CAN ENERGY EFFICIENCY MEANINGFULLY IMPROVE CORPORATE PROFITABILITY?[1]

PETER A. SOYKA
Director, Strategic Environmental Services
GeoTrans, Inc.

and

JOHN R. POWERS
Economist
U.S. Environmental Protection Agency
Mail Code 4102M
1200 Pennsylvania Ave., N.W.
Washington, D.C. 20460
Tel: (202) 564-5776
Fax: (202) 564-0500
E-mail: Powers.John@epa.gov

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Abstract

Using a two-pronged analysis of data that was reported by participants in EPA's Green Lights program, we find evidence that energy efficiency strategies create substantial and discernible new corporate wealth. The first prong of our analysis yields the finding that lighting upgrades performed by 1,271 program partners from 1989 to 1998 created approximately $2.4 billion in new private- and public-sector wealth from program-related energy savings. The second prong of our analysis shows a subtle, but statistically significant, positive impact of these investments on the operating margins of the publicly traded companies in the program for which we could obtain financial data. These findings suggest that, in the aggregate, the wealth created by the Green Lights program may be substantial, and that for the companies included in our second analysis, the financial benefits to participation in the program are of sufficient magnitude to be discernible at the corporate level.

INTRODUCTION

In recent years, energy efficiency has quietly become an important element of corporate strategies to control costs and raise productivity. Moreover, using less energy for lighting, ventilation, heating, and air conditioning of buildings reduces the adverse environmental impacts from the use of fossil fuels and provides other benefits to society. The building and energy management literature suggests that effective energy management enables organizations to save substantial amounts of money, while improving the safety and comfort of the indoor environment for their work forces (Koomey, Sanstad, & Shown, 1996; Kessler, 1998; Larson, 1998; DeCanio, 1998; Vine, Mills, & Chew, 2000).

Nevertheless, in most organizations, optimizing energy use to meet production, distribution, and health and comfort needs, as well as manage costs, has generally been viewed as a tactical, site-based, middle management issue, rather than one of potential strategic importance at the corporate level. In larger organizations, designated energy managers play the principal role, while in smaller companies and public-sector organizations, facility managers often are responsible for energy issues along with a host of other matters.

In recent years, however, low global energy costs have tempered interest in energy savings initiatives in general (Hollander & Schneider, 1996) and, in many U.S. companies, as a means of controlling costs. As the U.S. economy enters an era of uncertain deregulated production, transmission, distribution, and marketing of electricity, it is fair to ask whether an energy efficiency strategy adds value to a corporate portfolio of wealth-building initiatives, as well as what evidence there is of such a value-added proposition.

For firms wishing to manage their energy use more effectively, there are numerous sources of assistance. Indeed, the global market for energy efficiency products and services has been estimated at more than $80 billion per year (Hagler Bailly Consulting, Inc. 1996), and providers of both technologies and services are widely available. In addition to long-standing electric utility demand-side management (DSM) programs, a number of public and private initiatives have been developed over the past decade or so to promote more widespread adoption of active energy use strategies. A prominent example is the U.S. Environmental Protection Agency's (EPA) Energy Star Buildings and Green Lights Partnership (ESB/GL), which has been in place since 1991. The Partnership contributes in a material way to the process of educating and encouraging facility and energy managers to conserve energy and save money by providing tools and guidance for identifying energy efficiency targets that offer the best payoff. It also assists managers in quantifying, in monetary terms, the prospective benefits of investing in energy efficiency.

Results to date indicate that, in general, energy-efficient buildings programs have been successful and have yielded noteworthy results (EPA, 1999; Parformak & Lave, 1996; Eto, Kito, Shown, & Sonnenblick, 2000; Eto, Vine, Shown, Sonnenblick, & Payne, 1996; DeCanio, 1988). To this point, however, few studies have been performed that provide insight into the overall *financial* (as opposed to environmental) benefits of such programs and the voluntary actions that have been taken in response to them. Although a small number of studies have reported on the estimated savings that result from energy efficiency upgrades or the net financial or societal benefits created by government- and utility-sponsored DSM programs, none addresses whether the benefits to the organization of adopting more energy-efficient behavior are of a significant magnitude. Indeed, even some proponents of publicly financed energy efficiency programs, such as Energy Star, argue that, while energy savings from implementation of such programs are quite substantial, the accompanying cost savings are small for many participating organizations

(Howarth, Haddad, & Paton, 2000). Detailed examination of the data collected by EPA's program over an extended period offers a unique opportunity to develop a more complete understanding of the extent to which lighting upgrades have been implemented, and the attendant measurable financial benefits (or lack thereof) that have accrued to program participants.

This article provides new evidence that suggests that energy efficiency strategies implemented through GL activities (and, implicitly, those conducted under the broader ESB program) create discernible and substantial new corporate wealth. The implication of this work is that every organization should consider energy efficiency strategies as a means of achieving permanent increases in earnings resulting from lower operating costs. Furthermore, due to the predictable nature of the energy efficiency investments, the reduction in operation costs is fairly certain compared to other investment alternatives faced by firms, meaning reduced financial risk from, among other sources, energy price shocks.

More specifically, this article describes a new, two-pronged analysis of data reported by participants in EPA's GL program[2] since its inception. The first prong of the analysis yields the finding that lighting upgrades performed by 1,271 program partners as a consequence of the program have created approximately $2.4 billion in new private- and public-sector wealth from energy savings alone.

The second prong of the analysis is a regression analysis that shows a subtle, but statistically significant, impact of investments in lighting upgrades on publicly traded companies' operating margins. This finding suggests that the financial benefits to ESB/GL program partners of investments in lighting are of sufficient magnitude to be discernible at the overall corporate

[2] The GL program was incorporated into the broader ESB program in 1997. We focus on EPA's lighting program because the data for the GL program is more extensive than that available for the broader program.

financial level. Energy efficiency therefore may represent a means of creating financial value in organizations that have not yet embraced the philosophy.

ANALYTICAL METHODS

We began our analysis with an examination of data collected by EPA's ESB/GL program on the results of upgrades of lighting equipment by organizations to determine whether and to what extent such investments repaid their capital investment costs or generated incremental cash flows from energy savings. Upon demonstrating that, on balance, the investments yield substantial savings and creation of (permanent) new wealth, we investigated whether the savings are broadly distributed and of sufficient magnitude to be quantifiable at the organizational (corporate) level. That is, we examined whether lighting upgrades contribute to overall corporate financial performance in a meaningful way. Our approach to the two analytical phases is presented below.

Financial Impact of Green Lights Investment

Our first analysis is based on an empirical evaluation of the extent and cost-effectiveness of lighting upgrades made by participants in EPA's program, which have reported lighting upgrade information since 1991. The analysis is limited in scope to the lighting portion of the ESB program because it has operated for a longer period than the full program, and therefore offers more data to evaluate the extent of energy efficiency upgrades and the rate at which they have been implemented. Because lighting upgrades are generally the first steps in the more comprehensive ESB program, our results understate (to an unknown extent) the effect of the ESB/GL Partnership as a whole in terms of wealth creation.

Our data on specific lighting upgrades were submitted by ESB/GL partner organizations to EPA in response to routine solicitation of reports on upgrades over a nine-and-a-half-year period. Reported data elements generally included the installed cost of the upgrade(s), any rebates or subsidies received to defray that cost, the expected yearly electricity savings, and other supporting information. We reviewed the data as reported to identify anomalies, corrected or removed a small number (fewer than ten) of obviously erroneous values, and conferred with ESB program experts to resolve remaining issues related to data quality. That process yielded individual data records on 14,675 upgrade projects performed by 1,271 partners. Of those partners, almost 1,000 are corporate partners and program "allies,"[3] 208 are educational institutions (primary and secondary schools and colleges and universities), and 83 are public-sector entities (that is, state and municipal governments).

Program participants are a diverse group of public- and private-sector organizations, as presented in Table 1 below. A wide array of resource extraction, manufacturing, distribution, wholesaling, retailing, and service industries are represented in the group.

[*Insert Table 1 about here*]

The organizations collectively installed lighting upgrades in all 50 states, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands. In the aggregate, the upgrades are expected to save 5.52 billion-kilowatt hours per year through enhanced lighting efficiency.

The availability of the data set confers a number of important advantages. First, it is large and represents many diverse organizations and their behavior over an extended period. Second, it contains data on many variables of interest from an analytical standpoint, including information

[3] Energy Star "allies" are providers of energy, energy services, energy efficiency equipment, and related products and services that have endorsed the program.

about technology choices, the rate at which new capital equipment has been introduced, and the internal data that were used to support investment decisions.

At the same time, however, the data have certain limitations. The organizations that comprise the GL partner population are not selected randomly, nor are they distributed evenly across the industries represented in this analysis. Those circumstances necessarily limit the strength of our conclusions about how fundamental the observed relationships between lighting upgrades and indicators of the creation of wealth are in the U.S. economy. Because participants self-select into the voluntary ESB program, it is possible that they have achieved results that would not be replicated by some other set of organizations.

Moreover, reflecting the voluntary nature of the program, the self-generated and self-reported information provided to EPA is quite variable in several ways. The frequency of and level of aggregation in reports on upgrades and the completeness of those reports differ substantially from organization to organization. In a small number of cases, the interpretation of what constitutes a "lighting upgrade" may have been overly broad, making the reported costs and benefits not truly comparable. Some of the more than 14,000 records examined for the analysis contained values that we believe may be erroneous. In the absence of specific and clear evidence that a reported value was incorrect, however, we retained and analyzed the data as reported. One consequence of that approach is that certain calculated results exhibit extreme values. For that reason, the results presented herein are best interpreted in the aggregate, with particular attention paid to totals and indicators of central tendency, rather than to minimum or maximum values.

We adjusted the data for inflation (to December 1999 dollars) using separate factors to account for inflation in the lighting fixtures industry (for cost data) and in retail electricity sales (for savings data). We then developed some additional data needed to quantify financial benefits at the level of the individual organization. The key variable of interest was each organization's weighted average cost of capital (ω), or opportunity cost of capital, which we used as a discount rate for calculating the net present value of the lighting investments.[4]

We computed ω for all publicly traded companies (i=1,…, n) in our GL data set using data obtained from the CompuStat® database.[5] For each organization for which data were available, ω was calculated by using corporate debt and equity levels as weights for averaging the "interest rates" each organization pays for financing it's investments with debt and equity. In the case of private sector organizations for which we were unable to estimate a value for ω, we applied the mean ω derived from the first group of companies. Public-sector organizations were assigned ω on the basis of U.S. Treasury Bill rates (federal) or typical municipal bond yields (nonfederal).

It is worthy of note that the empirically derived ω values generally clustered around a median value of about 10 percent (real) for private-sector organizations, a figure that is substantially lower than typical "hurdle rates" used in many companies.[6] Values of ω for public sector organizations (including applicable educational institutions) are on the order of four percent (real), reflecting the lower risk and tax-advantages associated with public-sector debt instruments.

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4 In an analysis of this type, it would be preferable to use a measure of the discount rate that reflects returns on projects of comparable risk (DeCanio (1988)). These data are generally unavailable, leaving us to use each organization's average cost of capital. Every organization i has its own individual ω_i, which reflects its unique capital structure, credit worthiness, and other characteristics. By using ω_i in our calculations we assume that the risks of the energy efficiency investments are comparable to the *average* investment for organization i. This is a conservative assumption that likely results in an understatement of the wealth created by the energy efficiency investments, since the predictable nature of the energy cost reductions are likely to be less risky than the organization's other investments. As such, lower discount rates would result in larger NPVs.

5 CompuStat® is a widely used database of corporate financial data and indicators and is owned and marketed by Standard & Poor's, Inc.

The net energy cost savings to firm *i* produced by an investment in energy efficient lighting is a function of the initial (one-time; assuming no operating and maintenance [O&M] costs) net investment expenditure ($I_{i,0}$) in time period 0 (t=0), and the present value of the future stream of energy cost savings (assuming no O&M costs), which accrue as annual savings "payments" (S_i) (assumed constant). For an equipment lifespan (L) of 15 years,[7] the NPV of the stream of savings for firm *i* is expressed as:

$$NPV_i = \sum_{t=0}^{L} \frac{S_i}{(1+\omega_i)^t} - I_{i,0} \,. \tag{1}$$

We also computed the payback period (PBP), or the time (in years) required for organization *i* to repay the initial investment ($I_{i,0}$) made in time 0 with the savings accrued annually (S_i) that are obtained from making the investment. This measure of financial performance, which is the ratio of $I_{i,0}$ to S_i, is a simple indicator of cost-effectiveness.

Impact of Energy Savings on Overall Corporate Financial Performance

In the second phase of the research, we examined whether the incremental cash flows generated by successful lighting upgrades produced discernible effects upon an indicator of overall corporate financial performance. Our general approach entailed use of multiple regression analysis to isolate and quantify meaningful changes, if any, in corporate operating earnings margins as a result of the installation of lighting upgrades. Our approach involved the

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6 This is not surprising, as Dixit and Pindyck (1994) point out, that hurdle rates are often set high so as to account for uncertainty and irreversibility.

7 Reflecting the professional judgement of lighting design and engineering experts at ICF Consulting and EPA, we believe that 15 years is the best approximation of the life span of lighting equipment installed in owner-occupied space. That time period is generally consistent with values reported previously by other investigators (Eto, Kito, Shown, & Sonnenblick (2000) and Eto, Vine, Shown, Sonnenblick, & Payne (1996)).

development of a basic model to explain changes in individual companies' earnings margins over time and then to test the null hypothesis that there is no significant relationship between the energy efficiency variable and the earnings margin. On the basis of the results of our NPV analysis, described above and in previous work,[8] our belief was that we would reject that hypothesis and observe a positive relationship between energy efficient lighting investments and earnings margins.

Model specification and the data.

Our basic model describing the predictors of corporate operating earnings margins, defined as the ratio of earnings before interest, taxes, depreciation and amortization (EBITDA) to sales, includes variables that control for cyclical variation and a time trend, industry and macroeconomic business conditions, and firm-specific business factors. We chose operating earnings margin as the dependent variable because that ratio is the financial indicator that most likely would exhibit the effect of energy cost savings over time. This variable may be thought of as "pure profitability" in the sense that it reflects the percentage of profit earned from operations, before factoring the effects of other corporate activities, taxes, and other potentially confounding factors.

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[8] Soyka, P. A. 1998. Energy Star® Buildings and its effects on corporate margins and shareholder value. Presented at SRI in the Rockies, Breckenridge, CO.

Our model is represented by the following equation:

$$E_i = E_i\left(\rho, U, P_i, L_i^F, L_i^O, \lambda\right), \tag{2}$$

where E_i is the dependent variable, EBITDA margin; ρ is the unit price margin in firm i's industrial sector;[9] U is the capacity utilization for the U.S. economy; P_i is firm i's productivity as measured by the ratio of sales to fixed assets; L_i^F is firm i's financial leverage as measured by the ratio of book value of debt to total assets; L_i^O is firm i's operating leverage as measured by the ratio of sales to current assets; and λ is the ratio of the (actual) upgraded space (measured in square feet) to the amount of space that the company has made a commitment to the ESB/GL program to upgrade.[10] Descriptive statistics and a correlation matrix of our candidate independent variables are presented in Table 2.

[*Insert Table 2 about here*]

Our specific objective was to test the null hypothesis that λ=0. Our conjecture was that our regression analysis would lead to the rejection of that hypothesis and that the sign of the λ-coefficient would be positive, indicating that investments in lighting efficiency produce a positive impact on financial performance. We conjectured that ρ, U, and P_i would be positively related to E_i and L_i^F would be negatively related to E_i. We did not have a prior conjecture about

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9 Our analysis includes firms from the following broad sector designations: construction; finance, insurance, and real estate; retail; manufacturing; wholesale; transportation and communications; mining; and services.

10 The sources for the data are: E_i, P_i, L_i^F, L_i^O: CompuStat®; U: Federal Reserve Board, Federal Reserve Statistical Release; ρ: Bureau of Economic Analysis (BEA), Gross Product Originating data (2-digit SIC code) available on the BEA web site; and λ: EPA's ESB/GL program. The price index for gross product originating by industry was used in the analysis. The price index for gross product originating reflects the difference in the price index for gross output originating and the price index for intermediate inputs originating, by industrial sector. The cumulative measure of energy-efficient lighting investment (λ) theoretically is bounded for each company by 0 percent and 100 percent (although, as noted below, several companies upgraded a larger space than they have made a commitment to the ESB/GL program to do so), thus normalizing across otherwise disparate companies. Because it is bounded, this variable serves in the regression analysis as an indicator of structural change, much like a 0-1 dummy variable, though the broad range between the lower and upper bounds allows a more accurate reflection of the incremental changes that we expected to influence the firm's financial performance.

the sign of L_i^O but included that variable to account for and control for as much of the variability in operating earnings margin as possible before formally testing our hypothesis.

Of the more than 1,200 organizations that participate in the ESB/GL program, we were able to collect financial data for only 148, because the data were available only for those publicly traded companies that are required by SEC regulations to make financial performance data publicly available. Of those 148 companies, we removed 34 because of a lack of data for at least one of the variables in the model, leaving a sample of 114 companies. For those companies, we arrayed quarterly data for each variable for 38 quarters (1989:I to 1998:II), implying a potential panel data set with 4,332 data points. Unfortunately, the lack of available financial data led to the exclusion of many organizations that participate in the program. Because of that selection bias, our analysis focuses on large, publicly traded companies. Therefore, as a matter of course, the regression analysis does not include privately held companies, nor does it include government entities; nonprofit organizations, such as educational institutions; or other bodies for which operating earnings and margins are not meaningful indicators of financial performance.

Econometric analysis

The panel structure of our data required that we select an econometric method that accounted for both cross-sectional and time-series characteristics. In addition, the companies in our data set were not selected randomly and cannot be viewed in any meaningful way as "representative" of all organizations that could participate in the ESB/GL program. We also had several potential sources of heteroskedasticity, including variability across the cross-sectional (company) dimension (caused by company size or sector), and as a result of small and varied samples within the cross-sections (caused by lack of data). In combination, those factors made it necessary that we: (1) use a pooled regression procedure that accommodates both the time series and the cross-sectional dimensions of our data; (2) control for heteroskedasticity, both within and between cross-sections (companies); and (3) control for autocorrelation resulting from the time-series dimension of the data for each cross-section.[11]

In general terms, the regression procedure for panel data analysis estimates equations of the form

$$y_{it} = \alpha_{it} + \beta_i' x_{it} + \varepsilon_{it} \tag{3}$$

for i=1,2,…,N cross-section units (companies) and t=1,2,…,T periods (quarters), where y_{it} is the dependent variable and x_{it} and β_i are vectors of k nonconstant regressors and parameters for each of the N cross-section units. For this set of equations, the residual covariance matrix is given by:

$$\Omega = E(\varepsilon\varepsilon') = E\begin{pmatrix} \varepsilon_1\varepsilon_1' & \varepsilon_1\varepsilon_2' & \cdots & \varepsilon_1\varepsilon_N' \\ \varepsilon_2\varepsilon_1' & \varepsilon_2\varepsilon_2' & & \\ & & \ddots & \\ \varepsilon_N\varepsilon_1' & \cdots & & \varepsilon_N\varepsilon_N' \end{pmatrix}. \tag{4}$$

When the residuals are contemporaneously uncorrelated and time-period and cross-section homoskedastic, an ordinary least squares (OLS) regression can be used to estimate the system of (stacked) equations created by the pooled specification.

The OLS estimator produces a common constant term, $\alpha_{it}=\alpha$, implying an identical intercept for all cross-sectional units (companies). Because of variability in the companies that were included in our data set, however, we believed that assumption to be inappropriate, and

[11] We used EViews to conduct the econometric analysis. Additional sources regarding the econometric analysis are Greene (2000) and Wooldridge (2000).

instead selected a fixed effects model that estimates unique intercepts for each cross-section *i* (company).[12]

Mathematically, the fixed effects model estimates $\alpha_{it}=\alpha_i$ while assuming that $E(\alpha_i\varepsilon_{it})\neq 0$. The different constants are estimated for each cross-section by subtracting the "within" mean from each variable and estimating OLS, using the transformed data:

$$y_i - \bar{y}_i = \beta_i^{'}\left(x_i - \bar{x}_i\right) + \left(\varepsilon_i - \bar{\varepsilon}_i\right), \tag{5}$$

where $\bar{y} = \frac{\sum_t y_{it}}{N}$, $\bar{x} = \frac{\sum_t x_{it}}{N}$, and $\bar{\varepsilon} = \frac{\sum_t \varepsilon_{it}}{N}$.[13] The coefficient covariance matrix estimates are given by applying the usual OLS covariance formula to the mean difference model in equation (7):

$$\text{var}\left(b_{FE}\right) = \hat{\sigma}_W^2\left(\tilde{X}'\tilde{X}\right)^{-1}, \tag{6}$$

where $\hat{\sigma}_W^2 = \frac{e_{FE}^{'}e_{FE}}{NT-N-K} = \frac{\sum_{it}\left(\tilde{y}_{it} - \tilde{x}_{it}^{'}b_{FE}\right)^2}{NT-N-K}$, in which $e_{FE}^{'}e_{FE}$ is the sum of squared residuals from the fixed effects model, and $\tilde{X}$ is the mean differenced X.[14] The "fixed effects," or constants, are then estimated from $\hat{\alpha}_i = \frac{\sum_t\left(\bar{y}_i - \bar{x}_i^{'}b_{FE}\right)}{N}$.

This estimation procedure is not sufficient, however, to mitigate the effects of the heteroskedasticity described earlier. Specifically, OLS is inefficient in the presence of

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12 We also considered using a random effects model. We rejected that approach, however, on the grounds that it requires treating the individual cross-sectional effects as uncorrelated with the other regressors, an assumption that is inconsistent with our belief that our data are cross-sectional heteroskedastic.

13 In a fixed effects model, $\beta_i=\alpha_i+\beta$, where α_i varies to capture heterogeneity between the *i* cross-sections; however, the marginal effects, described by β, are the same across *i*.

14 Note that because our data set is unbalanced, NT is replaced by the total number of observations, excluding the missing values, implying that the missing data reduce the degrees of freedom and raise var(b_{FE}).

heteroskedasticity.[15] To account for that factor, we performed feasible generalized least squares (FGLS) estimation by assuming the residuals were contemporaneously uncorrelated and cross-sectional heteroskedastic. In the first stage of FGLS, $\hat{\sigma}_i^2$ are estimated from a pooled OLS regression in which the estimated variances are computed as $\hat{\sigma}_i^2 = \frac{\sum_{t=1}^{T_i}\left(y_{it} - \hat{y}_{it}\right)^2}{T_i}$, where $\hat{y}_{it}$ are the fitted values from OLS. Then, in the second stage, $\hat{\sigma}_i^2$ are used as cross-section weights by the standard generalized least squares (GLS) estimator (weighted least squares) to estimate the coefficient values and the covariance matrix. The FGLS estimator is nonlinear and asymptotically efficient.

Use of the FGLS estimator was important to our ability to estimate our model. Specifically, between-group heteroskedasticity is caused by at least two sources: (1) considerable variation in our data because of differences in company-specific factors, such as size and sector; and (2) an unbalanced data set (that is, missing data). While our data are comparatively rich and indicative of the variety of organizations that may benefit from participating in the ESB/GL program, that characteristic is itself a source of inefficiency in the estimation process and should be controlled. The FGLS estimation procedure accomplishes such control by inversely weighting the groups, placing less weight on those cross-sections that have a larger error variance and more weight on those cross-sections that have a smaller error variance.

15 Inefficiency implies that, in repeated sampling, on average, the coefficient estimates in OLS will equal the true values, but the variance of the coefficient estimates will not be minimized because information about the heteroskedastic errors is not used in the estimation procedure. While efficiency implies a minimized variance of the coefficient estimate, and therefore an estimate that is more likely to have a small ("statistically significant") probability of a Type I error, an inefficient estimator is likely to produce a coefficient estimate having a large probability of a Type I error.

This procedure does not, however, ensure maximum efficiency in the estimation of the coefficients unless $\hat{\sigma}_i^2 = \sigma_i^2$ is known; because we do not know σ_i^2 and must estimate $\hat{\sigma}_i^2$ using the same heteroskedastic data, FGLS is no longer unbiased. It is consistent, though, and asymptotically more efficient than OLS. Thus, in large samples, FGLS is preferable to OLS.

To control for remaining heteroskedasticity, we also computed White's heteroskedasticity consistent covariance to estimate the asymptotic covariance matrix of the least squares estimator b. The covariance matrix (using a stacked model) is given by

$$\mathrm{var}(b) = \frac{NT}{NT-K}\left(X'X\right)^{-1}\left(\sum_{i,t} u_{it}^2 x_{it} x_{it}'\right)\left(X'X\right)^{-1}, \tag{7}$$

where K is the total number of estimated parameters.[16] As indicated below, we report the results for four different estimation procedures: (1) OLS alone, (2) OLS and White, (3) FGLS alone, and (4) FGLS and White.

RESULTS

In this section, we present in turn the results of our analyses of direct organization-level wealth creation (savings) from lighting upgrades and of potential corporate-level financial impacts arising from increasing energy efficiency.

Financial Impact of Green Lights Investments

Table 3 presents the results of our analysis of the financial impacts of the lighting upgrades. In the aggregate, the upgrades have produced \$2.4 billion of new wealth and typically

[16] The use of both FGLS and White to control for heteroskedasticity is discussed in Greene (2000: 522) and Wooldridge (2000: 268).

are paid back in just over 3 years (median).[17] The sectors that account for the largest contributions to the new wealth are retail trade, educational services, manufacturing, public administration (state and local government), and health care and social assistance. In all sectors except one,[18] and in the aggregate, the mean NPV is greater than the median NPV value, suggesting that, in every sector, a small number of organizations are having an unusually large impact on statistics for the sector.

[*Insert Table 3 about here*]

Businesses in the Accommodation and Food Services and Information sectors obtained the most favorable results at the sector level, with median payback periods of less than two years. The Health Care and Social Assistance; Administrative and Support and Waste Management and Remediation Services; Construction; Mining; Wholesale Trade; Retail Trade; Real Estate and Rental and Leasing; Professional, Scientific, and Technical Services; and Manufacturing sectors each exhibited median payback periods of less than three years. The results demonstrate that the benefits of making financially appropriate lighting upgrades are not limited to any particular type of organization or industrial or commercial sector.

Interestingly, payback periods generally are longer for sectors that are dominated by regulated or public-sector organizations, such as the Utilities, Educational Services, and Public

[17] It is worth noting that 84 of the 1,271 organizations reporting data, representing 16 of the 20 NAICS sectors included in this analysis, have a negative projected NPV associated with their investment projects, indicating that not all upgrades reported by program partners have paid off. Negative NPVs mean that the present value of the future expected benefits (in the form of electricity cost savings) are not sufficient to repay the investment cost, considering the organization's true cost of capital. In such cases, wealth is destroyed rather than created. Such an outcome may result from a variety of circumstances, including improper equipment specification or incorrect reporting of costs (for example, overstating costs by including renovation costs not strictly associated with lighting upgrades) or an understatement of estimated energy savings. Approximately one-half of the organizations generating negative NPVs are Energy Star allies that may have undertaken extensive lighting upgrades for reasons other than anticipated direct financial payoff (for example, for demonstration or marketing purposes).

Administration sectors, all of which have median payback periods of four years or more. That phenomenon might reflect the broader social objectives pursued by those organizations, which may induce them to undertake investment activities that produce socially desirable (external) benefits that generally are not favored by profit-maximizing (private-sector) organizations. It also could be a reflection of the lower costs of capital available to public-sector organizations, allowing them to invest in projects that have marginally lower returns.

Figure 1 further illustrates the overall experience of Green Lights partner organizations, displaying a frequency distribution of overall payback periods projected for those organizations in the aggregate.[19] The chart shows that some 10 percent of partner organizations achieved an overall payback of capital invested in lighting upgrades of less than one year, while approximately half the partners recovered their investments within a one- to three-year time horizon. At the other end of the scale, approximately 10 percent of partner organizations have projected payback periods of more than 10 years, showing once again that not all program participants have made energy efficiency investments that satisfy typical financial evaluation criteria.

[*Insert Figure 1 about here*]

Notwithstanding the unprofitable investments made by certain Green Lights partners, a number of organizations created substantial new wealth for their owners or stakeholders by undertaking lighting upgrades. Of the partners, 42, representing 10 of the sectors (about half the

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[18] The Management of Companies and Enterprises sector includes only one ESB/GL partner company. Therefore, the mean and median (as well as maximum and minimum) values for that category are identical.

[19] The shape of this frequency distribution is similar to that presented in DeCanio's (1998) for the first four years of the GL program.

sectors in our data), captured aggregate benefits from their upgrades of more than $10 million each. Approximately three of four of those organizations primarily provide services.

To provide an indication of the effect of the investments, we show in Table 4 the NPV and payback period results for the top 20 wealth-creating ESB/GL partners, along with the financial components used to calculate those indicators of financial performance. The results show that lighting upgrades have created substantial savings in both public- and private-sector organizations. Note that all the organizations listed in Table 4 have upgraded more than five million square feet of building space. Given the substantial net investment costs[20] incurred by those organizations, it is clear that organizations that have captured the most benefits also have made very substantial capital investments.

[*Insert Table 4 about here*]

Importantly, these results have limitations. The data used in the NPV calculations are essentially engineering estimates of expected energy cost reductions, and therefore do not represent other cost or benefit categories that extend beyond the reach of our data. For example, we are not able to account for management's opportunity cost or the cost of disposing of the replaced lighting equipment. Nor are we able to capture the environmental benefit of the reduced energy consumption or the productivity increase often found with improved lighting. As such, the specific values of our NPV and payback period calculations are only approximations of the welfare effect resulting from such investments. The analysis of financial data in the next section circumvents many of these data problems by assessing the impact of the energy efficiency

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[20] Many of the participants obtained rebates and other financial incentives from power companies, equipment suppliers and installers, and other parties on the supply side of energy use that dramatically reduced the effective cost (and correspondingly increased the organizational benefit) associated with installing lighting upgrades.

investments at the corporate level, which allows us to implicitly control for other factors such as management quality.

Impact of Energy Savings on Overall Corporate Financial Performance

Table 5 presents our principal regression results. Four sets of results are presented to show how our use of both FGLS and White's heteroskedasticity consistent covariance was necessary to produce a statistically significant estimate of the ESB/GL coefficient. The results are listed by estimation procedure in the following order: OLS without the White correction, OLS with the White correction, FGLS without the White correction, and FGLS with the White correction.

[*Insert Table 5 about here*]

Before presenting our key finding, it is important to set forth several crucial econometric steps that were necessary to produce that result. As described earlier, we anticipated heteroskedasticity in our data, particularly between cross-sections. When OLS is run alone, without the FGLS or White corrections, the model performs poorly, producing an adjusted R^2 of only 0.004. Interestingly, three of the coefficient estimates are significant at either the 1 percent or the 5 percent type I error levels. When the White correction procedure is used in conjunction with OLS, the overall performance of the model remains the same (adjusted R^2=0.004 and the coefficient estimates do not change), but only two of the coefficient estimates are significant. We were surprised by the presence of any significant coefficient estimates at all, expecting the heteroskedasticity to result in sizable standard errors across the board that would produce large t-

Because the cost of rebates is borne by another party (often an electric utility or other program ally), total societal wealth does not increase to the extent implied by the NPV estimates provided here.

statistics and little explanatory power. In this case, correcting with White clearly did little to improve the efficiency of the overall estimation.

When we ran FGLS, however, the cross-section weighting controlled for a substantial portion of the heteroskedasticity and the model performed significantly better. In the FGLS (without White) estimation, the adjusted R^2 increases to 0.237, indicating that our model is doing a reasonable job of controlling for important factors that affect earnings margins, thereby allowing us to assess the effect of the ESB/GL variable.[21] Still, however, the standard errors generally are large, compared with the coefficient estimates, producing only four statistically significant coefficient estimates. When we use the White correction along with FGLS, the adjusted R^2 and coefficient estimates remain the same, but the standard errors decline for all the independent variables, to such an extent that all the coefficient estimates are significant at the 5 percent type I error level. Clearly, controlling for heteroskedasticity, particularly between cross-sections, is crucial to generating our result.[22]

As for the specific results using the FGLS & White estimation, the coefficient estimates largely exhibit the expected signs. The unit price margin and capacity utilization both have a positive and significant effect on the earnings margin, as does productivity (sales to fixed assets).

21 As discussed in Greene (2000: 467), R^2 is not bounded by 0 and 1 in a generalized regression model, making it difficult to interpret. However, because we are concerned with R^2 only to the extent that it suggests our model controls for a sufficient portion of the variability in earnings margin to estimate the effect of ESB/GL lighting investments on the earnings margin, we can accept the imprecision of the R^2 calculation.

22 Controlling for autocorrelation was also important, as indicated by the significant coefficient on the AR(1) term. While we would expect that earnings *levels* would be (positively) serially correlation, we had no priors on the serial correlation of the earnings margin. Because the earnings margin is the the earnings level normalized by sales, which is also likely to be serially correlated, we find no reason to expect that the earnings margin will systematically increase, decrease, or stay the same over time across many companies in many sectors. We interpret the negative AR(1) term to imply a quarterly reversion-to-the-mean for each firm, in which a “high” (“low”) earnings margin one quarter is followed by a “low” (“high”) earnings margin the next quarter. Importantly, the presence of autocorrelation does not affect the FGLS estimator, since the estimation error in the autocorrelation coefficient does not influence the asymptotic distribution of the FGLS estimator (e.g., Wooldridge, 2000: 389).

Operating leverage (sales to current assets) and financial leverage (debt to total assets) have negative effects. The *F*-statistic is also sufficiently large to conclude that the independent variables are jointly significant at the 1 percent type I error level. Therefore, our model appears to be robust in the estimation of earnings margin and a reasonable platform for assessing the marginal contribution of participation in the ESB/GL program.

Our key finding is that the coefficient of the ESB/GL variable (λ) is estimated to be positive and significant at the 1 percent type I error level. Across the wide range of organizations included in our data, ESB/GL investments produce a small, yet statistically significant, increase in earnings margin.

To determine the generality of that result, we examined several subsets of the data. As Table 6 shows, we ran the model for each sector[23] and obtained widely varying results. For each of the seven sectors in our data set that are made up of at least two companies, the model generated an adjusted R^2 of 0.30 or higher, indicating better overall fit at the sector level than in the aggregate. The λ-coefficient estimates vary across sectors, in both magnitude and sign. For the three sectors for which significant λ-coefficient estimates were produced, two of the estimates are negative (mining and services) and one is positive (retail).

[*Insert Table 6 about here*]

We also attempted to discern a pattern of effects related to the degree to which an organization had fulfilled its commitment to the ESB/GL program. We sorted the organizations into three groups on the basis of their λ value in the latest time period. The first group, "leaders,"

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[23] In contrast to the approach taken to NPV analysis presented above, the sectors examined in the regression analysis were defined in keeping with past EPA practice, rather than by use of the recently issued NAICS categories. Doing so yielded fewer sectors and generally, larger sample sizes than would have been obtained using the NAICS classification scheme.

includes the organizations that had upgraded at least 50 percent of their space by 1999. Members of the second group, “laggards,” had upgraded less than 5 percent of their space by 1999. The third group, “middlings,” account for the organizations that fall between the two extremes. We specifically wished to determine whether there was an increasing or decreasing effect on earnings as more space was upgraded. As Table 6 shows, this exercise yielded non-significant results.

The findings suggest several things to us. First, the positive effect of ESB/GL upgrades is not universal at our level of estimation; some companies may simply not produce a discernible (positive) effect (as suggested by our earlier NPV analysis) from such investments, or, at least not in the contemporaneous fashion assumed in our model.[24] Second, the sample size may play an important role in observing the relationship between energy efficient investments and financial performance. Because standard errors of coefficient estimates generally are related inversely to the sample size (that is, as the sample size increases, the standard errors of the estimates decrease), the ability of our regression model to discern a statistically significant coefficient estimate is probably related directly to the amount of data we analyze.

Given the panel structure of our data, the implication is that increasing the number of time periods or companies should result in more efficient estimation. Therefore, the fact that our analysis of subsets of the data (by sector and by degree of progress in the GL program) did not produce statistically significant coefficient estimates in several cases may be simply the result of the reduction in the sample size, rather than the lack of a direct relationship between energy efficient investments and overall financial performance.

[24] We also examined the effect of using leads and lags in our analysis. A lead (i.e., $\lambda_{t+1},\ldots$) might be appropriate if there was a reporting lag between the time at which a company made an upgrade and the time at which it reported the upgrade to EPA. A lag (i.e., $\lambda_{t-1},\ldots$) might be appropriate if the benefit of the upgrade, in the form of lower costs and increased earnings, was delayed. We do not have evidence to suggest that either effect is present in our

From the foregoing, we conclude that, with reasonable assumptions, we have identified a discernible positive effect on corporate earnings margins due to energy-efficiency improvements under EPA's GL program. This result, however, is subtle and is sensitive to the model assumptions and specifications employed. The relationship that we have postulated is supported most strongly by the modeling results obtained using the overall sample, and only weakly supported, or not supported at all, by the analysis using smaller cross-sectional groups.

Limitations of the analysis include those inherent in using panel data, particularly a data set in which there are numerous missing values. Because our results suggest that the number of companies included in the analysis may influence our findings, we cannot rule out the possibility that we would have obtained a different result if we could have included more companies. Also, we cannot rule out the possibility that we insufficiently controlled for overall management performance and are observing correlation between management quality and earnings margin, rather than the effect of energy efficiency investments on earnings margin. We also cannot rule out the possibility that we are observing an earnings boost due to increased revenues resulting from a reputation effect from participation in the ESB/GL program.

Another caveat involves the nature of our sample. While undeniably extensive and rich, our data set comprises organizations that have self-selected into EPA's voluntary program.[25] That is, the companies examined in our analysis were not selected at random from a larger population, and by no means should be viewed as representative of the population of companies

data as a whole, although we cannot eliminate the possibility that either or both are present. Further, it is possible that the two effects work in opposition and cancel each other out at aggregated levels of analysis.

[25] Sample-selection also occurred as a result of missing data. The methods used by DeCanio and Watkins (1998) to replace missing observations may be a useful extension of our analysis.

that could benefit from energy-efficient lighting upgrades. Therefore, the positive results reported here do not demonstrate that other firms necessarily would experience similar benefits.

Notwithstanding those limitations, our overall conclusion is that well-chosen investments in energy efficiency generate a positive effect on the financial performance of a wide variety of private- and public-sector organizations. Our results show that individual and company-level lighting energy-efficiency improvement projects, in most cases, result in positive and meaningful wealth creation, as reflected in the NPV calculations described above. Moreover, the regression analysis suggests that the positive effect is discernible at the organizational (corporate) level, especially when examined at highly aggregated levels. We believe that our ability to isolate and quantify the effect of the energy efficiency strategy on overall financial performance is both somewhat surprising and highly noteworthy.

IMPLICATIONS

Our research documents what many knowledgeable people involved in energy management already understand at a local or intuitive level; well-chosen energy-efficiency upgrades can be exceptional investments. The best of those investments offer the somewhat unusual combination of a positive and often significant return on invested capital, a short payback period, and low (but not zero) investment risk. As is true of any other investment, however, negative returns are possible, so it is prudent to perform a careful financial evaluation of energy-efficiency upgrade potential using appropriate analytical methods (including a calculation of NPV under alternative scenarios) before making an investment in new equipment.

At a practical level, money invested in appropriate lighting and other energy-efficiency upgrades yields ongoing, continuous savings in operating costs that represent *permanent* increases in cash flow. For publicly traded corporations, increases in cash flow are related directly to positive changes in stock price, because the stock price represents the market's assessment of the discounted value of all future cash flows from all activities conducted by the corporation. Accordingly, executives and managers in such corporations have the opportunity to create new shareholder wealth, at comparatively less risk, by making well-considered energy-efficiency investments; our findings suggest there is less uncertainty than there may have been previously about the likelihood of the investments paying off. As lighting upgrade data collected by EPA show, the market leaders in numerous industries have responded effectively to such opportunities to create new wealth through EPA's voluntary energy efficiency programs, and, clearly, many other organizations have adopted similar strategies on their own initiative. In addition, numerous public entities have saved substantial amounts of money in reduced energy consumption by upgrading lighting systems. While the investor and market pressures of publicly traded companies do not apply to such entities, budgetary constraints assuredly do. Energy cost savings reduce the consumption of taxpayer funds or free up resources for other uses.

The evidence and overall trends suggest that wise decisions about energy use and efficiency reasonably could be expected of managers of all well-run organizations. Accordingly, corporate and public-sector managers should seek additional opportunities to create shareholder wealth or manage public funds wisely by making appropriate lighting and, by implication, other energy-efficiency investments. In addition, investors should encourage managers to make energy-efficiency investments because they improve the observable earnings profile of the company, while diminishing its vulnerability to price or supply changes in an evolving energy marketplace. In the final analysis, the issue is one of optimizing the use of the organization's resources to obtain the maximum financial benefit for its owners and other stakeholders.

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TABLE 1
General characteristics of ESB/GL program participants, by NAICS

Sector (NAICS Codes)	**N[a]**	**Floor Space Upgraded (mill. Ft.^{2})**	**No. Projects Reported [b]**
Mining (211-213)	3	8.11	153
Utilities (221)	58	44.30	1,865
Construction (233-235)	35	2.24	90
Manufacturing (241-339)	276	310.71	3,027
Wholesale Trade (421-422)	112	16.96	612
Retail Trade (441-454)	39	494.97	852
Transportation and Warehousing (481-488)	17	14.46	80
Information (511-514)	23	46.07	440
Finance and Insurance (522-525)	54	100.54	1,416
Real Estate and Rental and Leasing (531-532)	28	21.07	86
Professional, Scientific, and Technical Services (541)	56	7.72	233
Management of Companies and Enterprises (551)	1	0.08	1
Administrative and Support and Waste Management and Remediation Services (561-562)	30	3.54	143
Educational Services (611)	208	383.66	2,447
Health Care and Social Assistance (621-624)	144	148.91	529
Arts, Entertainment, and Recreation (711-713)	8	10.39	33
Accommodation and Food Services (721-722)	24	62.73	1,209
Other Services (except Public Administration) (811-813)	31	2.44	67
Public Administration (921-928)	83	300.02	1,318
Not Otherwise Classified (-99)	41	1.12	74
Total	**1,271**	**1,980.05**	**14,675**

[a] N = Number of organizations
[b] The number of projects is not defined consistently. Effectively, each firm defines what it considers to be a project when it reports to the ESB/GL program.

TABLE 2

Descriptive statistics for regression variables (levels)

	Earnings margin	Total Capacity Utilization	Unit Price Margin	Sales to Fixed Assets	Sales to Current Assets	Debt to Total Assets	ESB/GL
mean	14.20	82.11	99.86	1.44	0.93	0.24	0.16
SD	13.86	1.53	10.49	1.43	0.67	0.16	0.30
n	4,008	4,332	3,762	4,226	4,152	4,136	4,332

Correlation matrix for regression variables (levels)

	Earnings margin	Total Capacity Utilization	Unit Price Margin	Sales to Fixed Assets	Sales to Current Assets	Debt to Total Assets	ESB/GL
Earnings margin	1						
Total Capacity Utilization	0.086	1					
Unit Price Margin	0.045	-0.070	1				
Sales to Fixed Assets	-0.203	0.017	-0.069	1			
Sales to Current Assets	-0.053	0.006	0.021	0.101	1		
Debt to Total Assets	-0.028	-0.005	0.080	-0.146	0.150	1	
ESB/GL	0.029	0.187	0.067	0.013	-0.009	0.013	1

TABLE 3
Wealth creation (NPV) of ESB/GL investments, by sector (1,000s of December 1999 $)

Sector	N[a]	NPV per Organization		Sector NPV	Median Payback Period (years)
		Median	Mean		
Mining	3	$706	$4,634	$13,902	2.6
Utilities	58	238	1,182	68,547	5.5
Construction	35	8	77	2,707	2.3
Manufacturing	276	177	1,422	392,586	3.0
Wholesale Trade	112	21	139	15,559	2.8
Retail Trade	39	978	15,996	623,833	2.4
Transportation and Warehousing	17	160	773	13,148	3.5
Information	23	311	3,615	83,140	1.9
Finance and Insurance	54	630	2,623	141,641	3.8
Real Estate and Rental and Leasing	28	271	1,029	28,813	2.4
Professional, Scientific, and Technical Services	56	18	163	9,124	2.8
Management of Companies and Enterprises	1	189	189	189	2.6
Administrative and Support and Waste Management and Remediation Services	30	13	185	5,562	2.8
Educational Services	208	673	2,304	479,302	4.5
Health Care and Social Assistance	144	268	1,154	166,181	2.5
Arts, Entertainment, and Recreation	8	141	720	5,756	3.8
Accommodation and Food Services	24	447	3,844	92,257	1.6
Other Services (except Public Administration)	31	36	77	2,371	3.3
Public Administration	83	348	3,474	288,363	4.6
Not Otherwise Classified	41	7	18	733	2.9
Total	**1,271**	**$165**	**$1,914.8**	**$2,433,713**	**3.2**

[a] N = Number of organizations

FIGURE 1
Distribution of overall payback periods achieved by ESB/GL partners

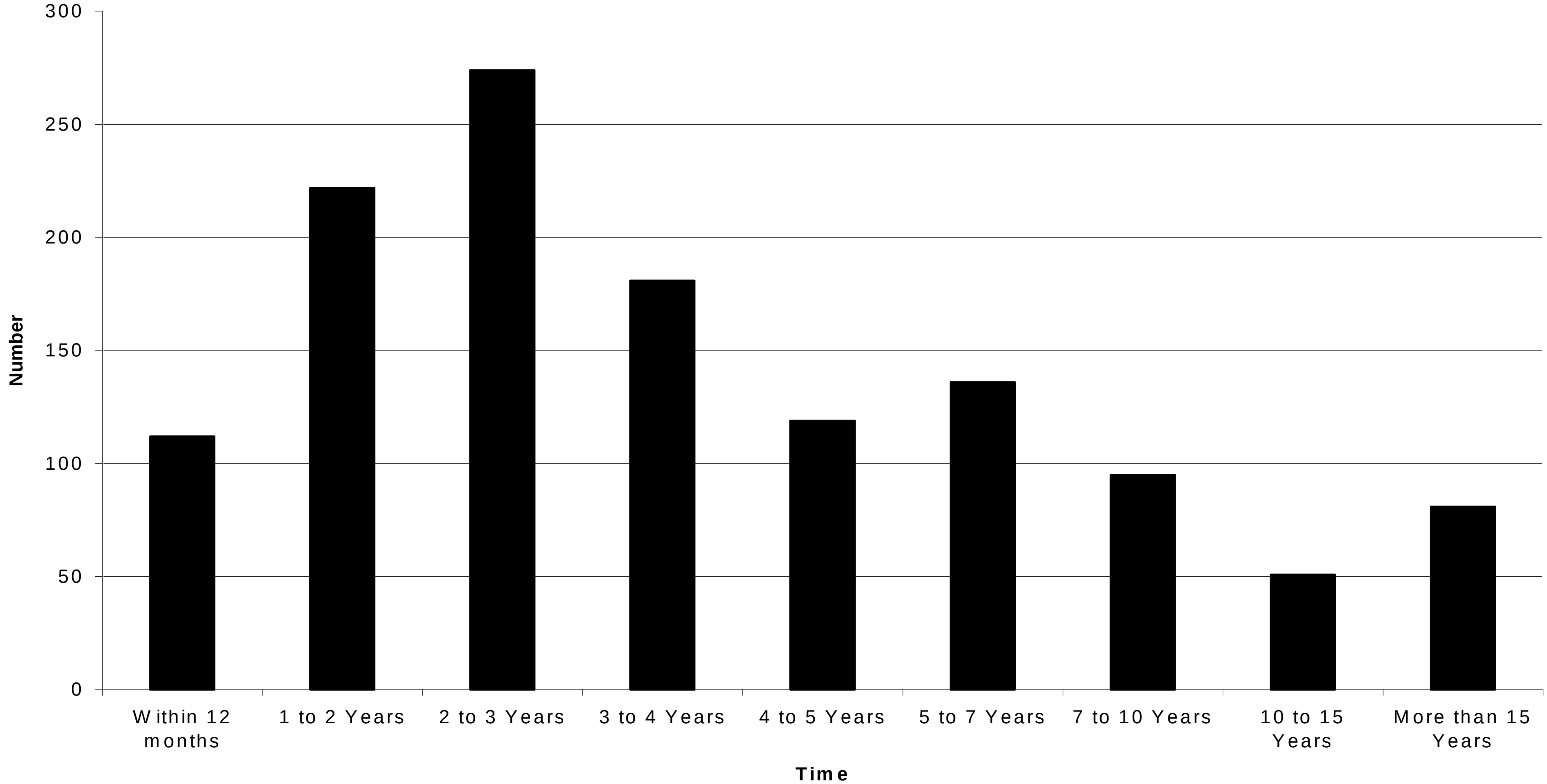

TABLE 4
Top 20 wealth-creating ESB/GL partners

Rank	Sector of Partner Organization	Expected Annual Benefit (savings)	Gross Investment Expenditure	Rebates Received	Net Investment Expenditure	NPV	Median Payback Period
		(1,000s of December 1999 $)					(years)
1	Retail Trade	$28,523	$48,407	$74	$48,333	$190,421	4
2	Public Administration	16,943	82,017	33,092	48,925	144,305	3
3	Retail Trade	17,043	43,239	7,564	35,675	118,906	2
4	Retail Trade	15,591	51,440	512	50,929	85,644	3
5	Educational Services	9,711	31,599	5,161	26,438	84,309	4
6	Health Care and Social Assistance	12,239	43,506	744	42,762	58,710	3
7	Retail Trade	10,464	33,428	498	32,930	57,607	1
8	Educational Services	5,358	23,982	11,563	12,418	48,686	2
9	Public Administration	6,906	39,976	4,200	35,776	42,982	9
10	Manufacturing	5,991	23,310	9,663	13,647	39,727	4
11	Information	5,714	11,706	0	11,706	35,353	3
12	Finance and Insurance	6,367	14,943	131	14,812	33,247	2
13	Retail Trade	4,845	14,217	0	14,217	32,642	3
14	Accommodation and Food Services	3,895	5,299	730	4,569	27,724	1
15	Retail Trade	3,823	10,933	7,648	3,285	26,880	1
16	Health Care and Social Assistance	5,036	17,544	391	17,153	25,909	4
17	Information	3,733	8,169	3,108	5,061	25,886	2
18	Accommodation and Food Services	3,105	2,189	1,048	1,141	25,028	1
19	Educational Services	2,780	10,232	2,566	7,666	24,034	3
20	Retail Trade	4,234	16,539	501	16,038	22,845	3

TABLE 5
Regressions results

Dependent Variable: EBITDA/Sales (*E*)	**Coefficient Estimate (standard error)**			
Independent Variables	**OLS**	**OLS & White**	**FGLS**	**FGLS & White**
Time	0.016 (0.015)	0.016 (0.012)	0.002 (0.003)	0.002[a] (0.001)
Q1	0.766 (0.414)	0.766 (0.408)	-0.053 (0.116)	-0.053[b] (0.026)
Q2	0.048 (0.399)	0.048 (0.390)	0.160 (0.084)	0.160[a] (0.018)
Q3	0.763 (0.409)	0.763 (0.412)	-0.211 (0.119)	-0.211[a] (0.025)
Unit Price Margin (ρ)	0.022 (0.094)	0.022 (0.080)	0.042 (0.025)	0.042[a] (0.008)
Total Capacity Utilization (*U*)	0.448[b] (0.200)	0.448[b] (0.178)	0.076 (0.039)	0.076[a] (0.009)
Sales/Fixed Assets (P_i)	2.280[a] (0.413)	2.280[a] (0.361)	2.460[a] (0.160)	2.460[a] (0.080)
Sales/Current Assets (L_i^O)	1.305 (0.798)	1.305 (0.919)	-0.705[a] (0.179)	-0.705[a] (0.061)
Debt/Total Assets (L_i^F)	-8.266[b] (3.421)	-8.266 (7.005)	-1.942[b] (0.871)	-1.942[a] (0.296)
ESB/GL (λ)	-1.953 (1.768)	-1.953 (1.494)	0.226 (0.390)	0.226[a] (0.081)
AR(1)	-0.120 (0.019)	-0.120 (0.073)	-0.410[a] (0.017)	-0.410[a] (0.018)
F-statistic	13.672	13.672	103.222	103.222
Prob(F-statistic)	0.000	0.000	0.000	0.000
Adj. R^2	0.004	0.004	0.237	0.237
Durbin-Watson Statistic	2.033	2.033	2.168	2.168

[a] Significant at 1% Type I error level (two-tail)
[b] Significant at 5% Type I error level (two-tail)

TABLE 6
Comparison of λ – Coefficient estimates across sectors and for different levels of participation

Sector	Sample Size	λ - Coefficient Estimate (standard error)	Adj.R^2 for model
Finance, Insurance, and Real Estate	CS=2 n=62	3.780 (2.210)	0.758
Manufacturing	CS=63 n=1,605	0.027 (0.085)	0.288
Mining	CS=5 n=100	-6.061[a] (1.752)	0.334
Retail	CS=20 n=488	0.464[b] (0.215)	0.298
Services	CS=12 n=340	-10.453[a] (2.284)	0.566
Transportation and Communication	CS=7 n=194	-4.055 (2.092)	0.300
Wholesale	CS=4 n=118	0.111 (0.331)	0.336
"Leaders"	CS=53 n=1,412	0.081 (0.060)	0.403
"Middlings"	CS=38 n=974	-0.352 (0.108)	0.224
"Laggards"	CS=23 n=542	38.646 (22.033)	0.209

[a] Significant at 1 percent Type I error level (two-tail)
[b] Significant at 5 percent Type I error level (two-tail)
CS = Number of companies (cross-sections) in the sample
n = Total number of observations