addition, the substantial majority of PAs practice in metropolitan status areas (83%). Utilizing the estimates of the AAPA 2005 Census Report and population estimates of the US Census Bureau of 2000, a geographic distribution of PAs per

100,000 population was developed to facilitate comparisons with physician workforce studies and previously presented in Chapter II (Figure 3).

Practice Selection by Specialty and Setting

With over 60 different specialty fields reported, 41% of PAs currently practice in one of the primary care fields: family/general medicine (28%), general internal medicine (8%), general pediatrics (3%), and obstetrics/gynecology (2%). General surgery and surgical subspecialty practices accounted for 25% of respondents with emergency medicine and subspecialties of internal medicine represented 10% each (Figure 5). In addition to the AAPA census reports, self-reported practice selection data was obtained from the NCCPA for certified PAs eligible to practice in the United States. Unfortunately, the latter had a high missing value rate (>50%) and could not be utilized for comparative purposes.

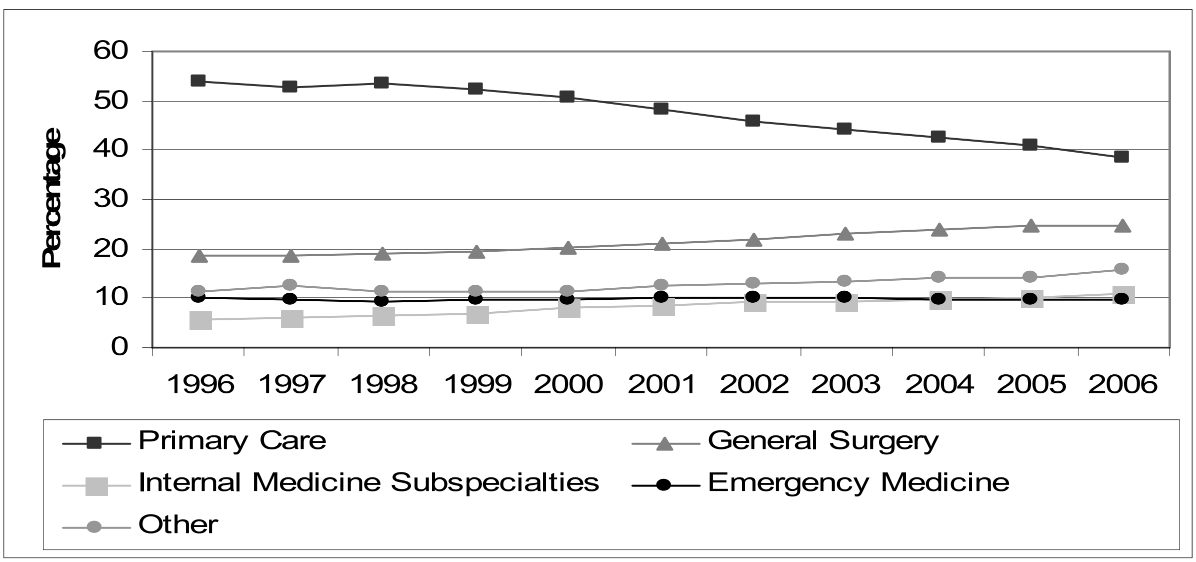

Figure 6. PA specialty selection trend (AAPA Census Reports).

The majority of PAs are found either in single/multi-specialty physician group practices (43%) or in solo physician offices (14%) and many are employed by hospitals

(22%) (Figure 6). As the NCCPA databases do not include practice setting as a variable, no comparative analyses were possible.

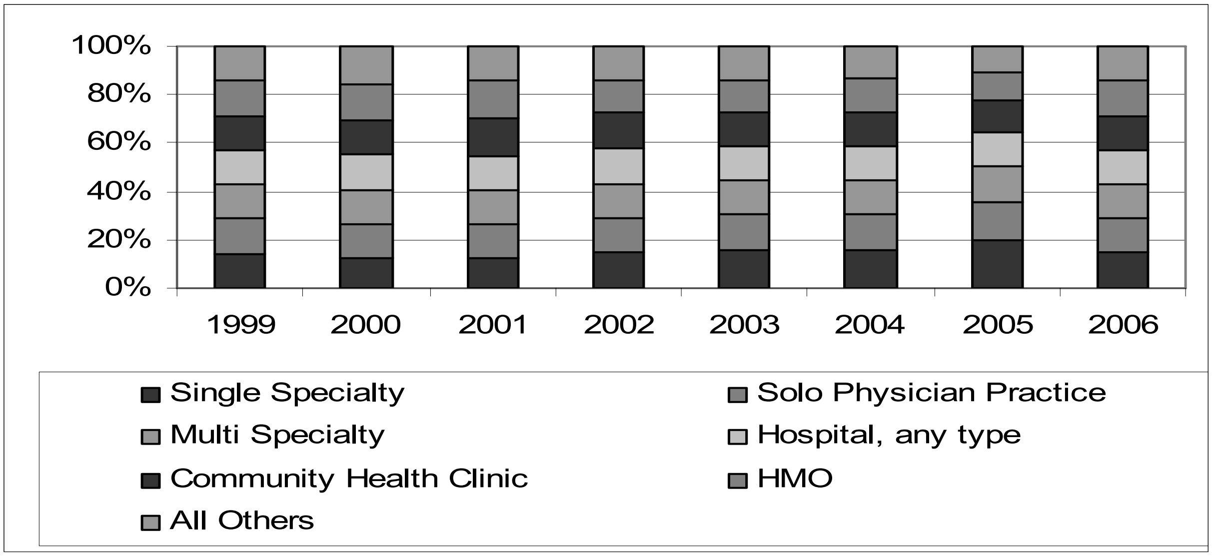

Figure 7. PA practice type trend (AAPA Census Reports).

Demand Model Delineation for PA Utilization

The delineation of the demand model was conducted in several phases prior to forecast production. These included the identification of the underlying time series processes, the estimation of models for the explanatory variable, the estimation of the preliminary transfer function model, and the estimation of the final transfer function model. This section provides detailed explanations and results of each phase.

Identification of Time Series Processes

The initial identification phase began with the submitting each of the variable series to Dickey Fuller Unit Root testing to assess stationarity. Results of the Dickey Fuller Unit Root testing suggested that all three time series would benefit from differencing (Table 2). The next step utilized the SAS: PROC ARIMA to produce the autocorrelation (ACF), inverse autocorrelation (IACF) and the partial autocorrelation

(PACF) plots for each of the differenced time series. In addition, the Minimum Information Criterion (MINIC) method and the Smallest Canonical (SCAN) correlation method were utilized to tentatively identify the autoregressive orders of each series. The ACF plot for the GDP time series tailed off exponentially indicating a stationary series. The ICF plot showed a large spike at lag 1 with a subsequent drop to zero. This finding suggested an autoregressive process of order 1. However, examination of the results from the MINIC and SCAN methods suggested the GDP series had a higher probability of exhibiting an autoregressive order of 2. Finally, the *Q*-statistics were examined to assess whether the series were "white noise" or a purely random process in no need of modeling. The highly significant value of <0.001 suggested a high degree of autocorrelation that could be modeled. The plots and statistical testing are provided in Appendix A.

The examination of the US Population and the PA series resulted in similar findings. Both ACF plots revealed a stationary series as demonstrated by their exponential tailing. Both ICF plots had large spikes at lag 1, further suggesting an autoregressive process of at least order 1. For the US Population series, both the MINIC and SCAN method results suggested an autoregressive order of 2 and a moving average (MA) order of 1. For the PA time series, these methods suggested an autoregressive order of 2. Finally both series exhibited *Q*-statistics were less than 0.001 supporting the hypothesis that the series were not random processes. Having tentatively identified that an autoregressive model was a suitable candidate for each series, the estimation of the models was undertaken.

Table 2

Results of Sequential Dickey-Fuller Unit Root Tests

Variable Series	Initial	1st Difference	2nd Difference
GDP	0.99981	0.0999	0.0215
POP	0.99972	0.0211	
PA	0.97702	0.62461	0.13680

Estimation of the Explanatory Variables, GDP and US Population

The estimation of the explanatory variables was based on the identification process. The GDP model estimated as an AR order 2 having taken the second difference while the US Population model was estimated as an ARMA (2,1) with first differencing applied. These estimates were subsequently crosscorrelated with the PA series and the required plots generated (Appendix B). Interpretation of the plots was then utilized to preliminarily identify the transfer function component of the model. First, the plots were examined for the presence of significant spikes at negative lags. Neither, the GDP or Population series exhibited such findings indicating that no feedback was present in the preliminary model. This supported the utilization of dynamic regression as a methodology. This finding was further verified by the significant values of the *S*-statistic for the crosscorrelation check between series (0.0085 and <0.0001 respectively). The amount of delay present in the plot was assessed. The GDP series revealed a spike at lag 6. In keeping with the Cooper Trend Model, a lag of 3 was included in preliminary transfer function model rather than a lag of 5 as indicated by this plot. As no additional spikes were noted, the identification process moved to the plots of the US Population series to tentatively identify the number of numerator parameters required in the transfer function. Following the initial spike, five additional spikes were identified. This suggests that five or fewer parameters were required in the numerator of the function. The tail of the plot exhibited immediate drop to the zero level. As a result there was no indication for the need of denominator parameters. The results of the plot analysis were formulated into a preliminary transfer function model for the PA series that included GDP and the US Population as the input series with a lag of 3 and five or fewer numerator factors.

Estimation of the Preliminary Transfer Function Model

The approach to the estimation of the preliminary transfer function model required the evaluation of several models beginning with the one that incorporated the previously derived lags and factors. Each model was estimated and evaluated for appropriateness through the examination of residual autocorrelation plots and statistical testing. The estimation of the initial model utilizing a lag of 3 with 5 numerator factors failed to converge. Additional models that varied the numerator factors were also evaluated but failed to meet acceptable levels of appropriateness as delineated below. This lead to the testing of a model with a lag of 3 for the input series (GDP and Population) and 2 numerator factors that served as the preliminary transfer function for the PA series. Appendix C provides the results of this estimation process.

At this stage of the analyses, the parameter estimates cannot be used as evidence for or against the model as the error process is yet to be determined. This is further demonstrated by the statistically significant *Q*-statistic under the autocorrelation check of residuals. The ACF plot of the residuals was examined for the tailing pattern. The residuals exhibited quick tailing suggesting the autoregressive process inherent in this data and in need of delineation during the final estimation. Neither the IACF or the

PACF plots showed significant spikes at any lags. Finally, non-significant *S*-statistics of the crosscorrelation checks of the residuals with both the GDP and Population inputs supported the adequacy of fit to the data.

Estimation of the Final Transfer Function Model

The estimation of the final transfer function model required fitting an error autoregressive process. Selection of the order of the AR process was derived from the evaluation of the ACF plot of the residuals from the preliminary transfer function model. The exponential drop pattern suggested an AR order 1 or higher process. Appendix D demonstrates the results of the selected model with AR 2 order.

Once again, the analysis of model fit was conducted through the examination of the ACF plot of the residuals and the statistical testing of the crosscorrelation check of the residuals. As no significant spikes were identified and no statistically significant *Q*-statistics were present, the final model was deemed an appropriate fit from which forecasts could be generated.

Alternative Transfer Function Models: GDP Only and US Population Only

For comparative purposes, two additional transfer function models were delineated using the same methods as described above. One model considered GDP as the predictor variable while the other considered US Population as the single predictor. Appendices E and F provide the model specifications of each respectively.

The final transfer function GDP Only Model included an AR 2 error process, with two denominator factors. No significant spikes were identified in the autocorrelation plot of the residuals and no significant *Q*-statistics were present in the crosscorrelation check of the residuals. The demonstrated appropriateness of fit allowed forecasts to be generated using this model. For the final transfer function US Population Only Model, a lag of 4 was utilized with an AR 2 error process. The final assessment of this model revealed no significant spikes or significant *Q*-statistics.

Forecasts of PA Supply

Following the delineation of the three transfer function models, forecasts for the next fifteen periods were generated. Table 3 exhibits these forecasts with the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBC) to aid in further comparisons and selection of the model with the best data fit.

Table 3

Forecasts of PA Demand by Modell

Forecast Period	GDP & POP Model	GDP Only Model	US Population Only Model
2007	74296	74552	74802
2008	77799	78369	78516
2009	80891	82091	82264
2010	83817	85751	85557
2011	86423	89364	88915
2012	88956	92924	91834
2013	91198	96426	94851
2014	93420	99874	97466
2015	95415	103272	100217
2016	97450	106622	102605
2017	99316	109925	105167
2018	101276	113186	107401
2019	103112	116407	109840
2020	105079	119589	111981
2021	106954	122734	114354
Akaike's Information Criterion	374.89	411.16	386.02
Schwarz Bayesian Information Criterion	382.21	417.82	391.05

As the combined GDP and US Population Model provided the lowest values for the AIC and SBC, it was selected as the model by which to compare the PA Supply Model.

PA Supply Model Delineation

As discussed in Chapter III, the development of the supply model for the PA profession utilized the following basic equation:

$$PA_t = \sum_{a=24}^{75} PA_{a,t-1}(1 - r_{a,t-1}) + E_t$$

where PA_t is the number of PAs in period *t*;

$PA_{a,t-1}$ is the number of PAs who were *a* years old in period *t*-1

$r_{a,t-1}$ is the retirement rate for PAs who were age *a* in period *t* – 1.

The baseline figure of currently certified PAs in the United States as provided by the NCCPA (59,776). Of these, 147 reported ages of 68 or higher and thus were subtracted from the pool. The remaining 59,629 served as the initial set point for period 1. For each subsequent time period the pool of PAs was adjusted by

(1) aging each member;

(2) decreasing the pool by removal of those members who obtained the age of 67(assumed retirement rate); and

(3) increasing the pool by the number of new entrants into the PA profession.

The initial set point for the number of new entrants was determined through a review of the published class size of each PA program in existence as of October 2006 resulting in a total of 5707 available seats. For each database used in the various scenarios, the assumed attrition (non-graduation) rate of 7% was applied. This was followed by adjustments made for the passage of the national certification rate. The average first time taker pass rate over the last five years was 90%, while for all takers the average was 82%. This implies that those who initially fail the examination may pass on second or more attempts. For the purposes of this study, a 95% pass rate was applied.

As the feminization of the PA profession may influence the number of clinically active PAs in the future, gender was also incorporated into the databases. The assignment was determined in accordance with the published data of both the AAPA and PAEA that suggests a 70:30 female to male ratio and was applied across age groups. Table 4 displays the results of the database development for *status quo*, 10% increase, and a 25% increase in institutional capacity. In addition, it should be noted that the *status quo* figures were utilized for Years 2006-2008 as any increase in enrollment would not effect the number on new entrants until 2009 due to the length of PA programs.

Table 4

Supply Databases by Scenario

Year	Status Quo Total New Entrants			10% Increase Total New Entrants			25% Increase Total New Entrants		
	Total	Female	Male	Total	Female	Male	Total	Female	Male
2006	59,629	35,775	35,775	59,629	35,775	35,775	59,629	35,775	35,775
2007	64,621	39,280	39,280	64,621	39,280	39,280	64,621	39,280	39,280
2008	69,581	42,767	42,767	69,581	42,767	42,767	69,581	42,767	42,767
2009	74,517	46,249	28,268	75,021	46,602	28,419	75,777	47,031	28,746
2010	79,402	49,721	29,681	80,410	50,427	29,983	81,922	51,285	30,637
2011	84,223	53,170	31,053	85,735	54,229	31,506	88,003	55,516	32,487
2012	88,993	56,585	32,408	91,009	57,997	33,012	94,033	59,713	34,320
2013	93,696	60,006	33,690	96,216	61,771	34,445	99,996	63,916	36,080
2014	98,217	63,379	34,838	101,241	65,497	35,744	105,777	68,071	37,706
2015	102,454	66,654	35,800	105,982	69,125	36,857	111,274	72,128	39,146
2016	106,680	69,929	36,751	110,712	72,753	37,959	116,760	76,185	40,575
2017	110,789	73,129	37,660	115,325	76,306	39,019	122,129	80,167	41,962
2018	114,893	76,298	38,595	119,933	79,828	40,105	127,493	84,118	43,375
2019	118,861	79,386	39, 475	124,405	83,269	41,136	132,721	87,988	44,733
2020	122,715	82,388	40,327	128,763	86,624	42,139	137,835	91,772	46,063

The predicted gender distribution for each of the three scenarios resulted in similar results with less than 0.5% variation. The NCCPA data of currently certified PAs (October 2006) noted a 60:40 ratio of female to male PAs. When extrapolated across age groups, this feminization continues to slowly expand over the next fifteen years. By the year 2021, the predictions suggest that 67% of the PA population will be female (Figure 8).

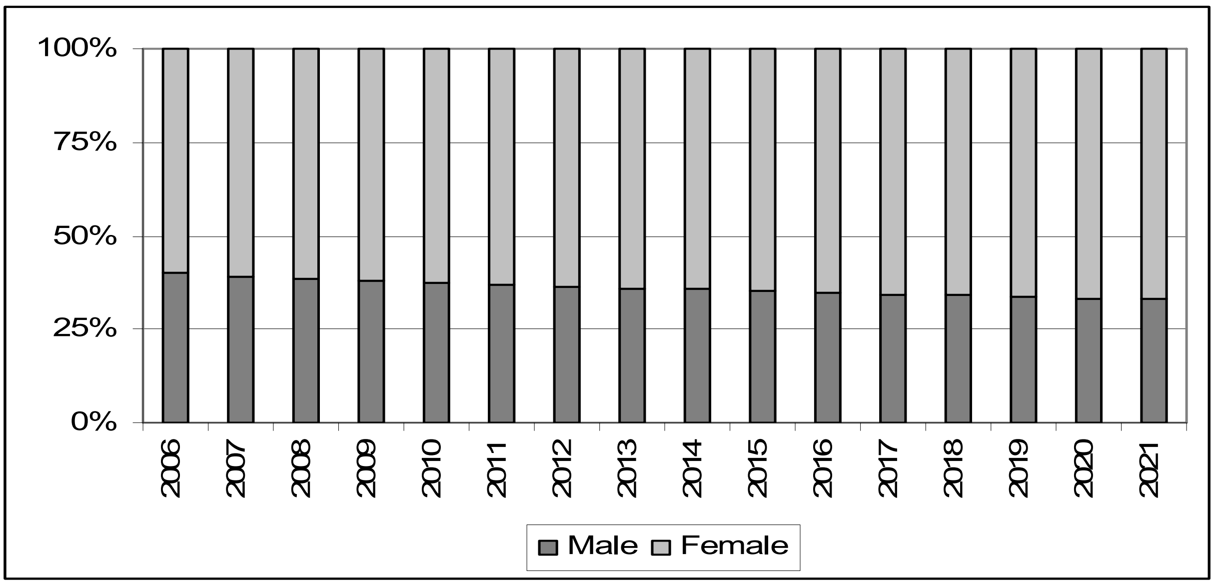

Figure 8. Predicted gender distribution

Supply and Demand for PAs

The final analyses focused on the comparison of the GDP and US Population Model demand forecasts to the supply predictions established within the three scenarios described above. Depicted graphically in Figures 8 through 10, each scenario demonstrates the existence of a shortage of PAs to meet predicted demand until 2010 at the earliest. This shortage remains present even when considering the lower 95% confidence interval of the demand predictions. At this point, the consequences of the scenarios begin to diverge and are discussed separately below.

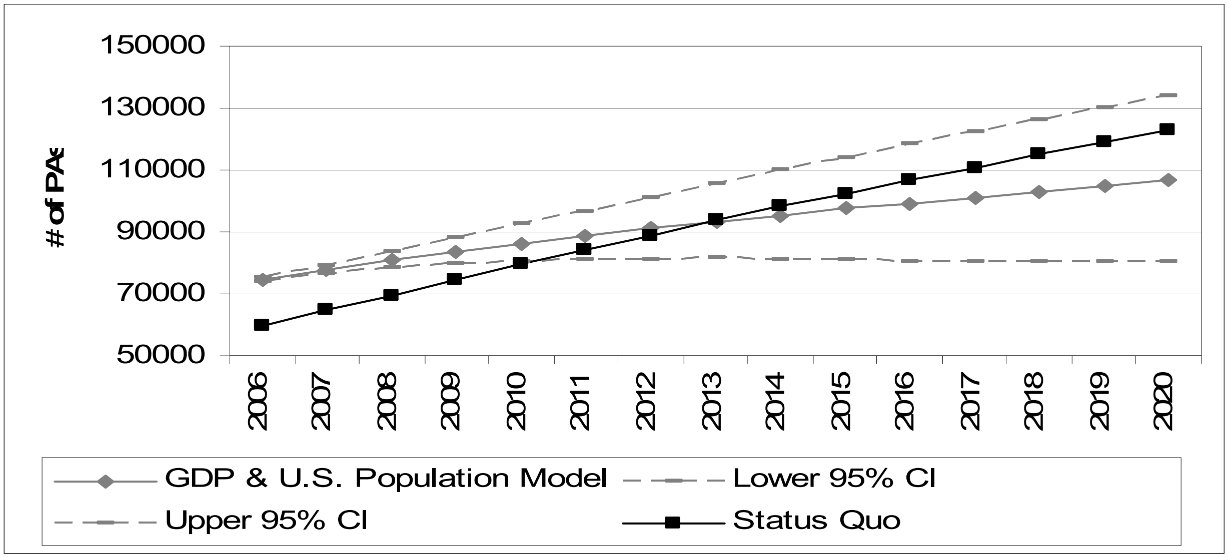

Figure 9. Status quo scenario.

The *Status Quo* Scenario assumed maintenance of the current enrollment rates at existing PA programs with no addition of programs over the forecast period. The apparent shortage of PAs remains for a period of 7 years (2013) at which time a slight excess would be noted. In absolute numbers, the excess would be approximately 2500 PAs. If the upper 95% confidence interval of the demand prediction is considered, however, the maintenance of institutional capacity will fail to meet predicted demand for the entire forecast period.

The 10% Increase Scenario reflects a minimal and logistically obtainable expansion of PA institutional capacity put into effect with the next admission cycle (2007). The supply of PAs would potentially meet predicted demand as early as 2010, but more likely an excess would be realized by 2012. The excess of PAs at this point would reach approximately 2000. If, however, the future demonstrates that the higher 95% confidence interval values are accurate, this modest increase will also fail to meet the demand for PA services.

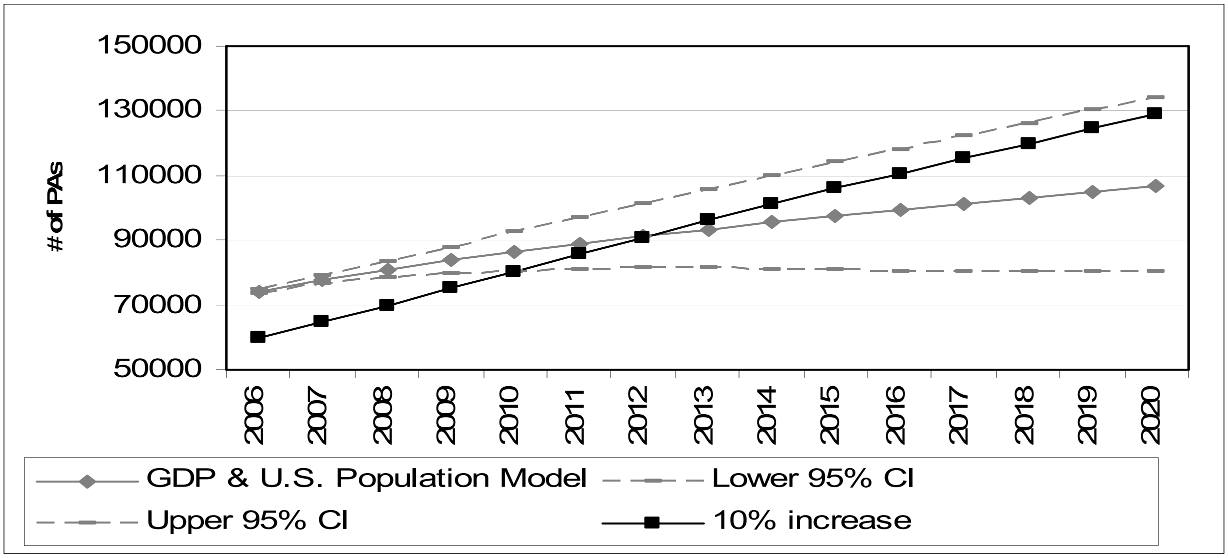

Figure 10. 10% increase scenario.

The final scenario considered represents a substantial increase in institutional capacity at existing PA programs. The net effect however can readily be appreciated. By 2011, a short 5-year period, an excess of 1500 PAs is noted. More importantly, if the higher prediction rates prove accurate, this scenario was the only one to meet that level of demand within the next decade.

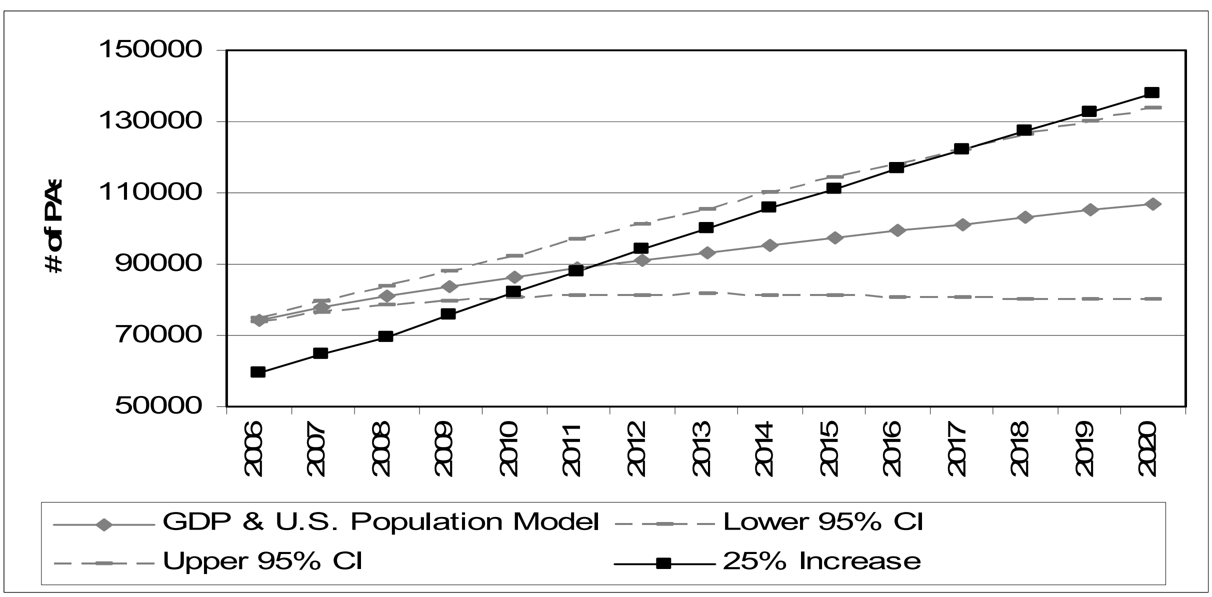

Figure 11. 25% increase scenario.

Summary

This chapter provided the results of the first four research objectives established for this dissertation. The historical and current trends with the PA profession were considered to include gender, specialty, and practice setting. The specification and estimation results of the PA Demand Models were presented with justification provided for the selection of the GDP and US Population Model for forecasting. The database development for the PA Supply Models under three scenarios was further delineated. Finally, the supply models were compared and contrasted with the demand model. Chapter V focuses on the implications of these findings.

CHAPTER V

DISCUSSION

Introduction

This chapter draws on the results that revealed under a current scenario of 5,300 physician assistant (PA) graduates per year the supply and demand equilibrium will be reached in year 2013. This circumstance is adjusted to 2012 under a 10 percent increase in PA matriculation rates and 2011 with a twenty-five percent increase. Cooper has show that gross domestic product (GDP) is the prime predictor of medical demand for services and suggests that PAs are part of this demand curve (Cooper, Getzen, & Laud, 2003). As GDP rises, the need for healthcare services in the US increases proportionally.

The calls for estimating the supply and demand of PAs in the US healthcare workforce lead to the review of the current status of the profession and the development of models presented in Chapter IV (Results). Comparison of the supply and demand models is discussed from the standpoint of PA educational institutions and the effect on the future composition of the medical workforce within the US.

In this study the following research question was posed: *Will the projected supply of PAs in the US meet the projected demand over the next fifteen years?*
This study approached the question through the evaluation of several objectives:

1) the examination of the current status of PA practice in the US,
2) the delineation of a demand model for PA utilization,
3) the delineation of a supply model for the profession, and
4) the comparison of these models under various scenarios.

The discussion of the implications posed by the results of the developed prediction model given the alternative scenarios provides the main focus of this chapter. In addition, limitations of the study and suggestions for future research are proposed.

Implications to Workforce Composition

What will the composition of the healthcare workforce be in the year 2020? The pressures to contain costs in light of increasing numbers of the underinsured population and the approach of the retirement of “baby boomers” have fostered more intense efforts to answer this question. This dissertation approached a single aspect of the workforce, that of the PA profession. Yet its results must be taken in perspective with the supply and demand of its physician colleagues. Unlike their predecessors, the projections of supply and demand from the early 2000s predict a shortage of physicians, of approximately 85,000 to 100,000 by 2020 (Cooper et al., 2003; Council on Graduate Medical Education, 2005; U.S.Department of Health & Human Services, 2006). The shortages are likely to be felt by specialists and those serving the elderly. Though the Council on Graduate Medical Education (COGME) report did not undertake scenario building that addressed the utilization of PAs, the more recent Department of Health and Human Services (DHHS) report included a situation that assumed the number of active nonphysician clinicians (NPC) will increase 60 percent between 2005 and 2020. It was also assumed that they will provide 40% of the work currently provided by a physician. Under this picture it was predicted that physician projections would be lessened by 90,000. The authors suggested that a greater impact from NPC utilization would be realized in reducing the demand for generalist physicians (U.S.Department of Health & Human Services, 2006). The PA Supply Model created herein suggests a doubling of the number of clinically active PAs by the year 2020 given current institutional capacity and with no expansion in enrollment: a 100% increase. If the same holds true for other NPC professions (primarily that of nurse practitioners (NP)), the percentage used by DHHS significantly underestimates this hidden workforce. Many state medical board rules and regulations allow a single physician to employ as many as three PAs. Fuller utilization of PAs could substantially exceed the DHHS assumptions of work provided previously by physicians as well.

Historically PAs have practiced in primary care settings; the review of the current status of the profession suggests a trend towards specialization. Whether the impact of increased utilization of PAs and NPs will reduce generalist physician requirements are difficult to predict. More likely, the growing shortages of specialist physicians coupled with the reduction in resident work hours will continue to attract PAs into these areas (Cawley et al., 2006). A recent workforce study commissioned by the American College of Rheumatology (ACR) predicted shortages of adult rheumatologists of approximately 1,000 by 2015. In addressing how practices intended to meet demand, the study included survey results of practice hiring patterns. Of the respondents, 30% were noted as currently hiring and 50% planning to hire a rheumatologist, PA or NP over the next five years. In addition, the ACR has developed a Web-based curriculum for NPs and PAs as part of its strategy to expand their roles in rheumatology practices (Deal et al., 2007). Similar efforts are occurring for dermatology PAs (P. Eugene Jones, personal communication, October 1, 2006). It appears clear that the movement of PAs to specialty practice will continue and could greatly effect the composition of the healthcare workforce.

Implications to PA Educational Institutions

While the *status quo* projections suggest that the current levels of PA enrollment will meet demand requirements by 2013, the confidence intervals of the demand projections are wide. If the true demand requirements are realized near the upper limits rather than the midpoint levels, the maintenance of 2006 matriculate levels will result in a continuation of PA supply deficits. In addition, the full impact of resident hour reductions, physician specialty shortages, and continued geographic maldistribution of healthcare providers has yet to be considered. Institutional expansion may be required should the projections prove to underestimate demand for PAs. Whether the institution capacity of PA programs can meet the demand requirements will be dependent upon its ability to successfully meet the challenges inherent in program maintenance and growth: adequate faculty and clinical facilities to serve current enrollees. In addition, the ethnic diversity of students (and ultimately the workforce) needs improvement (Institute of Medicine, 2004).

Foremost among these challenges is maintaining a cadre of capable faculty. The “town versus gown” struggle for recruitment of experienced clinicians away from practice is challenging when job opportunities and attractive compensation packages abound. Efforts to retain talented faculty requires significant resources in administrative support and compensation. Unlike graduate medical education, PA programs do not benefit from funding sources such as Medicare. The primary source of internal funding is provided by the program sponsoring institution. On average 86% of total budget is from the parent institution and the remaining 14% is derived from federal training grants administered through the DHHS (Simon et al., 2005). In 2006 this federal source was eliminated (American Academy of Physician Assistants, 2007). Faculty salaries continue to lag behind the national average of clinically employed PAs by approximately $12,000 per year when considering base figures (Simon et al., 2005; American Academy of Physician Assistants, 2006a). Often clinical PAs derive additional income from call sharing and incentive pay based on productivity that are generally not included in faculty compensation packages. Of greater concern is that faculty salaries are often the same or lower than those garnered by new entrants into the profession (American Academy of Physician Assistants, 2006a). Although, the Physician Assistant Education Association (PAEA) and the AAPA advocate for continued federal support, maintaining the current level as well as expansion of PA programs could be hampered without additional financial revenues to assist in faculty recruitment and retention.

Maintaining sufficient numbers of training sites and preceptors utilized for the clinical phase of PA education poses an additional challenge. Whereas physician training is primarily conducted within hospital settings, a significant proportion of PA experiences are accomplished in outpatient venues. As the pressures to increase patient care visits and increasing enrollment in medical schools mount, site availability will be at a premium whether or not PA programs matriculation rates change from 2006 rates. Calls for purchasing clinical sites may be warranted. Academic health centers sponsoring PA programs need to consider how to balance the clinical experience of these two professions as they continue to merge.

If the PA profession is to meet the needs of a diverse nation then it must meet the challenge of increasing the racial and ethnic diversity of its matriculates. The US Census Bureau identifies that over twenty five percent of the population are composed of under-represented minorities, yet less than 10% of all healthcare providers come from this group (Institute of Medicine, 2004). Racial and ethnic minority providers are more likely to serve the medically underserved communities and assist in the reduction of cultural and linguistic barriers. Patients from minorities groups report greater satisfaction with care given by same race or ethnic health professionals as well. Aside from the benefits to the healthcare system, diversity in the educational setting has been associated with better outcomes among all students (Institute of Medicine, 2004). The less than two percent gain in PA diversity growth since 1996 suggests additional strategies are needed.

Limitations and Future Research Considerations

All labor economists lack true clairvoyance and this student has been humbled by this revelation:

> [Workforce prediction is a} daunting enterprise . . . to estimate the physician surplus or shortage one or two decades into the future. Any of the variables in the equation can change over time, sometimes in unforeseen ways.
>
> Uwe Reinhardt (2002)

Limitations in predicting the future abound and this undertaking is no exception. While the past shows remarkable correlation of the growth of the PA profession with GDP, any prediction more than five years out is problematic. How other elements of this demand (technological advancement, longevity of citizens, sustainability of chronic diseases, and lifestyle changes) will evolve remains unknown (Ginzberg, 1989; Cooper, 1994; Blumenthal, 2004; Council on Graduate Medical Education, 2005). Thus the greatest limitation of this study is the fact that no economic prediction is without uncertainty.

The accuracy of healthcare workforce analysis projections is dependent upon the resources and information available to discern the variety of factors influencing supply and demand. This is particularly true regarding the PA profession segment. Evidence from comparative empirical models to identify sound methods of predicting demand for services in various situations is imperative (Armstrong & Green, 2006). Structured research should draw upon focus group analysis, case studies, and triangulation of data. National studies such as MEPS, the NAMCS and the NHAMES are remiss in their lack of full inclusion of PAs and NPs in national studies (Morgan et al., 2006). This shortcoming precluded their inclusion within the model specifications conducted herein. Understanding the full nature of how healthcare is delivered requires knowledge of all the players and the contributions they make to the outcome of care. Several areas need further explication including the effect of lifestyle changes among women and newer entrants into the profession, the productivity levels of current PAs by specialty selection and delineation of other potential demand factors such as that required by the physician community for PA services.

While studies have been conducted with the physician workforce regarding lifestyle changes (Schwartz et al., 1989; Schwartz et al., 1990; Jarecky, Schwartz, Haley, & Donnelly, 1991), relatively little is known if similar preferences exist among the PA profession. With the growing domination of women in this sector, studies should be conducted to elucidate practice patterns in terms of number of hours worked and the impact of lengthy departures from practice for child rearing or caring for elderly family members. It remains unknown whether more recent PA graduates desire a more balanced professional career with personal activities, as do their physician counterparts. While scenarios could have been derived within this study to simulate the impact of lifestyle preferences, a deeper understanding of these phenomena would enhance the ability to more accurately construct models that include these effects.

While several studies have addressed the productivity of PAs (Lin et al., 2002; Hooker, 1999; Hooker, 2000; Hooker et al., 2001; Hooker, 2002; Cawley et al., 2006), more research is required to understand the changing face of PA practice in light of the continuing trend towards specialization. The impact of PA productivity on physician efficiency could substantially influence predictions of supply. The current models neglected this importance aspect due to an insufficient ability to establish reasonable assumptions.

Further study into the factors affecting the demand for PA services should be conducted. In particular, the influence of predicted shortages in several medical and surgical specialties may be driving the PA trend towards specialization. National surveys of physician specialty organization membership practices about intending hiring patterns of PAs may provide insight into factors more directly affecting the demand for PA services. The national agenda for healthcare workforce analysis should incorporate the utilization of PAs in its consideration rather than relegating it to the “factors not included” portion of its reports.

Conclusion

The choice of GDP and the U.S Population trends serve as substantial predictors for the demand of PA services. The use of available data resources to support the investigation was maximized. The results demonstrate that the growth of American PAs is substantial and appears to be on a positive trajectory. By the second decade of this millennium the supply and demand equilibrium for PAs services will be reached that heretofore had not been predicted. How this will be incorporated into medical workforce planning remains to be determined.

It is appropriate to forecast PA demand. Strategic planning calls for all institutions to estimate what the demand for their services will be and plan for resources accordingly. The PA profession faces numerous challenges if demand for its services exceeds supply. The viability of its educational institutions, from its faculty to its facilities, is paramount to the profession's ability to meet anticipated expectations.

Although the field of organizational forecasting is reaching maturity, its application to the PA profession is in its infancy and far more is needed just to reach adolescence. While much research remains to be done, the goal of this dissertation was to establish baseline projections of a segment of the medical workforce whose contributions have previously been under appreciated and to further inform the debate of how the US will meet the healthcare needs of its population in the future. Time will tell whether these predictions come to fruition and if PAs provide part of the solution to the healthcare problems facing our nation. Yet if their delineation spurs increased awareness of how PAs have and will continue to impact the health care system of the US, then the goal was obtained.

APPENDIX A

IDENTIFICATION OF TIME SERIES PROCESSES

```
                              The SAS System
                           The ARIMA Procedure

                          Name of Variable = GDP

                    Mean of Working Series    7401.136
                    Standard Deviation        2078.577
                    Number of Observations          32

                             Autocorrelations

Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1 StdEr
  0      4320483       1.00000   |                    |********************|  0
  1      3887225       0.89972   |             .      |******************  |  0.176777
  2      3479966       0.80546   |         .          |****************    |  0.286083
  3      3077091       0.71221   |      .             |**************      |  0.349844
  4      2708763       0.62696   |    .               |*************  .    |  0.392548
  5      2347460       0.54333   |   .                |***********     .   |  0.422683
  6      1963478       0.45446   |  .                 |*********        .  |  0.443973
  7      1558987       0.36084   |  .                 |*******          .  |  0.458279

                       "." marks two standard errors

                        Inverse Autocorrelations

                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
                  1       -0.48271    |          **********|      .             |
                  2       -0.03255    |             .     *|      .             |
                  3        0.03037    |             .      |*     .             |
                  4        0.00519    |             .      |      .             |
                  5       -0.02134    |             .      |      .             |
                  6       -0.04111    |             .     *|      .             |
                  7        0.04695    |             .      |*     .             |

                        Partial Autocorrelations
                Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

                  1        0.89972    |             .      |******************  |
                  2       -0.02120    |             .      |      .             |
                  3       -0.04603    |             .     *|      .             |
                  4       -0.01208    |             .      |      .             |
                  5       -0.04180    |             .     *|      .             |
                  6       -0.08124    |             .    **|      .             |
                  7       -0.08604    |             .    **|      .             |
```

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	--------Autocorrelations--------					
6	106.78	6	<.0001	0.900	0.805	0.712	0.627	0.543	0.454

Squared Canonical Correlation Estimates

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	0.9839	0.9394	0.8662	0.7725	0.6594	0.5240
AR 1	0.7258	0.6583	0.5986	0.6434	0.6323	0.4989
AR 2	0.0715	0.0022	0.0144	0.0005	0.0029	<.0001
AR 3	0.0130	0.0042	0.0040	0.0030	0.0023	0.0378
AR 4	0.0402	0.0037	0.0054	0.0009	0.0236	0.0215
AR 5	0.0449	0.0025	0.0017	0.0043	0.0009	0.0008

SCAN Chi-Square[1] Probability Values

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	<.0001	0.0002	0.0060	0.0249	0.0572	0.1059
AR 1	<.0001	<.0001	<.0001	0.0006	0.0677	0.1188
AR 2	0.1356	0.8159	0.5565	0.9147	0.8057	0.9675
AR 3	0.5379	0.7824	0.7985	0.8157	0.8342	0.3902
AR 4	0.2838	0.7904	0.7918	0.9144	0.5507	0.6031
AR 5	0.2656	0.8346	0.8866	0.8112	0.9154	0.9388

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	14.98299	13.52745	13.29962	13.07548	12.84571	12.58119
AR 1	10.97622	10.0531	10.00499	10.0207	9.770493	9.62616
AR 2	9.888447	9.863605	9.969782	9.859557	9.839474	9.688822
AR 3	9.849911	9.8108	9.831657	9.919819	9.91691	9.768189
AR 4	9.667218	9.738683	9.810244	9.908061	10.0163	9.620122
AR 5	9.498014	9.606258	9.714561	9.82222	9.775513	9.724108

Error series model: AR(5)
Minimum Table Value: BIC(5,0) = 9.498014

ARMA(p+d,q) Tentative Order Selection Tests

---------SCAN--------		
p+d	q	BIC
2	0	9.888447
0	4	12.84571

(5% Significance Level)

```
                              The SAS System
                           The ARIMA Procedure

                         Name of Variable = POP

                  Mean of Working Series    2.7318E8
                  Standard Deviation        36467981
                  Number of Observations          46


                             Autocorrelations

 Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1  Std Error

   0   1.32991E15       1.00000   |                    |********************|         0
   1   1.24549E15       0.93652   |              .     |******************* |  0.147442
   2   1.16259E15       0.87419   |          .         |*****************   |  0.244689
   3   1.07934E15       0.81159   |        .           |****************    |  0.305121
   4   9.95838E14       0.74880   |      .             |***************     |  0.348908
   5   9.13076E14       0.68657   |     .              |**************.     |  0.382250
   6   8.30322E14       0.62434   |    .               |************   .    |  0.408179
   7   7.62035E14       0.57300   |   .                |***********     .   |  0.428437

                       "." marks two standard errors

                         Inverse Autocorrelations

             Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

               1       -0.49418    |          **********|     .              |
               2       -0.00510    |              .     |     .              |
               3       -0.00292    |              .     |     .              |
               4        0.00412    |              .     |     .              |
               5       -0.04369    |              .    *|     .              |
               6        0.06940    |              .     |*    .              |
               7       -0.02633    |              .    *|     .              |

                         Partial Autocorrelations

             Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

               1        0.93652    |              .     |******************* |
               2       -0.02349    |              .     |     .              |
               3       -0.03533    |              .    *|     .              |
               4       -0.03614    |              .    *|     .              |
               5       -0.03137    |              .    *|     .              |
               6       -0.03677    |              .    *|     .              |
               7        0.05065    |              .     |*    .              |
```

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	--------------Autocorrelations--------------					
6	191.59	6	<.0001	0.937	0.874	0.812	0.749	0.687	0.624

Squared Canonical Correlation Estimates

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	0.9901	0.9715	0.9399	0.8943	0.8362	0.7653
AR 1	0.1454	0.3120	0.3366	0.2784	0.3367	0.3929
AR 2	0.2318	0.0200	0.0036	0.0060	0.0013	<.0001
AR 3	0.1847	0.0130	0.0061	0.0063	0.0005	<.0001
AR 4	0.0690	0.0016	0.0004	<.0001	0.0002	0.0005
AR 5	0.0528	<.0001	<.0001	0.0002	0.0001	0.0002

SCAN Chi-Square[1] Probability Values

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	<.0001	<.0001	0.0009	0.0058	0.0166	0.0336
AR 1	0.0078	0.0005	0.0003	0.0011	0.0003	0.0002
AR 2	0.0007	0.4902	0.7744	0.7159	0.8647	0.9748
AR 3	0.0030	0.5546	0.7170	0.7174	0.9101	0.9943
AR 4	0.0832	0.8348	0.9062	0.9830	0.9437	0.9147
AR 5	0.1358	0.9995	0.9906	0.9431	0.9496	0.9396

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	34.56417	33.9303	33.57735	33.37951	33.2409	33.1009
AR 1	30.17257	30.1711	30.02098	29.89982	29.90571	29.92876
AR 2	30.12396	29.64277	29.72288	29.80459	29.88673	29.83215
AR 3	29.96025	29.72361	29.74499	29.8195	29.9003	29.89226
AR 4	29.84464	29.80323	29.81857	29.86112	29.94129	29.96516
AR 5	29.85731	29.88613	29.90032	29.94018	29.99408	30.02485

Error series model: AR(5)
Minimum Table Value: BIC(2,1) = 29.64277

ARMA(p+d,q) Tentative
Order Selection Tests

---------SCAN--------		
p+d	q	BIC
2	1	29.64277
4	0	29.84464

(5% Significance Level)

```
                                 The SAS System
                              The ARIMA Procedure

                             Name of Variable = PA

                        Mean of Working Series    27765.28
                        Standard Deviation        18197.03
                        Number of Observations          32

                                Autocorrelations

Lag    Covariance    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1    Std Error

  0     331131974        1.00000    |                    |********************|            0
  1     291095254        0.87909    |             .      |******************  |     0.176777
  2     251796994        0.76041    |         .          |***************     |     0.282046
  3     214073053        0.64649    |      .             |*************.      |     0.340131
  4     178409803        0.53879    |     .              |***********   .     |     0.376578
  5     145272728        0.43872    |    .               |*********      .    |     0.399943
  6     114955129        0.34716    |   .                |*******         .   |     0.414709
  7      87628585        0.26463    |   .                |*****           .   |     0.423693

                          "." marks two standard errors

                            Inverse Autocorrelations

            Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

              1       -0.50402    |          **********|      .             |
              2        0.00267    |             .      |      .             |
              3        0.00056    |             .      |      .             |
              4        0.00143    |             .      |      .             |
              5        0.00114    |             .      |      .             |
              6       -0.01017    |             .      |      .             |
              7        0.01468    |             .      |      .             |

                            Partial Autocorrelations

            Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

              1        0.87909    |             .      |******************  |
              2       -0.05453    |             .     *|      .             |
              3       -0.04635    |             .     *|      .             |
              4       -0.04138    |             .     *|      .             |
              5       -0.03565    |             .     *|      .             |
              6       -0.03105    |             .     *|      .             |
              7       -0.02709    |             .     *|      .             |
```

Autocorrelation Check for White Noise

To Lag	Chi-Square	DF	Pr > ChiSq	--------Autocorrelations--------					
6	87.85	6	<.0001	0.879	0.760	0.646	0.539	0.439	0.347

Squared Canonical Correlation Estimates

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	0.9839	0.9311	0.8378	0.7074	0.5526	0.3938
AR 1	0.9744	0.9061	0.7959	0.6562	0.5034	0.3578
AR 2	0.0107	0.0827	0.0654	0.0046	0.0268	0.0012
AR 3	0.1122	0.0176	0.0160	0.0307	0.0014	0.0003
AR 4	0.1139	0.0309	0.0552	0.0017	0.0003	0.0001
AR 5	0.0051	0.0336	<.0001	<.0001	0.0002	0.0003

SCAN Chi-Square[1] Probability Values

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	<.0001	0.0002	0.0052	0.0247	0.0675	0.1431
AR 1	<.0001	0.0002	0.0061	0.0288	0.0783	0.1618
AR 2	0.5693	0.1180	0.2082	0.7674	0.5107	0.9118
AR 3	0.0632	0.5835	0.6006	0.5375	0.9054	0.9622
AR 4	0.0657	0.4379	0.2864	0.8822	0.9479	0.9769
AR 5	0.7096	0.3502	0.9696	0.9797	0.9639	0.9609

Minimum Information Criterion

Lags	MA 0	MA 1	MA 2	MA 3	MA 4	MA 5
AR 0	19.39893	16.7902	15.88911	15.2213	14.77164	14.36187
AR 1	15.22343	11.32106	11.35294	11.43565	11.4567	11.55374
AR 2	11.40664	11.40516	11.41254	11.48454	11.55662	11.61883
AR 3	11.49129	11.4012	11.4802	11.58204	11.62698	11.72037
AR 4	11.47931	11.463	11.54516	11.64859	11.73378	11.81601
AR 5	11.44605	11.54953	11.61308	11.71965	11.82367	11.90646

Error series model: AR(5)
Minimum Table Value: BIC(1,1) = 11.32106

ARMA(p+d,q) Tentative
Order Selection Tests

----SCAN----		
p+d	q	BIC
2	0	11.40664
0	4	14.77164

(5% Significance Level)

APPENDIX B

ESTIMATION OF EXPLANATORY VARIABLES:

GDP AND US POPULATION

```
                                 The SAS System
                              The ARIMA Procedure

                         Name of Variable = PA

          Period(s) of Differencing                           2
          Mean of Working Series                       4203.933
          Standard Deviation                           2700.538
          Number of Observations                             30
          Observation(s) eliminated by differencing           2

                              Autocorrelations

Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0     7292903      1.00000  |                    |********************|
  1     6809135      0.93367  |             .      |******************* |
  2     6094652      0.83570  |        .           |*****************   |
  3     5266835      0.72219  |     .              |**************.     |
  4     4355842      0.59727  |   .                |************    .   |
  5     3403079      0.46663  |  .                 |*********        .  |
  6     2414372      0.33106  |  .                 |*******          .  |
  7     1505623      0.20645  | .                  |****              . |

                       "." marks two standard errors

                         Inverse Autocorrelations

     Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

       1       -0.56260    |         ***********|      .             |
       2        0.06871    |             .      |*     .             |
       3       -0.01950    |             .      |      .             |
       4        0.04012    |             .      |*     .             |
       5       -0.07833    |             .    **|      .             |
       6        0.05978    |             .      |*     .             |
       7       -0.00452    |             .      |      .             |

                         Partial Autocorrelations

     Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

       1        0.93367    |             .      |******************* |
       2       -0.28094    |             .******|      .             |
       3       -0.12677    |             .   ***|      .             |
       4       -0.12286    |             .    **|      .             |
       5       -0.09371    |             .    **|      .             |
       6       -0.11427    |             .    **|      .             |
       7        0.01041    |             .      |      .             |

                   Autocorrelation Check for White Noise

 To      Chi-         Pr >
Lag    Square   DF   ChiSq  ---------------Autocorrelations---------------

  6     97.26    6  <.0001   0.934   0.836   0.722   0.597   0.467   0.331
                    Variable GDP has been differenced.
```

```
                 Correlation of PA and GDP

   Period(s) of Differencing                          2
   Number of Observations                            30
   Observation(s) eliminated by differencing          2
   Variance of transformed series PA            1719716
   Variance of transformed series GDP          17130.55

             Both series have been prewhitened.

                      Crosscorrelations

Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 -7  -15039.201     -.08762   |             .    **|      .             |
 -6   15949.717     0.09293   |             .      |**    .             |
 -5   36317.652     0.21159   |             .      |****  .             |
 -4   22446.157     0.13078   |             .      |***   .             |
 -3   40620.067     0.23666   |             .      |***** .             |
 -2   43594.416     0.25399   |             .      |***** .             |
 -1   47363.185     0.27595   |             .      |******.             |
  0   60290.756     0.35127   |             .      |*******             |
  1   55170.928     0.32144   |             .      |******.             |
  2   47299.138     0.27557   |             .      |******.             |
  3   55384.920     0.32268   |             .      |******.             |
  4   51015.765     0.29723   |             .      |******.             |
  5   48351.617     0.28171   |             .      |******.             |
  6   66300.700     0.38628   |             .      |********            |
  7   44086.937     0.25686   |             .      |***** .             |

                 "." marks two standard errors

            Crosscorrelation Check Between Series

 To     Chi-        Pr >
Lag    Square  DF   ChiSq  ---------------Crosscorrelations--------------

  5     17.23   6  0.0085   0.351   0.321   0.276   0.323   0.297   0.282

   Both variables have been prewhitened by the following filter:

                     Prewhitening Filter
                    Autoregressive Factors

       Factor 1:  1 - 0.99068 B**(1) + 0.48106 B**(2)

             Variable POP has been differenced.
                 Correlation of PA and POP

   Period(s) of Differencing                          2
   Number of Observations                            30
   Observation(s) eliminated by differencing          2
   Variance of transformed series PA            4768053
   Variance of transformed series POP          2.641E12

             Both series have been prewhitened.
```

Crosscorrelations

```
Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 -7   -189626471       -.05344   |             .     *|      .             |
 -6     13123814       0.00370   |             .      |      .             |
 -5     97325108       0.02743   |             .      |*     .             |
 -4    346136909       0.09754   |             .      |**    .             |
 -3    615738685       0.17352   |             .      |***   .             |
 -2   1031582998       0.29071   |             .      |******.             |
 -1   1223207225       0.34471   |             .      |*******             |
  0   1614882260       0.45509   |             .      |*********           |
  1   1741515889       0.49078   |             .      |**********          |
  2   1958262049       0.55186   |             .      |***********         |
  3   1887185712       0.53183   |             .      |***********         |
  4   1924788479       0.54242   |             .      |***********         |
  5   1767917331       0.49822   |             .      |**********          |
  6   1176783403       0.33163   |             .      |*******             |
  7    269323427       0.07590   |             .      |**    .             |
```

"." marks two standard errors

Crosscorrelation Check Between Series

To Lag	Chi-Square	DF	Pr > ChiSq	Crosscorrelations					
5	47.33	6	<.0001	0.455	0.491	0.552	0.532	0.542	0.498

Both variables have been prewhitened by the following filter:

Prewhitening Filter
Autoregressive Factors

Factor 1: 1 + 0.6755 B**(1) - 0.08251 B**(2)

Moving Average Factors

Factor 1: 1 + 0.99998 B**(1)

APPENDIX C

ESTIMATION OF PRELIMINARY TRANSFER FUNCTION MODEL:

GDP AND US POPULATION

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-3582.1	1490.7	-2.40	0.0163	0	PA	0
NUM1	0.0007374	0.0001931	3.82	0.0001	0	POP	3
NUM1,1	-0.0006336	0.0002069	-3.06	0.0022	2	POP	3
NUM2	1.49635	2.12523	0.70	0.4814	0	GDP	0

Constant Estimate	-3582.07
Variance Estimate	3790065
Std Error Estimate	1946.809
AIC	453.2854
SBC	458.1609
Number of Residuals	25

Correlations of Parameter Estimates

Variable		PA	POP	POP	GDP
Parameter		MU	NUM1	NUM1,1	NUM2
PA	MU	1.000	-0.582	0.442	-0.287
POP	NUM1	-0.582	1.000	0.039	-0.139
POP	NUM1,1	0.442	0.039	1.000	0.399
GDP	NUM2	-0.287	-0.139	0.399	1.000

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	26.05	6	0.0002	0.769	0.479	0.250	0.013	-0.100	-0.109
12	28.26	12	0.0051	-0.081	-0.048	-0.017	-0.024	-0.083	-0.169
18	54.08	18	<.0001	-0.239	-0.287	-0.321	-0.288	-0.198	-0.105
24	54.36	24	0.0004	-0.014	0.021	0.025	0.018	0.006	0.002

```
                      Autocorrelation Plot of Residuals
Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0     3790065      1.00000  |                    |********************|
  1     2914013      0.76886  |             .      |***************     |
  2     1815872      0.47911  |         .          |********** .        |
  3      948435      0.25024  |        .           |*****       .       |
  4   49173.355      0.01297  |        .           |            .       |
  5     -379900      -.10024  |        .         **|            .       |
  6     -414921      -.10948  |        .         **|            .       |
  7     -308774      -.08147  |        .         **|            .       |

                         "." marks two standard errors
```

```
                  Inverse Autocorrelations

 Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1       -0.67863    |      **************|       .            |
   2        0.34145    |             .      |*******.            |
   3       -0.31033    |             . ******|       .            |
   4        0.23365    |             .      |*****  .            |
   5       -0.07824    |             .    **|       .            |
   6        0.02844    |             .      |*      .            |
   7       -0.01673    |             .      |       .            |

                  Partial Autocorrelations

 Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1        0.76886    |             .      |***************     |
   2       -0.27399    |             .  *****|       .            |
   3       -0.02220    |             .      |       .            |
   4       -0.24524    |             .  *****|       .            |
   5        0.14250    |             .      |***    .            |
   6        0.01198    |             .      |       .            |
   7        0.03966    |             .      |*      .            |
```

Crosscorrelation Check of Residuals with Input POP

To Lag	Chi-Square	DF	Pr > ChiSq	---------------Crosscorrelations-------------					
5	0.29	5	0.9978	-0.019	-0.028	-0.047	-0.049	0.052	0.068
11	1.56	11	0.9995	0.063	0.025	-0.031	-0.087	-0.139	-0.160
17	3.90	17	0.9996	-0.169	-0.172	-0.160	-0.125	-0.080	-0.028

Crosscorrelation Check of Residuals with Input GDP

To Lag	Chi-Square	DF	Pr > ChiSq	---------------Crosscorrelations-------------					
5	11.54	6	0.0732	-0.075	0.086	0.356	0.366	0.344	0.263
11	13.91	12	0.3063	0.021	-0.032	-0.058	-0.093	-0.160	-0.236
17	14.50	18	0.6957	-0.045	0.066	0.077	0.035	-0.095	-0.031
23	17.19	24	0.8404	0.075	-0.233	-0.216	0.025	-0.019	0.013

Model for variable PA

Estimated Intercept	-3582.07
Period(s) of Differencing	2

Input Number 1

Input Variable	POP
Shift	3
Period(s) of Differencing	2

Numerator Factors

Factor 1: 0.00074 + 0.00063 B**(2)

Input Number 2

Input Variable	GDP
Period(s) of Differencing	2
Overall Regression Factor	1.496355

APPENDIX D

ESTIMATION OF FINAL TRANSFER FUNCTION MODEL:

GDP AND US POPULATION

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	4063.5	1584.1	2.57	0.0103	0	PA	0
AR1,1	1.76535	0.13382	13.19	<.0001	1	PA	0
AR1,2	-0.80612	0.14226	-5.67	<.0001	2	PA	0
NUM1	0.00001293	0.00003770	0.34	0.7316	0	POP	3
NUM1,1	-0.0000472	0.00005185	-0.91	0.3630	2	POP	3
NUM2	0.40612	0.37391	1.09	0.2774	0	GDP	0

Constant Estimate	165.6846
Variance Estimate	125994.6
Std Error Estimate	354.9572
AIC	374.8937
SBC	382.2069
Number of Residuals	25

Correlations of Parameter Estimates

Variable		PA	PA	PA	POP	POP	GDP
Parameter		MU	AR1,1	AR1,2	NUM1	NUM1,1	NUM2
PA	MU	1.000	-0.296	0.337	-0.255	0.304	-0.085
PA	AR1,1	-0.296	1.000	-0.983	-0.031	0.048	0.016
PA	AR1,2	0.337	-0.983	1.000	0.014	-0.021	-0.027
POP	NUM1	-0.255	-0.031	0.014	1.000	-0.684	-0.224
POP	NUM1,1	0.304	0.048	-0.021	-0.684	1.000	0.009
GDP	NUM2	-0.085	0.016	-0.027	-0.224	0.009	1.000

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	5.09	4	0.2784	-0.047	-0.136	0.364	-0.084	-0.075	0.016
12	12.67	10	0.2429	0.036	-0.032	-0.198	0.160	0.097	-0.286
18	20.12	16	0.2148	0.127	-0.078	-0.283	-0.014	0.006	-0.088
24	20.96	22	0.5235	-0.051	0.047	0.009	0.010	0.019	0.012

Autocorrelation Plot of Residuals

```
Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0      125995      1.00000  |                    |********************|
  1   -5918.094      -.04697  |             .     *|       .            |
  2  -17137.602      -.13602  |             .   ***|       .            |
  3   45824.841      0.36370  |             .      |*******.            |
  4  -10553.691      -.08376  |            .     **|        .           |
  5   -9434.177      -.07488  |            .      *|        .           |
  6    2062.452      0.01637  |            .       |        .           |
  7    4580.926      0.03636  |            .       |*       .           |
```

"." marks two standard errors

Inverse Autocorrelations

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
```

```
   1       -0.18713    |            .   ****|       .          |
   2        0.20368    |            .       |****   .          |
   3       -0.42003    |            ********|       .          |
   4        0.19378    |            .       |****   .          |
   5       -0.05803    |            .      *|       .          |
   6        0.13343    |            .       |***    .          |
   7       -0.09313    |            .     **|       .          |

                    Partial Autocorrelations

 Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1       -0.04697    |            .      *|       .          |
   2       -0.13853    |            .    ***|       .          |
   3        0.35756    |            .       |*******.          |
   4       -0.09581    |            .     **|       .          |
   5        0.02286    |            .       |       .          |
   6       -0.16077    |            .    ***|       .          |
   7        0.11988    |            .       |**     .          |

             Crosscorrelation Check of Residuals with Input POP
 To      Chi-         Pr >
Lag    Square   DF   ChiSq   ---------------Crosscorrelations--------------

  5      0.50    5  0.9922   0.076   0.016  -0.120  -0.034   0.030  -0.014
 11      1.41   11  0.9997  -0.045  -0.064  -0.078  -0.097  -0.107  -0.092
 17      1.73   17  1.0000  -0.091  -0.072  -0.018  -0.018   0.000   0.020

             Crosscorrelation Check of Residuals with Input GDP
 To      Chi-         Pr >
Lag    Square   DF   ChiSq   ---------------Crosscorrelations--------------
  5     10.29    6  0.1131   0.178   0.286  -0.191   0.300   0.247  -0.333
 11     11.44   12  0.4914  -0.017  -0.075  -0.057  -0.078  -0.110   0.138
 17     14.75   18  0.6789  -0.081  -0.100   0.214  -0.179  -0.100   0.168
 23     16.83   24  0.8557  -0.228  -0.071   0.141  -0.041  -0.057   0.035

                     Model for variable PA
              Estimated Intercept         4063.537
              Period(s) of Differencing          2

                     Autoregressive Factors
          Factor 1:  1 - 1.76535 B**(1) + 0.80612 B**(2)

                        Input Number 1
                 Input Variable              POP
                 Shift                         3
                 Period(s) of Differencing     2

                       Numerator Factors
                Factor 1:  0.00001 + 0.00005 B**(2)

                       Input Number 2
              Input Variable                   GDP
              Period(s) of Differencing          2
              Overall Regression Factor   0.406123
```

APPENDIX E

GDP ONLY MODEL SPECIFICATION

Estimation of Explanatory Variable: GDP Only

```
                         The ARIMA Procedure

                        Name of Variable = PA

        Period(s) of Differencing                           1
        Mean of Working Series                       2124.097
        Standard Deviation                           1363.468
        Number of Observations                             31
        Observation(s) eliminated by differencing           1

                           Autocorrelations

Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0     1859046      1.00000  |                    |********************|
  1     1742953      0.93755  |              .     |******************* |
  2     1573365      0.84633  |         .          |*****************   |
  3     1373321      0.73872  |      .             |***************     |
  4     1143543      0.61512  |    .               |************    .   |
  5      912288      0.49073  |   .                |**********       .  |
  6      665984      0.35824  |   .                |*******          .  |
  7      424264      0.22822  | .                  |*****             . |

                    "." marks two standard errors

                      Inverse Autocorrelations

     Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

       1       -0.56109    |          ***********|      .             |
       2        0.08832    |              .      |**    .             |
       3       -0.09059    |              .    **|      .             |
       4        0.12776    |              .      |***   .             |
       5       -0.10036    |              .    **|      .             |
       6        0.01904    |              .      |      .             |
       7        0.02063    |              .      |      .             |

                      Partial Autocorrelations

     Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

       1        0.93755    |              .      |******************* |
       2       -0.27005    |              . *****|      .             |
       3       -0.14127    |              .   ***|      .             |
       4       -0.16089    |              .   ***|      .             |
       5       -0.03252    |              .     *|      .             |
       6       -0.14997    |              .   ***|      .             |
       7       -0.04752    |              .     *|      .             |

                Autocorrelation Check for White Noise

  To      Chi-         Pr >
 Lag    Square   DF   ChiSq  ---------------Autocorrelations---------------
```

```
  6    104.24    6  <.0001   0.938   0.846   0.739   0.615   0.491   0.358

                 Variable GDP has been differenced.

                     Correlation of PA and GDP

          Period(s) of Differencing                          2
          Number of Observations                            30
          Observation(s) eliminated by differencing          2
          Variance of transformed series PA           461628.2
          Variance of transformed series GDP          17130.55

                 Both series have been prewhitened.

                          Crosscorrelations

Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 -7    -3511.956       -.03949   |             .     *|      .             |
 -6    12713.833       0.14297   |             .      |***   .             |
 -5    12745.093       0.14332   |             .      |***   .             |
 -4     9512.502       0.10697   |             .      |**    .             |
 -3    19587.146       0.22026   |             .      |****  .             |
 -2    24180.650       0.27192   |             .      |***** .             |
 -1    25248.091       0.28392   |             .      |******.             |
  0    34151.683       0.38404   |             .      |********            |
  1    25049.816       0.28169   |             .      |******.             |
  2    22133.627       0.24890   |             .      |***** .             |
  3    37157.289       0.41784   |             .      |********            |
  4    18648.831       0.20971   |             .      |****  .             |
  5    29339.861       0.32993   |             .      |*******             |
  6    33067.999       0.37186   |             .      |*******             |
  7    14699.399       0.16530   |             .      |***   .             |

                   "." marks two standard errors

                 Crosscorrelation Check Between Series

 To      Chi-         Pr >
Lag     Square   DF   ChiSq   ---------------Crosscorrelations--------------

  5      18.49    6  0.0051   0.384   0.282   0.249   0.418   0.210   0.330

      Both variables have been prewhitened by the following filter:

                         Prewhitening Filter


                        Autoregressive Factors

            Factor 1:  1 - 0.99068 B**(1) + 0.48106 B**(2)
```

Estimation of Preliminary Transfer Function: GDP Only

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	-7585.7	3467.2	-2.19	0.0287	0	PA	0
NUM1	2.14740	0.26219	8.19	<.0001	0	GDP	0
DEN1,1	0.90700	0.03573	25.38	<.0001	1	GDP	0

Constant Estimate	-7585.72
Variance Estimate	538501.4
Std Error Estimate	733.8265
AIC	467.8315
SBC	471.9334
Number of Residuals	29

Correlations of Parameter Estimates

Variable	Parameter	PA MU	GDP NUM1	GDP DEN1,1
PA	MU	1.000	0.067	-0.947
GDP	NUM1	0.067	1.000	-0.381
GDP	DEN1,1	-0.947	-0.381	1.000

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	23.49	6	0.0006	0.698	0.239	-0.125	-0.274	-0.239	-0.119
12	35.37	12	0.0004	0.039	0.142	0.239	0.319	0.260	0.063
18	57.90	18	<.0001	-0.134	-0.253	-0.272	-0.291	-0.268	-0.145
24	80.79	24	<.0001	0.013	0.170	0.176	0.015	-0.164	-0.263

Autocorrelation Plot of Residuals

```
Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0      538501      1.00000  |                    |********************|
  1      376009      0.69825  |             .      |**************      |
  2      128484      0.23860  |          .         |*****    .          |
  3  -67480.328      -.12531  |         .       ***|          .         |
  4     -147744      -.27436  |         .     *****|          .         |
  5     -128667      -.23894  |         .     *****|          .         |
  6  -64233.451      -.11928  |         .        **|          .         |
  7   21178.231      0.03933  |        .           |*          .        |
```

"." marks two standard errors

```
                     Inverse Autocorrelations

 Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1       -0.62592    |       *************|      .              |
   2        0.12886    |             .      |***   .              |
   3        0.05205    |             .      |*     .              |
   4        0.03201    |             .      |*     .              |
   5       -0.09971    |             .    **|      .              |
   6        0.10596    |             .      |**    .              |
   7       -0.05075    |             .     *|      .              |
```

```
                     Partial Autocorrelations

 Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1
   1        0.69825    |             .      |**************       |
   2       -0.48582    |          **********|      .              |
   3       -0.08588    |             .    **|      .              |
   4        0.01297    |             .      |      .              |
   5        0.00003    |             .      |      .              |
   6       -0.01034    |             .      |      .              |
   7        0.11117    |             .      |**    .              |
```

Crosscorrelation Check of Residuals with Input GDP

To Lag	Chi-Square	DF	Pr > ChiSq	---------------Crosscorrelations--------------					
5	7.71	5	0.1727	0.194	-0.141	-0.311	-0.069	0.155	0.288
11	12.53	11	0.3251	0.259	0.170	0.214	0.120	0.055	-0.083
17	15.70	17	0.5449	-0.223	-0.209	-0.095	-0.054	-0.047	-0.047
23	19.00	23	0.7014	-0.021	0.046	-0.024	-0.097	-0.249	-0.198

```
        Model for variable PA
Estimated Intercept          -7585.72
Period(s) of Differencing           1

           Input Number 1
Input Variable                    GDP
Period(s) of Differencing           2
Overall Regression Factor    2.147401
          Denominator Factors

      Factor 1:  1 - 0.907 B**(1)
```

Estimation of Final Transfer Function Model: GDP Only

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	2342.6	1378.7	1.70	0.0893	0	PA	0
AR1,1	1.26583	0.21010	6.02	<.0001	1	PA	0
AR1,2	-0.29928	0.22578	-1.33	0.1850	2	PA	0
NUM1	0.27121	0.32937	0.82	0.4103	0	GDP	0
DEN1,1	-0.48072	0.89708	-0.54	0.5921	2	GDP	0

Constant Estimate	78.36286
Variance Estimate	106172.4
Std Error Estimate	325.8411
AIC	411.1586
SBC	417.8196
Number of Residuals	28

Correlations of Parameter Estimates

Variable		PA	PA	PA	GDP	GDP
Parameter		MU	AR1,1	AR1,2	NUM1	DEN1,1
PA	MU	1.000	-0.282	0.379	-0.181	-0.251
PA	AR1,1	-0.282	1.000	-0.978	0.097	0.262
PA	AR1,2	0.379	-0.978	1.000	-0.110	-0.286
GDP	NUM1	-0.181	0.097	-0.110	1.000	0.534
GDP	DEN1,1	-0.251	0.262	-0.286	0.534	1.000

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	8.52	4	0.0744	-0.109	0.324	0.268	0.042	0.214	-0.126
12	15.48	10	0.1156	0.151	-0.043	-0.092	-0.004	0.127	-0.302
18	22.17	16	0.1379	0.123	-0.179	-0.119	-0.106	-0.160	0.057
24	29.52	22	0.1306	-0.262	0.063	-0.058	0.023	0.007	-0.015

Autocorrelation Plot of Residuals

```
Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0      106172      1.00000  |                    |********************|
  1  -11620.341      -.10945  |          .       **|       .            |
  2   34427.091      0.32426  |          .         |****** .            |
  3   28404.936      0.26754  |          .         |*****  .            |
  4    4453.935      0.04195  |         .          |*        .          |
  5   22710.930      0.21391  |         .          |****     .          |
  6  -13413.574      -.12634  |         .       ***|         .          |
  7   16071.248      0.15137  |         .          |***      .          |
                               "." marks two standard errors
```

Inverse Autocorrelations

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1        0.24571    |             .       |*****  .             |
  2       -0.29594    |             . ******|       .             |
  3       -0.42981    |            *********|       .             |
  4       -0.15183    |             .    ***|       .             |
  5        0.05077    |             .       |*      .             |
  6        0.18666    |             .       |****   .             |
  7        0.01374    |             .       |       .             |
```

Partial Autocorrelations

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1       -0.10945    |             .     **|       .             |
  2        0.31606    |             .       |****** .             |
  3        0.36702    |             .       |*******.             |
  4        0.02831    |             .       |*      .             |
  5        0.02000    |             .       |       .             |
  6       -0.26412    |             .  *****|       .             |
  7       -0.02002    |             .       |       .             |
```

Crosscorrelation Check of Residuals with Input GDP

To Lag	Chi-Square	DF	Pr > ChiSq	Crosscorrelations					
5	7.29	5	0.1998	0.168	0.117	0.035	0.448	-0.066	0.111
11	12.00	11	0.3635	0.053	-0.298	0.050	-0.270	-0.036	0.008
17	15.23	17	0.5792	-0.161	0.022	-0.003	-0.227	0.083	-0.174
23	19.98	23	0.6432	-0.299	-0.047	-0.234	0.020	-0.145	-0.044

Model for variable PA

Estimated Intercept	2342.644
Period(s) of Differencing	1

Autoregressive Factors

Factor 1: 1 - 1.26583 B**(1) + 0.29928 B**(2)

Input Number 1

Input Variable	GDP
Period(s) of Differencing	2
Overall Regression Factor	0.271214

Denominator Factors

Factor 1: 1 + 0.48072 B**(2)

APPENDIX F

US POPULATION ONLY MODEL SPECIFICATION

Estimation of Explanatory Variable: US Population Only

```
                          The ARIMA Procedure

                        Name of Variable = PA

        Period(s) of Differencing                           2
        Mean of Working Series                       4203.933
        Standard Deviation                           2700.538
        Number of Observations                             30
        Observation(s) eliminated by differencing          2

                           Autocorrelations

Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0     7292903      1.00000  |                    |********************|
  1     6809135      0.93367  |              .     |******************* |
  2     6094652      0.83570  |         .          |*****************   |
  3     5266835      0.72219  |      .             |**************.     |
  4     4355842      0.59727  |    .               |************    .   |
  5     3403079      0.46663  |   .                |*********         .  |
  6     2414372      0.33106  |   .                |*******           .  |
  7     1505623      0.20645  | .                  |****               . |

                     "." marks two standard errors

                        Inverse Autocorrelations

    Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

      1       -0.56260    |          ***********|      .             |
      2        0.06871    |              .      |*     .             |
      3       -0.01950    |              .      |      .             |
      4        0.04012    |              .      |*     .             |
      5       -0.07833    |              .    **|      .             |
      6        0.05978    |              .      |*     .             |
      7       -0.00452    |              .      |      .             |

                        Partial Autocorrelations

    Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

      1        0.93367    |              .      |******************* |
      2       -0.28094    |              .******|      .             |
      3       -0.12677    |              .   ***|      .             |
      4       -0.12286    |              .    **|      .             |
      5       -0.09371    |              .    **|      .             |
      6       -0.11427    |              .    **|      .             |
      7        0.01041    |              .      |      .             |

                  Autocorrelation Check for White Noise

  To      Chi-          Pr >
 Lag    Square    DF    ChiSq    ---------------Autocorrelations---------------

   6     97.26     6   <.0001    0.934    0.836    0.722    0.597    0.467    0.331
```

```
                 Variable POP has been differenced.

                     Correlation of PA and POP

        Period(s) of Differencing                          2
        Number of Observations                            30
        Observation(s) eliminated by differencing          2
        Variance of transformed series PA            4768053
        Variance of transformed series POP          2.641E12

                 Both series have been prehwitened.


                          Crosscorrelations

Lag   Covariance   Correlation   -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

 -7   -189626471       -.05344   |             .     *|      .             |
 -6     13123814       0.00370   |             .      |      .             |
 -5     97325108       0.02743   |             .      |*     .             |
 -4    346136909       0.09754   |             .      |**    .             |
 -3    615738685       0.17352   |             .      |***   .             |
 -2   1031582998       0.29071   |             .      |******.             |
 -1   1223207225       0.34471   |             .      |*******             |
  0   1614882260       0.45509   |             .      |*********           |
  1   1741515889       0.49078   |             .      |**********          |
  2   1958262049       0.55186   |             .      |***********         |
  3   1887185712       0.53183   |             .      |***********         |
  4   1924788479       0.54242   |             .      |***********         |
  5   1767917331       0.49822   |             .      |**********          |
  6   1176783403       0.33163   |             .      |*******             |
  7    269323427       0.07590   |             .      |**    .             |

                   "." marks two standard errors

                 Crosscorrelation Check Between Series

 To      Chi-          Pr >
Lag     Square   DF   ChiSq   ---------------Crosscorrelations--------------

  5      47.33    6  <.0001   0.455    0.491    0.552    0.532    0.542    0.498


      Both variables have been prewhitened by the following filter:

                          Prewhitening Filter

                         Autoregressive Factors

              Factor 1:  1 + 0.6755 B**(1) - 0.08251 B**(2)

                         Moving Average Factors

                      Factor 1:  1 + 0.99998 B**(1)
```

Estimation of Preliminary Transfer Function: US Population Only

The ARIMA Procedure

Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	27.85295	1310.1	0.02	0.9830	0	PA	0
NUM1	0.0008264	0.0002290	3.61	0.0003	0	POP	4

Constant Estimate	27.85295
Variance Estimate	5593536
Std Error Estimate	2365.066
AIC	479.6689
SBC	482.1851
Number of Residuals	26

Correlations of Parameter Estimates

Variable		PA	POP
Parameter		MU	NUM1
PA	MU	1.000	-0.935
POP	NUM1	-0.935	1.000

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	Autocorrelations					
6	38.36	6	<.0001	0.700	0.523	0.529	0.368	0.238	0.117
12	43.86	12	<.0001	0.048	-0.004	-0.079	-0.129	-0.180	-0.232
18	80.44	18	<.0001	-0.262	-0.294	-0.324	-0.336	-0.302	-0.234
24	91.96	24	<.0001	-0.211	-0.182	-0.107	-0.059	-0.032	-0.030

Autocorrelation Plot of Residuals

```
Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0     5593536      1.00000  |                    |********************|
  1     3916034      0.70010  |             .      |**************      |
  2     2922951      0.52256  |          .         |**********.         |
  3     2958956      0.52900  |         .          |***********.        |
  4     2059417      0.36818  |      .             |*******      .      |
  5     1332355      0.23820  |      .             |*****        .      |
  6      652350      0.11663  |     .              |**            .     |
  7      268300      0.04797  |     .              |*             .     |
```

"." marks two standard errors

Inverse Autocorrelations

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1       -0.59960    |        ************|       .            |
  2        0.39401    |           .        |********            |
  3       -0.45900    |           *********|       .            |
  4        0.23835    |           .        |*****  .            |
  5       -0.17949    |           .    ****|       .            |
  6        0.16441    |           .        |***    .            |
  7       -0.03867    |           .       *|       .            |
```

Partial Autocorrelations

```
Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  1        0.70010    |             .       |**************      |
  2        0.06358    |             .       |*      .            |
  3        0.27944    |             .       |****** .            |
  4       -0.21864    |             .   ****|       .            |
  5       -0.01760    |             .       |       .            |
  6       -0.22007    |             .   ****|       .            |
  7        0.07716    |             .       |**     .            |
```

Crosscorrelation Check of Residuals with Input POP

To Lag	Chi-Square	DF	Pr > ChiSq	---------------Crosscorrelations--------------					
5	3.58	6	0.7333	-0.063	0.190	0.334	0.056	0.067	0.060
11	5.02	12	0.9574	0.028	-0.023	-0.072	-0.108	-0.143	-0.163
17	8.33	18	0.9733	-0.176	-0.193	-0.187	-0.158	-0.120	-0.092

Model for variable PA

Estimated Intercept	27.85295
Period(s) of Differencing	2

Input Number 1

Input Variable	POP
Shift	4
Period(s) of Differencing	2
Overall Regression Factor	0.000826

Estimation of Final Transfer Function Model: US Population Only

The ARIMA Procedure
Maximum Likelihood Estimation

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag	Variable	Shift
MU	4639.2	1754.3	2.64	0.0082	0	PA	0
AR1,1	1.74314	0.13401	13.01	<.0001	1	PA	0
AR1,2	-0.77584	0.14420	-5.38	<.0001	2	PA	0
NUM1	0.00001656	0.00002925	0.57	0.5712	0	POP	4

Constant Estimate	151.7143
Variance Estimate	117035.3
Std Error Estimate	342.1042
AIC	386.0203
SBC	391.0527
Number of Residuals	26

Correlations of Parameter Estimates

Variable		PA	PA	PA	POP
Parameter		MU	AR1,1	AR1,2	NUM1
PA	MU	1.000	-0.363	0.411	0.098
PA	AR1,1	-0.363	1.000	-0.985	-0.161
PA	AR1,2	0.411	-0.985	1.000	0.188
POP	NUM1	0.098	-0.161	0.188	1.000

Autocorrelation Check of Residuals

To Lag	Chi-Square	DF	Pr > ChiSq	---------------Autocorrelations---------------					
6	3.79	4	0.4356	-0.044	-0.150	0.258	0.010	0.143	-0.082
12	11.27	10	0.3371	-0.012	0.043	-0.201	0.167	0.084	-0.279
18	15.32	16	0.5010	0.086	-0.128	-0.182	0.000	-0.070	-0.023
24	16.92	22	0.7676	-0.110	0.005	0.043	-0.019	0.008	-0.000

Autocorrelation Plot of Residuals

```
Lag  Covariance  Correlation  -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

  0      117035      1.00000  |                    |********************|
  1   -5178.984      -.04425  |            .      *|       .            |
  2  -17517.528      -.14968  |            .    ***|       .            |
  3   30139.267      0.25752  |            .       |*****  .            |
  4    1176.176      0.01005  |           .        |        .           |
  5   16698.900      0.14268  |           .        |***     .           |
  6   -9547.056      -.08157  |           .      **|        .           |
  7   -1420.533      -.01214  |           .        |        .           |
```

"." marks two standard errors

Inverse Autocorrelations

```
   Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

     1       -0.14622    |            .    ***|       .            |
     2        0.26634    |            .       |*****  .            |
     3       -0.35150    |            .*******|       .            |
     4        0.08379    |            .       |**     .            |
     5       -0.21095    |            .   ****|       .            |
     6        0.13151    |            .       |***    .            |
     7       -0.04648    |            .      *|       .            |
```

Partial Autocorrelations

```
   Lag    Correlation    -1 9 8 7 6 5 4 3 2 1 0 1 2 3 4 5 6 7 8 9 1

     1       -0.04425    |            .      *|       .            |
     2       -0.15193    |            .    ***|       .            |
     3        0.24940    |            .       |*****  .            |
     4        0.00396    |            .       |       .            |
     5        0.23629    |            .       |*****  .            |
     6       -0.16053    |            .    ***|       .            |
     7        0.05787    |            .       |*      .            |
```

Crosscorrelation Check of Residuals with Input POP

To Lag	Chi-Square	DF	Pr > ChiSq	---------------Crosscorrelations--------------					
5	0.43	6	0.9986	0.017	-0.012	-0.124	-0.003	-0.000	-0.062
11	1.50	12	0.9999	-0.069	-0.083	-0.091	-0.100	-0.105	-0.087
17	1.78	18	1.0000	-0.087	-0.063	-0.017	-0.020	-0.011	0.016

Model for variable PA

Estimated Intercept	4639.226
Period(s) of Differencing	2

Autoregressive Factors

Factor 1: 1 - 1.74314 B**(1) + 0.77584 B**(2)

Input Number 1

Input Variable	POP
Shift	4
Period(s) of Differencing	2
Overall Regression Factor	0.000017

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