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The influence of operational resources and activities on indirect personnel costs: A multilevel modeling approach

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ABSTRACT

Indirect activities often represent an underemphasized, yet significant, contributing source of costs for organizations. In order to manage indirect costs, organizations must understand how these costs behave relative to changes in operational resources and activities. This is of particular interest to the Air Force and its sister services, because recent and projected reductions in defense spending are forcing reductions in their operational variables, and insufficient research exists to help them understand how this may influence indirect costs. Furthermore, although academic research on indirect costs has advanced the knowledge behind the modeling and behavior of indirect costs, significant gaps in the literature remain. Our research provides important and timely advances to the indirect cost literature. First, our research disaggregates the indirect cost pool and focuses on indirect *personnel* costs, which represent 33% of all Air Force indirect costs and are a leading source of indirect costs in many organizations. Second, we employ a multilevel modeling approach to capture the hierarchical nature of an enterprise, allowing us to assess the influence that each level of an organization has on indirect cost behavior and relationships. Third, we identify the operational variables that influence indirect personnel costs in the Air Force enterprise, providing Air Force decision-makers with evidence-based knowledge to inform decisions regarding budget reduction strategies.

Introduction

Concern has turned into reality as overall defense contraction has taken effect. As a result of the Budget Control Act of 2011 and the American Taxpayer Relief Act of 2012, the Department of Defense (DoD) estimates a total reduction in planned defense spending between fiscal years 2012 to 2021 to exceed $1 trillion (DoD 2014). Consequently, the Air Force (AF), along with her sister services, will need a systematic methodology to plan and implement force and budget reductions in sound logical ways that align with its overall strategy. With indirect (also referred to as support[1]) mission activities historically representing over 40% of

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Color versions of one or more of the figures in the article can be found online at http://www.tandfonline.com/utee.

[1] For purposes of this research, the terms "support" and "indirect" will be used interchangeably.

the annual DoD budget (Defense Business Board 2008; Horowitz and Borga 1999) and nearly 60% of the AF budget (Boehmke et al. 2015a), strategically managing cost behavior of these indirect activities has the opportunity to generate significant savings.

Understanding cost behavior is fundamental to cost modeling and management. Cooper and Kaplan (1992) stated that in order to understand cost behavior one has to focus on how the underlying resource levels change in response to activity changes; however, research on indirect costs in the DoD and AF has centered around an aggregate "tooth-to-tail" ratio with the assumption that total direct costs (the "tooth") and total indirect costs (the "tail") are, or should be, related in a proportional manner (Boehmke 2015). Taken alone, this fails to provide senior leaders with a robust understanding of how indirect costs change in response to changes in the various operational variables that decision-makers can control and that ultimately influence the tooth. Furthermore, Boehmke et al. (2015a) show that focusing only on an aggregate-level relationship leads to biased presumptions based on a single level of analysis rather than a comprehensive understanding based on evidence from multiple levels in an organization.

The purpose of this research is to create a robust understanding of how indirect costs change in response to changes in AF operational variables and to illustrate the cost behavior and relationships at the multiple levels of the AF enterprise so that decision-makers understand where policy decisions are and are not applicable. The remainder of this article is organized as follows. The following section provides the background and theory for the problem at hand. The next section describes the conjectures analyzed. The following section outlines the methodology, and the next discusses the empirical analysis performed and its results. The next section provides further discussion regarding our results, future work, and limitations. The final section offers some concluding comments.

Background

Internal to the DoD and the AF, research has been scarcely conducted to better understand the economics of indirect activities. The policy emphasis has been on managing the DoD's and AF's tooth-to-tail ratio; hence, as front-line mission (*direct*) budgets change, indirect budgets change in a proportional manner. Past research focusing on the tooth-to-tail measure (Campbell and Velasco 2002; Defense Business Board 2008; Gansler and Lucyshyn 2014; Gebicke and Magid 2010; McGrath 2007) has primarily concentrated on whether the historic ratio is appropriate rather than gaining an understanding of economic behavior and relationships of indirect costs. Furthermore, ordinary least squares (OLS) regression has been used to regress indirect costs on total direct costs (Horowitz and Borga 1999), implying that the output of direct costs is the appropriate link to explain variance in the output of indirect costs. Recent research has brought more light to these indirect activities by analyzing cost trends (Boehmke et al. 2015b), consequences from force structure policy changes (Boehmke, Johnson et al. 2016), and improving the performance assessments of indirect activities (Boehmke, Jackson et al. 2016). However, a significant gap remains in understanding the underlying relationships and drivers of indirect costs.

External to the DoD and AF, academic research on indirect costs has focused heavily on the activity-based costing stream of research founded by Cooper and Kaplan (1992); however, similar to the tooth-to-tail approach, activity-based costing is a cost allocation method rather than a statistical process to identify underlying relationships between activities and processes. Additional academic research has focused on assessing relations between indirect costs and production volume, complexity, and efficiency using correlation and partial correlation analysis (Foster and Gupta 1990). A stream of research has assessed asymmetric behavior, referred to as "cost stickiness," of selling, general and administration (SG&A) overhead costs using multiple regression (M. Anderson et al. 2003; S. Anderson and Lanen 2009; Balakrishnan and Gruca 2008; Balakrishnan et al. 2004; Banker and Byzalov 2014; Noreen and Soderstrom 1994, 1997). Banker et al. (1990) regressed indirect costs on manufacturing production variables using multiple regression. Datar et al. (1993) and MacArthur and Stranahan (1998) applied a system of equations approach to model indirect cost interactions with endogenous production regression models in the manufacturing and health settings. Ittner and MacDuffie (1995) and S. Anderson (2001) applied path analysis to measure the impact of manufacturing cost drivers on both direct and indirect costs. Although these research streams have advanced the knowledge of the modeling and behavior of indirect costs, four principal concerns still exist that this research aims to address.

First, DoD and AF indirect costs have been analyzed as a single cost pool, which groups multiple cost categories (i.e., personnel costs, infrastructure sustainment, utilities, discretionary costs) into a single category. Furthermore, much of the academic research assesses indirect costs as a single pooled category. Pooling multiple cost categories can dull the underlying economic variance patterns of discrete costs, which can lead to reduced predictor variable signals. In addition, a key element of strategic and accurate cost analysis is the ability to analyze and understand the economics of discrete cost categories within and across the enterprise (S. Anderson 2006; Kaplan and Cooper 1998; Porter 1985; Shank 1989). Although an emphasis on overall support cost behavior is certainly important, decision-makers should also have a thorough understanding of the underlying discrete economic behavior so they have more insight for developing policy actions.

Second, DoD and AF research on enterprise-wide support costs has primarily been analyzed only at the DoD and AF aggregate level. Furthermore, academic research focusing on cost stickiness (M. Anderson et al. 2003; S. Anderson and Lanen 2009; Balakrishnan and Gruca 2008; Balakrishnan et al. 2004; Banker and Byzalov 2014) has also focused heavily on aggregated data. Although this may provide a macro-economic view of indirect cost behavior, aggregate-level relationships provide limited insight behind the economic behavior of lower level indirect costs. The effects of data aggregation have long been demonstrated to result in information loss and aggregation bias commonly referred to as the ecological fallacy (Clark and Avery 1976; Freedman 1999; Garrett 2003; Lubinski and Humphreys 1996; Orcutt et al. 1968; Robinson 1950). Furthermore, Boehmke et al. (2015a) identified that, specific to the AF enterprise, aggregation conceals significant differences in the underlying economic behaviors of indirect costs at the installation level. In addition, much of the remaining academic research (Banker et al. 1990; Datar et al. 1993; Foster and Gupta 1990; MacArthur and Stranahan 1998) have focused on analyzing individual plant or hospital level costs. With the exception of Boehmke et al. (2015a), which this research builds on, the authors are aware of no additional research that models economic behavior across the multiple levels of an organization to provide a multilevel enterprise view of indirect costs.

Third, a common assumption made in the majority of these analytic techniques is that the data structure represents a single level of analysis that fails to consider the hierarchical structure of organizations. Although segmenting can be applied in correlation and path analysis and categorical variables can be applied within multiple regression, these techniques fail to capture the unique variance structure of nested data found in the multilevel context of organizations and enterprises. Failing to capture this multilevel structure often results in violating assumptions of single level analysis techniques (Finch et al. 2014; Gelman and Hill 2006).

Fourth, specific to the DoD and the AF, research on indirect costs has focused on relating indirect costs to total direct costs. This makes the assumption that the direct cost output is the appropriate causal relationship to link with indirect costs rather than understanding which front-line activities and resources may be influencing indirect costs. To the authors' knowledge, research has yet to be performed to assess how the various front-line activities and resources (referred to as force structure variables) relate to support costs across the AF enterprise.

This article advances this stream of research focusing on indirect cost in the following manner: First, this research will focus on a single discrete indirect cost category, indirect personnel costs, which represents the single largest indirect cost category within the AF. Second, this analysis will extend the research by Boehmke et al. (2015a) in analyzing support cost behavior and relationships at the multiple levels of the AF enterprise rather than focusing only on aggregated relationships. Third, this research utilizes multilevel modeling (also referred to as hierarchical linear models, nested models, mixed models, or random-effects models) to capture the structural context of the enterprise data which has yet to be applied to model enterprise-wide indirect costs with the exception of Boehmke et al. (2015a). Fourth, rather than focus solely on the tooth, this research assesses how each of the force structure variables influence indirect personnel costs across the AF enterprise. This will provide knowledge of how indirect personnel costs adjustments are influenced by changes in the underlying operational activities, which could inform senior AF decision makers and result in more informed decisions when determining budget reduction strategies.

Conjectures

The underlying implication of managing indirect costs by a tooth-to-tail measure suggests that the output of direct costs is the appropriate causal link to explain variance in the output of indirect costs. This introduces the first presumption:

> *Conjecture 1: total direct costs, or the tooth, is the front-line mission force structure variable that provides the strongest link to indirect personnel costs.*

This research will assess whether the tooth is in fact the most appropriate force structure variable to link indirect personnel cost adjustments to changes in the operations on the direct side of the AF business.

Although it is important to understand relationships, it is equally important to understand how these relationships behave at the different levels of an organization. When implementing policy and making strategic decisions at different organizational levels, leaders and managers may rely too heavily on the assumption that a single relationship exists across the organization rather than understanding how relationships differ across the multiple levels of an organization. This introduces the second presumption:

> *Conjecture 2: relationships between front-line mission force structure variables and indirect personnel costs are consistent across the multiple levels of the enterprise.*

The ultimate goal in assessing conjecture 2 is to reveal the various relationships and economic behaviors of indirect personnel costs provided by the multilevel context of an enterprise.

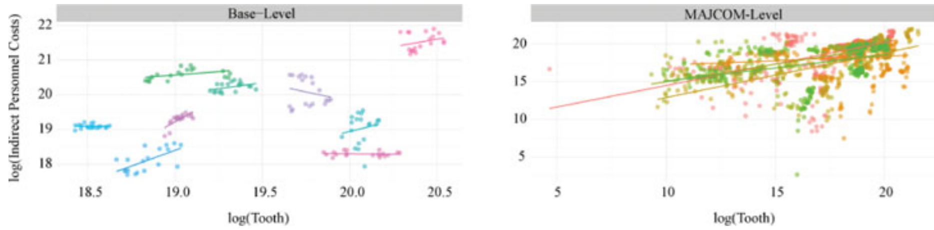

Figure 1. Evidence of varying relationships between indirect support costs and the tooth.

Approach

Methodology justification

Our rationale for applying a multilevel modeling (MLM) approach was based on three justifications: (1) theoretical, (2) statistical, and (3) empirical evidence.

The theoretical justification for MLM is founded on the contextual structure of the phenomena under investigation (Luke 2004). Social and organizational observations are often influenced by processes and attributes from multiple levels of the environment in which they exist (Gelman and Hill 2006). For instance, a child's education can be influenced by the classroom, school, and school district; an individual's economic status can be influenced by his or her level of education and career field; and an organization's cost structure can be influenced by its geographical locations, industry sector, and current phase of growth. Similarly, indirect support costs within the AF may be influenced by attributes and processes determined by a higher organizational level such as the type of mission it is supporting, the demographic population it is supporting,[2] or whether it is a headquarters or operational base. These characteristics, which can be influenced at the installation, Major Command[3] (MAJCOM), and AF level, can drive differing relationships between force structure and indirect costs. This can be captured by recognizing that individual support cost observations can be captured within a base and, furthermore, within a MAJCOM and each level can have a specific influence on the relationships within that observation. By ignoring this multilevel structure of the data, incorrect understanding or interpretation of relationships at the different levels may result.

Statistical justification for MLM results from two major flaws when the multilevel structure is not considered. First, all of the unmodeled contextual information ends up pooled into the single individual error term of the model (Duncan et al. 1998). This is problematic because observations belonging to the same groups within the various levels will presumably have correlated errors, which violates one of the basic assumptions of multiple regression (Luke 2004). These within-group correlations will in turn bias the standard errors estimate for the model parameters, which can lead to biased *p*-values. Second, by ignoring the multilevel context, the model assumes that the regression coefficients apply equally to all groups (Luke 2004), "thus propagating the notion that processes work out in the same way in different contexts" (Duncan et al. 1998, p. 98).

Evidential justification for MLM for this specific research can be provided through simple graphical representation. Figure 1 illustrates the relationship between indirect personnel costs and the tooth within selected MAJCOMs and bases across the AF. This illustrates that some

[2] Certain bases have higher concentrations of retiree populations that may require more support personnel.

[3] The U.S. AF is organized on a functional basis and a Major Command represents a major AF subdivision having a specific portion of the AF mission. Each Major Command is directly subordinate to the highest AF organizational level referred to as Headquarters Air Force. Therefore, a Major Command can be thought of as synonymous to a department or strategic business unit in the private sector.

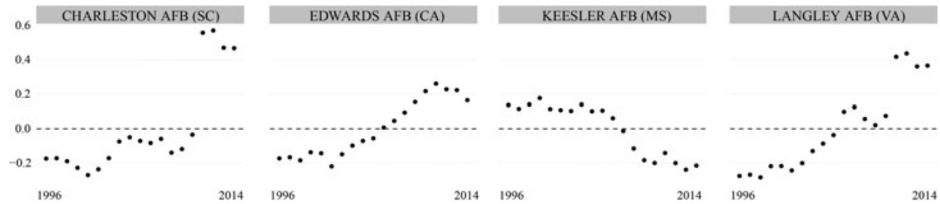

Figure 2. Illustration of correlated residual patterns within base-level groups.

variance in the relationship exists at the MAJCOM level and significant variance in relationship exists at the base level, suggesting that a single slope coefficient across all bases will not suffice.

Furthermore, Figure 2 illustrates residual errors that are produced when applying multiple regression to regress indirect support costs against the tooth.[4] This single-level model performs presumably well with all parameters being significant and an adjusted $R^2 = 0.96$. Moreover, the variance appears homoscedastic and the residuals do not appear to grossly violate the approximately normal assumption when assumed to be independent. If taken at face value, the slope coefficient suggests that for every 1% adjustment in the tooth there is a 0.08% adjustment in total indirect personnel costs across all bases; however, Figure 2 clearly shows that when residuals are diagnosed at the base level, residual correlation exists. This further supports the assumption that a single slope coefficient will not accurately represent the relationship experienced at individual bases.

Given these justifications, we now apply a methodical MLM approach to provide a comprehensive understanding of indirect cost behavior and the influence each level has across the AF enterprise. This approach sequentially applies a series of MLM models to assess the relationship between force structure variables and indirect personnel costs.

Methodology process

The dependent variable of concern in this research is indirect personnel costs. More specifically, we separate indirect civilian personnel costs ($CivPers^{ind}$) and indirect military personnel costs ($MilPers^{ind}$) to assess whether relationships differ based on the type of employment. As previously mentioned, personnel costs represent the largest discrete indirect cost pool and therefore is a logical starting point for identifying drivers of indirect costs. The predictor variables assessed include total direct costs (or the tooth) and eight additional variables that represent available measures of the underlying resources and activities that make up direct costs and that decision-makers generally adjust during fiscally constrained environments. Consequently, our motivation is to understand whether, and how, indirect personnel costs react when adjustments are made to these predictor variables. These variables of interest are summarized in Table 1.

To determine whether each indirect personnel cost category is influenced by changes in the identified operational variables, we sequentially apply the series of models listed in Table 2. This sequential approach provides two important forms of knowledge. First, each model provides useful information in which the next model builds on. The null model provides important baseline information in which to compare future models. Model 1 then introduces a fixed slope relationship and models 2 and 3 introduce random effects for the slope relationships at

[4] This particular model is represented as $\log(y_i) = \beta_0 + \beta_1 \log(x_i) + \beta_2 I_i + \epsilon_i$ in which y_i represents indirect support costs, x_i represents total direct costs (aka tooth), and I_i controls for the installation.

Table 1. Organizational variables analyzed.

Variable type	Variable of interest	Abbreviation	Description
Dependent variables			
	Civilian personnel costs	$CivPers^{ind}$	All civilian employees providing supporting roles located at AF installations
	Military personnel costs	$MilPers^{ind}$	All military employees providing supporting roles located at AF installations
Predictor variables			
	Tooth	Tooth	All direct operations and sustainment expenditures related to personnel, consumables, goods and services, and investments associated with the peacetime operations of weapon systems and programs.
	Total active inventory	TAI	Total number of major weapon systems (i.e., aircraft, intercontinental ballistic missiles, etc.) in inventory
	Flying hours	FH	Number of hours that weapon systems are flown
	End strength	ES	Total headcount of direct personnel
	Civilian end strength	ES^{civ}	Total headcount of direct civilian personnel
	Military end strength	ES^{mil}	Total headcount of direct military personnel
	Direct personnel costs	$Pers^{dir}$	Total cost of direct personnel
	Direct civilian personnel costs	$CivPers^{dir}$	Total cost of direct civilian personnel
	Direct military personnel costs	$MilPers^{dir}$	Total cost of direct military personnel

Table 2. Multilevel model building process.

Model	System of equations[a]	Multilevel model equation	Components	Description
Null	L1: $Y_{ij} = \beta_{0j} + \epsilon_{ij}$ L2: $\beta_{0j} = \gamma_{00} + u_{0j}$	$Y_{ij} = \gamma_{00} + u_{0j} + \epsilon_{ij}$	L1 fixed intercept (γ_{00}) L2 random intercept (u_{0j})	Output used to calculate intraclass correlation coefficient; provides information on how much variation in indirect personnel costs (Y_{ij}) exists between AF bases (j index represents base j)
(1)	L1: $Y_{ij} = \beta_{0j} + \beta_{1j}X + \epsilon_{ij}$ L2: $\beta_{0j} = \gamma_{00} + u_{0j}$ $\beta_{1j} = \gamma_{10}$	$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + \epsilon_{ij}$	L1 fixed intercept (γ_{00}) L2 random intercept (u_{0j}) L1 fixed slope (γ_{10})	Assesses the fixed relationship between base-level indirect personnel costs (Y_{ij}) and force structure variables (X_{ij}) across AF installations
(2)	L1: $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + \epsilon_{ij}$ L2: $\beta_{0j} = \gamma_{00} + u_{0j}$ $\beta_{1j} = \gamma_{10} + u_{1j}$	$Y_{ij} = \gamma_{00} + \gamma_{10}X_{ij} + u_{0j} + u_{ij}X_{ij} + \epsilon_{ij}$	L1 fixed intercept (γ_{00}) L2 random intercept (u_{0j}) L1 fixed slope (γ_{10}) L2 random slope (u_{ij})	Assesses the variability of the relationship between base-level indirect personnel costs and force structure variables across AF installations
(3)	L1: $Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{ijk} +$ ϵ_{ijk} L2: $\beta_{0jk} = \gamma_{00k} + u_{0jk}$ $\beta_{1jk} = \gamma_{10k} + u_{1jk}$ L3: $\gamma_{00k} = \delta_{000} + \upsilon_{00k}$ $\gamma_{10k} = \delta_{100} + \upsilon_{10k}$	$Y_{ijk} = \delta_{000} + \upsilon_{00k} + u_{0jk} +$ $(\delta_{100} + \upsilon_{10k} + u_{1jk})X_{ijk} + \epsilon_{ijk}$	L1 fixed intercept (δ_{000}) L2 random intercept (u_{0jk}) L3 random intercept (υ_{00k}) L1 fixed slope (δ_{100}) L2 random slope (u_{1jk}) L2 random slope (υ_{10k})	Assesses the influence of the MAJCOM on the base-level intercept and the variability of the relationship between base-level indirect personnel costs and force structure variables
(4)	L1: $Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{ijk} +$ $\beta_{2jk}T_{ijk} + \epsilon_{ijk}$ L2: $\beta_{0jk} = \gamma_{00k} + u_{0jk}$ $\beta_{1jk} = \gamma_{10k} + u_{1jk}$ $\beta_{2jk} = \gamma_{20k} + u_{2jk}$ L3: $\gamma_{00k} = \delta_{000} + \upsilon_{00k}$ $\gamma_{10k} = \delta_{100} + \upsilon_{10k}$ $\gamma_{20k} = \delta_{200} + \upsilon_{20k}$	$Y_{ijk} = \delta_{000} + \upsilon_{00k} + u_{0jk} +$ $(\delta_{100} + \upsilon_{10k} + u_{1jk})X_{ijk} +$ $(\delta_{200} + \upsilon_{20k} + u_{2jk})T_{ijk} + \epsilon_{ijk}$	L1 fixed intercept (δ_{000}) L2 random intercept (u_{0jk}) L2 random intercept (υ_{00k}) L1 fixed slope (δ_{100}) L2 random slope (u_{1jk}) L3 random slope (υ_{10k}) L1 fixed growth rate (δ_{200}) L2 random growth rate (u_{2jk}) L2 random growth rate (υ_{20k})	Incorporates the potential influence of a growth rate (T_{ij}) at the MAJCOM and base level and corrects for residual autocorrelation due to longitudinal structure of the data

[a] L1 represent the fixed and random components modeled at level 1 (individual observation level).
L2 represent the fixed and random components modeled at level 2 (installation level).
L3 represent the fixed and random components modeled at level 3 (MAJCOM level).

installation and MAJCOM levels, respectively. In essence, the modeling approach moves up the organizational hierarchy with each model to assess that organizational level's influence on the relationship. Model 4 then assesses the potential for growth rate effects and accounts for autocorrelation experienced in earlier models. As for the second knowledge form, the sequential approach helps to illustrate the resulting biases that can occur with fixed-effect assumptions and demonstrates that when these assumptions are relaxed, various evidence challenges tooth-to-tail relationships. The insights gained from these two forms of knowledge are expounded upon throughout the following section.

For purposes of this study, a log-log transformation is applied to reduce the chance of systematic heteroscedasticity biases that may influence the magnitude of the correlation coefficients. In addition, group mean centering is applied to the force structure predictor variables. Group mean centering allows for direct comparisons of variance components and minimizes correlation between random effects (Bates 2010). Furthermore, because the primary objective of our research is on understanding the relationship (slope) between force structure predictor variables and indirect personnel costs and whether this relationship varies across the organizational levels (level 1: base, level 2: MAJCOM), using group mean centering will provide unbiased estimates of these slopes and yield a more accurate estimate of the slope variance (Enders and Tofighi 2007; Raudenbush and Bryk 2002). Finally, the log-log transformation with group mean centered predictors provides for interoperable results. For example, Equation (1) models the relationship between $CivPers^{ind}$ and flying hours. The γ_{10} coefficient measures the percent change in support costs at base j for every 1% deviation from the mean flying hours (FH_{ij}).

$$\log\left(CivPers_{ij}^{ind}\right) = \gamma_{00} + \gamma_{10}\log\left(FH_{ij}\right) + U_{0j} + \epsilon_i. \quad (1)$$

Data

All data were extracted from the AFTOC database for the fiscal years 1996–2014 across 57 active-duty U.S.-based Air Force bases.[5] $CivPers^{ind}$ and $MilPers^{ind}$ were extracted from the AFTOC Indirect online analytical processing (OLAP) cube and categorized by element of expense and investment code (EEIC) 1* (civilian personnel compensation) and 201* (military personnel compensation). The force structure predictor variables were extracted from the AFTOC CAPE14 OLAP cube. Cost predictor variables represent all costs associated with Cost Analysis Improvement Group (CAIG) elements 1.0–4.0, which represent normal operational activities related to weapon systems at a base. Only bases in which all 19 years of data were available were included in the analysis. All dollar values were adjusted for inflation and represent base year 2014 values.

In 1996, indirect personnel costs across the entire AF totaled $25.1 billion and have since increased to $28.7 billion in 2014. This category alone accounts for approximately 60% of all personnel costs in the AF, 33% of all indirect costs, and 20% of total annual AF costs (direct + indirect). Within our data set (which restricts our research to 57 U.S. active-duty bases), indirect personnel costs were $17.2 billion in 1996 and have grown to $20.2 billion in 2014. This means that our research sample focuses on approximately 70% of the total AF population costs for this category. Within our data set, indirect personnel costs account for 64% of all

[5] AFTOC is the authoritative database for assessing indirect and direct costs at the base level; 1996 represents the first year AFTOC data was available and, at the time of this research, 2014 was the last year for which complete data was available and validated. This research only focused on U.S.-based active-duty AF installations that had both direct and indirect costs for all 19 years being assessed, resulting in 57 bases.

Table 3. Intercept coefficients and model fit for the null models.

Indirect cost category	Intercept (γ_{00})	τ^2	σ^2	ρ	AIC	BIC
$CivPers^{ind}$	17.9	0.88	0.05	0.94	206	221
$MilPers^{ind}$	18.9	0.58	0.02	0.96	−611	−596

personnel costs across the 57 selected bases, 47% of all indirect costs, and 35% of total annual AF costs.

Empirical analysis

Null model

The null model measures the level of indirect personnel cost variance across all observations (which we define with σ^2) and among the bases (τ^2), which can be used to calculate intraclass correlation by applying Equation (2):

$$\rho = \frac{\tau^2}{\tau^2 + \sigma^2}. \tag{2}$$

This allows us to interpret the level of correlation of indirect personnel cost variance within bases. Furthermore, the null model provides the baseline Akaike information criterion (AIC) and Bayesian information criterion (BIC) values, which are measures of model quality relative to other models. When comparing models, lower AIC and BIC values generally represent the preferred models given the model choices; however, the normal procedure of residual diagnostics is still required to assess model quality.

Table 3 displays the results of the null models for both military and civilian indirect personnel costs. The γ_{00} for each model, which are in natural log form, is the average value of the dependent variable across all observations. The high levels of variances accounted for between the bases (τ^2) compared to across all observations (σ^2) indicates that the correlation (ρ) of military and civilian indirect personnel costs within the same base is 96 and 94%, respectively. This high level of correlation further supports the need to treat observations within bases as nested rather than simply treat all observations independently.

Model 1

Model 1 allows for random intercepts and fits a fixed slope coefficient between the dependent variables and each force structure predictor variable. Model 1 is very similar to a multiple regression approach with a single fixed slope and categorical variables to adjust for differences in base-level intercepts. Table 4 displays the relationships between the indirect cost categories and each force structure variable.[6] Three important insights can be gleaned from these results. First, the elasticity in the indirect cost categories is low for the majority of the force structure variables suggesting that as force structure is adjusted, very small adjustments in both $CivPers^{ind}$ and $MilPers^{ind}$ are experienced. Second, by applying Bates's (2010) multilevel pseudo R^2 approach, we can calculate the amount of variance accounted for by each level in the

[6] For brevity the intercept and additional model output such as degrees of freedom and t-values are not displayed. The primary concern in this research is to understand the relationship between indirect personnel costs and force structure variables so the results will focus on these parameters; however, in the event of abnormalities or anomalies in non-displayed parameters specific discussion will be made to address these concerns.

Table 4. Slope parameters and model fit for model 1.

	CivPers^{ind}							*MilPers*^{ind}						
	Fixed effect		Random effect					Fixed Effect		Random Effect				
Predictor	γ_{10}	SE	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC	γ_{10}	SE	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC
Tooth	0.13***	0.020	0.881	0.050	4	166	186	0.04**	0.014	0.576	0.024	1	−619	−599
TAI	−0.04	0.021	0.904	0.041	22	−39	−19	−0.01	0.013	0.552	0.017	29	−887	−867
FH	−0.04*	0.019	0.903	0.041	22	−34	−14	0.05***	0.012	0.550	0.017	30	−893	−874
ES	0.08***	0.024	0.881	0.051	1	197	217	0.02	0.017	0.576	0.024	0	−610	−590
ES^{civ}	0.12***	0.017	0.881	0.050	4	162	182	0.03*	0.012	0.576	0.024	0	−614	−594
ES^{mil}	0.07**	0.022	0.881	0.051	1	198	218	0.02	0.015	0.576	0.024	0	−612	−592
$Pers^{dir}$	0.07***	0.019	0.881	0.051	2	192	212	0.00	0.013	0.576	0.024	0	−609	−589
$CivPers^{dir}$	0.09***	0.010	0.882	0.046	12	80	99	0.02**	0.006	0.584	0.019	21	−837	−817
$MilPers^{dir}$	0.07***	0.020	0.881	0.051	1	197	217	0.03*	0.013	0.576	0.024	0	−613	−593

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

model. By applying Equation (3), the R_1^2 values in Table 4 identify the variability of $CivPers^{ind}$ and $MilPers^{ind}$ explained by its linear relationship to each force structure variable.

$$R_1^2 = \frac{\sigma^2(\text{Null model}) - \sigma^2(\text{Model 1})}{\sigma^2(\text{Null model})}. \tag{3}$$

For the majority of the model 1 excursions, the low R_1^2 values in addition to only marginal changes in AIC and BIC values from the respective null models imply that incorporating a fixed slope relationship with each force structure variable provides minimal improvement in model performance. However, each indirect cost category did have model excursions that illustrate significant model performance leading to our third insight: for each indirect cost category, the tooth does not provide the strongest fixed slope effect link. For $MilPers^{ind}$, the strongest fixed slope effect link is with FH followed by $CivPers^{dir}$. The fixed linear relationship with these force structure variables, although very inelastic,[7] captures 21–30% of the variance in $MilPers^{ind}$ over and above the null model. For $CivPers^{ind}$, the strongest fixed slope effect link is with FH followed by $CivPers^{dir}$. The fixed linear relationship with these force structure variables suggests that a negative relationships exists with FH[8] and a positive relationship exists with $CivPers^{dir}$. These two fixed slope relationships account for 12–22% of the variance in $CivPers^{ind}$ over and above the null model.

Model 2

Model 2 applies a random coefficient model in which the relationship between the force structure variables and the indirect cost categories is allowed to vary from one base to another. This model assesses the variability of the slope relationships across the bases and will indicate the sufficiency of model 1's fixed slope relationship. Model 2 results are displayed in Table 5. All model 2 excursions were compared to their respective model 1 excursions to assess whether including random slopes improved the models. An analysis of variance (ANOVA) test and Bates's (2010) modified ANOVA test, which uses a mixture of χ_1^2 and χ_2^2 random variables with equal weights to produce a more accurate p-value as displayed in Equation (4), confirms that the addition of random slopes significantly improves all models at p-value < 0.001. This is also confirmed with the model fit parameters in Table 5 that show an increased R_1^2 and decreased AIC and BIC values for all models.

$$p\text{-value} = 0.5 \times P(\chi_1^2 > LR) + 0.5 \times P(\chi_2^2 > LR). \tag{4}$$

Model 2 results also show a change in the significance of several force structure predictor variable fixed effect coefficients (γ_{10}). This suggests that when the slope is allowed to vary across bases, there is no consistent relationship across the enterprise that is significantly different than zero.[9] This variability in the slope coefficient across AF bases can be assessed by the τ_2^2 parameter in Table 5. This also allows us to compare the variability in slopes (τ_2^2) against the variability in intercepts (τ_1^2) and individual observations (σ^2). This provides some useful insights. First, the largest source of variability for all model excursions is in the intercepts, followed by the slope, with the residuals representing the smallest source

[7] The γ_{10} value of 0.05 suggests that for every 1% change in FH, a 0.05% adjustment in $MilPers^{ind}$ occurs. Although not fixed, this suggests that the relationship is far from proportional.

[8] The γ_{10} value of -0.04 suggests that for every 1% change in FH, a -0.04% adjustment in $CivPers^{ind}$ occurs.

[9] The change in γ_{10} coefficient significance suggests that the fixed slope relationships and standard errors in Model 1 were likely biased from a possible Simpson's Paradox in which relationships that appear in different groups of data disappear or reverse when these groups are combined for an overall relationship.

Table 5. Slope parameters and model fit for model 2.

	CivPers^{ind}								*MilPers*^{ind}							
	Fixed effect		Random effect						Fixed effect		Random effect					
Predictor	γ_{10}	SE	τ_2^2	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC	γ_{10}	SE	τ_2^2	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC
Tooth	0.13	0.071	0.200	0.882	0.039	24	14	44	0.05	0.065	0.197	0.577	0.015	38	−970	−940
TAI	−0.14	0.123	0.678	0.905	0.029	45	−226	−196	−0.01	0.067	0.190	0.552	0.012	48	−1,058	−1,029
FH	−0.16	0.105	0.534	0.904	0.029	45	−202	−172	0.04	0.047	0.098	0.552	0.013	45	−1,004	−975
ES	0.09	0.078	0.243	0.882	0.039	25	14	43	0.11	0.060	0.169	0.577	0.014	42	−1,046	−1,016
ES^{civ}	0.25*	0.097	0.487	0.883	0.023	56	−444	−414	0.02	0.048	0.109	0.577	0.012	49	−1,146	−1,116
ES^{mil}	0.01	0.081	0.282	0.882	0.039	25	18	48	0.08	0.054	0.129	0.577	0.015	38	−985	−955
Pers^{dir}	0.42***	0.121	0.740	0.882	0.030	42	−195	−165	0.17*	0.070	0.240	0.577	0.013	45	−1,070	−1,041
CivPers^{dir}	0.20**	0.064	0.213	0.883	0.026	51	−339	−309	0.02	0.035	0.061	0.584	0.012	51	−1,163	−1,133
MilPers^{dir}	0.27**	0.097	0.445	0.882	0.035	32	−51	−21	0.18**	0.058	0.158	0.577	0.014	41	−1,029	−1,000

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

of variance. Second, the variability in force structure relationships is noticeable. For example, the variability in the $CivPers^{ind} \Leftrightarrow CivPers^{dir}$ relationship is 0.213, whereas the variability in the $CivPers^{ind} \Leftrightarrow ES^{\text{civ}}$ relationship is 0.487. This suggests that a more consistent relationship exists between $CivPers^{ind}$ and $CivPers^{dir}$ across the enterprise, which is confirmed when the confidence interval is assessed. This insight is important to policy makers because it illustrates which relationships are more consistent and pervasive across an enterprise versus relationships that are more variable across operational sites.

Notably, model 2 results suggest that a few common significant relationships exist across the AF enterprise. First, the force structure variables most strongly linked to $CivPers^{ind}$ include ES^{civ} and $CivPers^{dir}$. The relationships between $CivPers^{ind}$ and these two force structure variables maximize model performance and suggest a statistically significant coefficient. The similarity between these two predictor variables is self-evident, with the primary difference only being the growth rate in direct civilian personnel cost growth over and above inflation.

The γ_{10} for these model excursions suggest a higher elasticity than what was suggested in the fixed slope effect models. The $CivPers^{ind} \Leftrightarrow ES^{\text{civ}}$ γ_{10} coefficient of 0.25 suggests that a 1% change from the average ES^{civ} at a base typically results in a 0.25% change in $CivPers^{ind}$. Similarly, a 1% change from the average $CivPers^{dir}$ at a base typically results in a 0.20% change in $CivPers^{ind}$. However, as previously mentioned, the variability in the $CivPers^{ind} \Leftrightarrow CivPers^{dir}$ slope across AF bases is less than the variability in the $CivPers^{ind} \Leftrightarrow ES^{\text{civ}}$ slopes.

Similarly, the force structure variables most strongly linked to $MilPers^{ind}$ is $Pers^{dir}$ and $MilPers^{dir}$. These force structure relationships maximized model 2 performance with the highest R_1^2 value and lowest AIC and BIC values along with statistically significant coefficients. The γ_{10} coefficient of 0.17 suggests that a 1% change from the average $Pers^{dir}$ at a base typically results in a 0.17% change in $MilPers^{ind}$. Similarly, a 1% change from the average $MilPers^{dir}$ at a base typically results in a 0.18% change in $MilPers^{ind}$. This suggests that a greater elasticity exists than a fixed slope suggests. Furthermore, the τ_2^2 value of 0.158 for the $MilPers^{ind} \Leftrightarrow MilPers^{dir}$ slope compared to the τ_2^2 value of 0.240 for the $MilPers^{ind} \Leftrightarrow Pers^{dir}$ slope suggests that less variability in the $MilPers^{ind} \Leftrightarrow MilPers^{dir}$ relationship exists across the AF enterprise.

Ultimately, these results suggest that as the AF makes adjustments to its direct civilian and military workforce, the corresponding indirect workforce experiences a consistent adjustment of lesser magnitude but in the same direction; however, when other force structure variables, including the tooth, are adjusted, no consistent impact to the indirect workforce across the AF enterprise is experienced.[10]

Model 3

Model 3 assesses whether the MAJCOM that a base is assigned to influences the relationships; the objective is twofold: (1) to assess the variability in the slopes across bases and across MAJCOMs and (2) to assess the variability in the slopes across bases nested within MAJCOMs. Only the force structure variables that had a significant relationship in model 2 are assessed.

Table 6 provides the results for model 3a in which variability in the slopes across bases and across MAJCOMs are assessed. Although only marginal improvements in model fit were

[10] Interaction effects were evaluated to assess whether simultaneous influence of multiple force structure variables on $CivPers^{ind}$ and $MilPers^{ind}$ exist. No statistically significant interaction coefficients were identified.

Table 6. Slope parameters and model fit for model 3a.

	$CivPers^{ind}$									$MilPers^{ind}$								
	Fixed effect		Random effect							Fixed effect		Random effect						
Predictor	δ_{100}	SE	τ_2^3	τ_2^2	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC	δ_{100}	SE	τ_2^3	τ_2^2	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC
Tooth	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
TAI	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
FH	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
ES	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
ES^{civ}	0.25*	0.100	0.005	0.484	0.585	0.023	56	−450	−405	—	—	—	—	—	—	—	—	—
ES^{mil}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
$Pers^{dir}$	0.43***	0.129	0.013	0.738	0.588	0.030	42	−201	−156	0.35*	0.173	0.223	0.117	0.564	0.013	45	−1,078	−1,033
$CivPers^{dir}$	0.20**	0.065	0.001	0.212	0.584	0.026	51	−345	−300	—	—	—	—	—	—	—	—	—
$MilPers^{dir}$	0.27**	0.099	0.002	0.446	0.587	0.035	32	−57	−12	0.30*	0.128	0.108	0.095	0.566	0.014	41	−1,032	−987

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

achieved, an ANOVA test with the modified p-value indicates that allowing for MAJCOM random effects on each force structure's slope significantly improves all models.[11] Table 6 introduces a new parameter, τ_2^3, which indicates the variability in the slope across the MAJCOMs. By comparing τ_2^3 to τ_2^2, we can compare the variability in the slopes across MAJCOMs to the variability in the slopes across bases.

The results indicate that the relationships between $MilPers^{ind}$ and the relevant force structure variables vary more across MAJCOMs than across the bases, whereas the relationships between $CivPers^{ind}$ and the relevant force structure variables vary more across bases than across MAJCOMs. In fact, the variability in the $CivPers^{ind}$ relationships across MAJCOMs appears to be negligible relative to the variability across bases.

Table 7 provides the results for model 3b in which variability in the slopes across bases nested within MAJCOMs is assessed. These results suggest that variability in the relationships across bases nested within MAJCOMs exist. In fact, for both $CivPers^{ind}$ and $MilPers^{ind}$ relationships, the 95% confidence interval for the random slope coefficients is greater than zero, implying that the relationship between $CivPers^{ind}$ and $MilPers^{ind}$ and each relevant force structure variable differs across bases within MAJCOMs. As a result, no standard relationship can be implied across all bases within a MAJCOM.

Model 4

The final model assesses the influence of time and examines whether potential autocorrelation exists. We find that the empirical autocorrelation for the within-group residuals for our model 3 excursions ranges from 0.60 to 0.70, suggesting that autocorrelation may be biasing our results. As a result, model 4 incorporates an autoregressive error structure to correct for the high within-group residual autocorrelation and includes a time variable to assess whether a growth rate effect is occurring in the dependent variables. Table 8 displays the final results and illustrates some important insights.

First, although we can not directly compare the residual values to the orginal null models to produce R_2^2 values comparable to the previous models, comparing the residual values to updated null models with autoregressive error structures suggests that the $CivPers^{ind}$ models can account for approximately 80–85% of the variability in $CivPers^{ind}$ and the $MilPers^{ind}$ models can account for approximately 85–90% of the variability in $MilPers^{ind}$. Furthermore, an ANOVA test with the modified p-value indicates that accounting for the autoregressive error structure significantly improves all models, which is also confirmed by the significant reductions in the AIC and BIC values from previous models. Furthermore, diagnostics confirm that residual homoscadisticity and normality assumptions are satisfied.

Second, a growth rate effect appears to be influencing the $CivPers^{ind}$ models but not the $MilPers^{ind}$ models. This can be confirmed by the significant δ_{200} coefficients in Panel A of Table 8. These coefficient values suggest that for every year, a 0.01% growth rate in $CivPers^{ind}$ occurs. The near-zero variability values at the MAJCOM level (τ_3^3) suggest that very little variability in this growth rate exists between MAJCOMs. Furthermore, the near-zero variability values at the base level (τ_3^2) suggest that very little variability in this growth rate exists between AF bases. Together, this suggests that the 0.01% growth rate in $CivPers^{ind}$ appears to be a common rate occurring across all bases and all MAJCOMs. In comparison, the insignificant δ_{200} coefficients in Panel B indicate that no common growth rate in $MilPers^{ind}$ appears to be occurring across the AF enterprise.

[11] The ANOVA p-value results were $p < 0.01$ for $MilPers^{ind} \Leftrightarrow MilPers^{dir}$ and $p < 0.001$ for all other models.

Table 7. Slope parameters and model fit for model 3b.

	CivPers^{ind}								*MilPers*^{ind}							
	Fixed effect		Random effect						Fixed effect		Random effect					
Predictor	δ_{100}	SE	τ_2^2	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC	δ_{100}	SE	τ_2^2	τ_1^2	σ^2	R_1^2 (%)	AIC	BIC
Tooth	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
TAI	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
FH	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
ES	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
ES^{civ}	0.25*	0.097	0.487	0.586	0.023	56	−453	−418	—	—	—	—	—	—	—	—
ES^{mil}	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
Pers^{dir}	0.42***	0.121	0.742	0.588	0.030	42	−205	−170	0.17*	0.070	0.239	0.577	0.013	45	−1,068	−1,034
CivPers^{dir}	0.20**	0.064	0.213	0.588	0.026	51	−349	−314	—	—	—	—	—	—	—	—
MilPers^{dir}	0.27**	0.098	0.451	0.589	0.035	32	−61	−26	0.18**	0.058	0.158	0.577	0.014	41	−1,027	−993

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 8. Slope parameters and model fit for model 4.

Panel A: *CivPers*^{ind}

	Force structure fixed effect		Growth rate fixed effect		Force structure random effects		Growth rate random effects				
Predictor	δ_{100}	SE (δ_{100})	δ_{200}	SE (δ_{200})	τ_2^3	τ_2^2	τ_3^3	τ_3^2	σ^2	AIC	BIC
Tooth	—	—	—	—	—	—	—	—	—	—	—
TAI	—	—	—	—	—	—	—	—	—	—	—
FH	—	—	—	—	—	—	—	—	—	—	—
ES	—	—	—	—	—	—	—	—	—	—	—
ES^{civ}	0.08*	0.038	0.01**	0.003	0.003	0.023	0.000	0.000	0.116	−1,471	−1,386
ES^{mil}	—	—	—	—	—	—	—	—	—	—	—
$Pers^{dir}$	0.20**	0.068	0.01**	0.003	0.018	0.060	0.000	0.000	0.135	−1,471	−1,386
$CivPers^{dir}$	0.09	0.060	0.01**	0.004	0.025	0.023	0.000	0.000	0.155	−1,415	−1,331
$MilPers^{dir}$	0.12*	0.048	0.01**	0.004	0.006	0.035	0.000	0.000	0.097	−1,483	−1,398

Panel B: *MilPers*^{ind}

	Force structure fixed effect		Growth rate fixed effect		Force structure random effects		Growth rate random effects				
Predictor	δ_{100}	SE (δ_{100})	δ_{200}	SE (δ_{200})	τ_2^3	τ_2^2	τ_3^3	τ_3^2	σ^2	AIC	BIC
Tooth	—	—	—	—	—	—	—	—	—	—	—
TAI	—	—	—	—	—	—	—	—	—	—	—
FH	—	—	—	—	—	—	—	—	—	—	—
ES	—	—	—	—	—	—	—	—	—	—	—
ES^{civ}	—	—	—	—	—	—	—	—	—	—	—
ES^{mil}	—	—	—	—	—	—	—	—	—	—	—
$Pers^{dir}$	0.14**	0.034	0.00	0.004	0.013	0.023	0.000	0.000	0.027	−2,121	−2,036
$CivPers^{dir}$	—	—	—	—	—	—	—	—	—	—	—
$MilPers^{dir}$	0.15**	0.036	0.00	0.004	0.012	0.036	0.000	0.000	0.031	−2,147	−2,062

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 9. Relationships identified between indirect cost categories and force structure variables.[a]

	Force structure predictor variables								
Indirect category	Tooth	*TAI*	*FH*	*ES*	ES^{civ}	ES^{mil}	$Pers^{dir}$	$CivPers^{dir}$	$MilPers^{dir}$
$CivPers^{ind}$					•		•		•
$MilPers^{ind}$							•		•

[a] • Relationship exists.

Third, the autocorrelation and growth rate effect appears to bias the slope coefficients (δ_{100}) with the force structure variables. By comparing the δ_{100} values from model 3a with model 4, a sizable reduction in the coefficients appear for both $CivPers^{ind}$ and $MilPers^{ind}$ models. For example, in model 3b, the fixed $CivPers^{ind} \Leftrightarrow ES^{\text{civ}}$ slope effect is 0.25. When model 3 is refitted with the growth rate effect, the fixed slope effect is reduced to 0.19. Furthermore, once the autoregressive error structure is accounted for, this fixed slope effect is further reduced to 0.08 as displayed in Table 8. This suggests that both $CivPers^{ind}$ and $MilPers^{ind}$ are more inelastic to changes in the force structure variables than model 3 indicated. In addition, once the autocorrelation and growth rate effect are incorporated, model 4 finds that the relationship between $CivPers^{ind}$ and $CivPers^{dir}$ is not statistically significant as previously indicated.

Finally, the autocorrelation and growth rate effect also appears to influence the variance estimate of the force structure slope across the MAJCOMs. Model 3a suggested that the relationships between $MilPers^{ind}$ and the relevant force structure variables vary more across MAJCOMs than across the bases and the relationships between $CivPers^{ind}$ and the relevant force structure variables vary more across bases than across MAJCOMs. However, after correcting for autocorrelation and growth rates in model 4, the variability in the statistically significant force structure relationships across the MAJCOMs (τ_2^3) is less than the variability in the relationships across the AF bases (τ_2^2), as illustrated in Table 8.

Discussion, future work, and limitations

Discussion

So what can be concluded about AF indirect personnel costs and their relationship to force structure variables? Conjecture 1 presumed that total direct costs, or the tooth, is the front-line mission force structure variable that provides the strongest link to indirect personnel costs. Our analysis consistently finds this to be false; however, we find that relationships do exist between indirect personnel costs and other force structure variables as identified in Table 9. Furthermore, we find that these relationships are all directionally consistent. Primarily, $CivPers^{ind}$ and $MilPers^{ind}$ appear to have a relationship with $Pers^{dir}$ and $MilPers^{dir}$. This suggests that when the AF adjusts total personnel costs and/or military personnel costs on the direct operational side of the AF business, both civilian and military indirect personnel costs also experience adjustments. In addition, $CivPers^{ind}$ appears to have a relationship with ES^{civ}, suggesting that as the civilian headcount on the direct side is adjusted, indirect civilian personnel costs also experience an adjustment.

It should be pointed out that although single predictor variable models can cause misspecification concerns, the validity of our results come with further justification. From a theoretical perspective, this relationship is fairly intuitive because the majority of indirect personnel costs at operational bases are the by-product of providing installation support (i.e., facilities, equipment, and personnel) services to the operational force population at an installation. In other words; to feed, house, protect, provide medical support to, and otherwise support the operational force population in the performance of their day-to-day tasks (Mills et al. 2013). This is further supported from a practical perspective as the AF develops much of its installation support manpower requirements based on manpower standards and mathematical formulae that calculate manpower needs based, in part, on installation population[12] (Mills et al. 2013) . As a result, our model likely represents an approximate surrogate for the underlying formulae used by the AF.

In addition to identifying these relationships, we find that these linkages have very low elasticities, suggesting that adjustments in these direct personnel force structure variables do not lead to proportional adjustments in indirect personnel costs as a tooth-to-tail ratio metric would imply. Rather, when a 1% adjustment in these direct personnel force structure variables is made, indirect personnel costs typically experience a 0.08–0.20% adjustment. We also find that indirect civilian personnel costs are also being influenced by a growth rate, whereas indirect military personnel costs are not.

Conjecture 2 presumed that relationships between front-line mission force structure variables and indirect personnel costs are consistent across the multiple levels of the enterprise. Our analysis also finds this to be false. A crucial finding in our results is the fact that when fixed relationships are assumed, a relationship appears to exist between indirect personnel costs and force structure variables. However, when relationships are allowed to vary across the multiple levels of the enterprise, many of these relationships are found to be baseless and lacking sufficient evidence. For the force structure variables found to have a statistically significant relationship with $CivPers^{ind}$ and $MilPers^{ind}$, we find that allowing the slopes to vary both between bases and between MAJCOMs significantly improves the models; however, we also find that the relationships vary more between bases than they do between MAJCOMs. As a result, senior leaders should not assume that a common relationship between indirect personnel costs and force structure variables exists across the entire AF enterprise, let alone across all of the bases within a MAJCOM. Rather, it should be understood that a pervasive relationship does exist across the enterprise but that there is sufficient variability in this relationship across MAJCOMs and even more so across bases.

The one common relationship we did find was a growth rate in indirect civilian personnel costs. Our results indicate that a constant growth rate of 0.01% per year is occurring with very little variability in this growth rate across bases and MAJCOMs. Although this rate does not appear sizable, a 0.01% growth rate for our sample equates to $52 million per year. If AF leadership deems this cost growth a viable concern, then an enterprise-wide approach to control this cost is suggested.

Future work

Directly regarding our results, of particular interest for future research is to identify the underlying factors that may provide the rationale for why total headcount of direct civilian personnel would be linked to indirect civilian personnel costs but not the cost of that same headcount. This may signal that when operational positions are reduced, promotions for the remaining positions are more actively engaged, leading to minimal net changes in actual costs; however, further research is required to ground this finding to a theoretical basis. Future research should also identify nonoperational variables that may help to explain the remaining

[12] For more information, the reader can reference Air Force Instruction 38-201, *Management of Manpower Requirements and Authorizations* (Department of the Air Force 2011)

variance in indirect personnel costs. Contextual variables such as the retired military population surrounding an AF installation may influence changes in indirect costs and could provide further insights useful to decision-makers. Lastly, sufficient room exists to expand this analysis to the many other indirect cost categories that exist to provide a more comprehensive understanding of the behaviors of indirect costs and their relationships to operational resources and activities.

Of further interest, both regarding our results and more broadly applied to organizations as a whole, is for future research to establish a better understanding as to why such differences in relationships exist across the organizational hierarchy. Is this driven by existing manpower standards and formulae, as my be the case for the AF, or is this driven by managers' deliberate decisions? Furthermore, our research focuses on a large bureaucratic organization. This begs the question as to whether commercial industries experience similar effects, or are there significant differences between public and private organizations? This could even be expanded to assess differences dependent on commercial sectors, global locations, and technology infusion.

Limitations

It is important to note that certain organizational and analytical limitations exist in this research. First, the AF requirement to work within the strictures of the congressional budget may be a limiting factor in how cost and force structure adjustments can be made. Second, although AFTOC business rules categorize costs consistently across the MAJCOMs, individual bases do have some discretion in how they classify certain expenses. As a result, discrepancies in cost accounting may exist. Third, although this research identifies statistical relationships between operational variables and indirect personnel costs, this should not be interpreted as a causal relationship but, rather, correlational. However, contextual justifications provided, unique to how the AF uses manpower standards and formulae, likely support a causal interpretation for our specific results.

Conclusion

Although research has advanced the knowledge behind the modeling and behavior of indirect costs, several concerns still exist that this article addresses. First, much of existing research has treated indirect costs as a single cost pool, disregarding the established notion that a key element of strategic and accurate cost analysis is the ability to analyze and understand the economics of discrete cost categories within and across the enterprise. Our research focuses on the single indirect personnel cost pool, which can represent a significant contributing source to indirect costs, and assesses their relationships to operational resources and activities.

Second, indirect costs are primarily analyzed at a single level of analysis, aggregated either at the highest organizational level or only at the lowest operational level. This leads to limited understanding of how behaviors and relationships are influenced by the hierarchical nature of organizations. Edward Tufte stated, "Assorted views of the same underlying data are often helpful. Multiple portrayals may reveal multiple stories, or demonstrate that inferences are coherent, or that findings survive various looks at the evidence in a kind of internal replication," (2006, p. 108). Our research assesses indirect cost behavior and relationships at the multiple levels of an enterprise. By applying a multilevel modeling process, we provide an assorted enterprise view of indirect personnel costs. Furthermore, we identified that differing assumptions in fixed versus random effect relationships between indirect costs and operational variables at the hierarchical levels of an organization will lead to multiple, and sometimes contradictory, stories. Only by strategically applying a multilevel modeling approach do we identify evidential relationships that exist across an organizational enterprise.

Lastly, specific to the DoD and AF, past research on indirect costs have focused on relating indirect costs to total direct costs. We advance this stream of research by assessing how indirect costs relate to the underlying operational resources and activities. This provides senior AF decision-makers with evidence-based knowledge to inform decisions regarding budget reduction strategies. Recent and projected reductions in defense spending make the timing of our analytic contribution all the more meaningful and relevant.

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