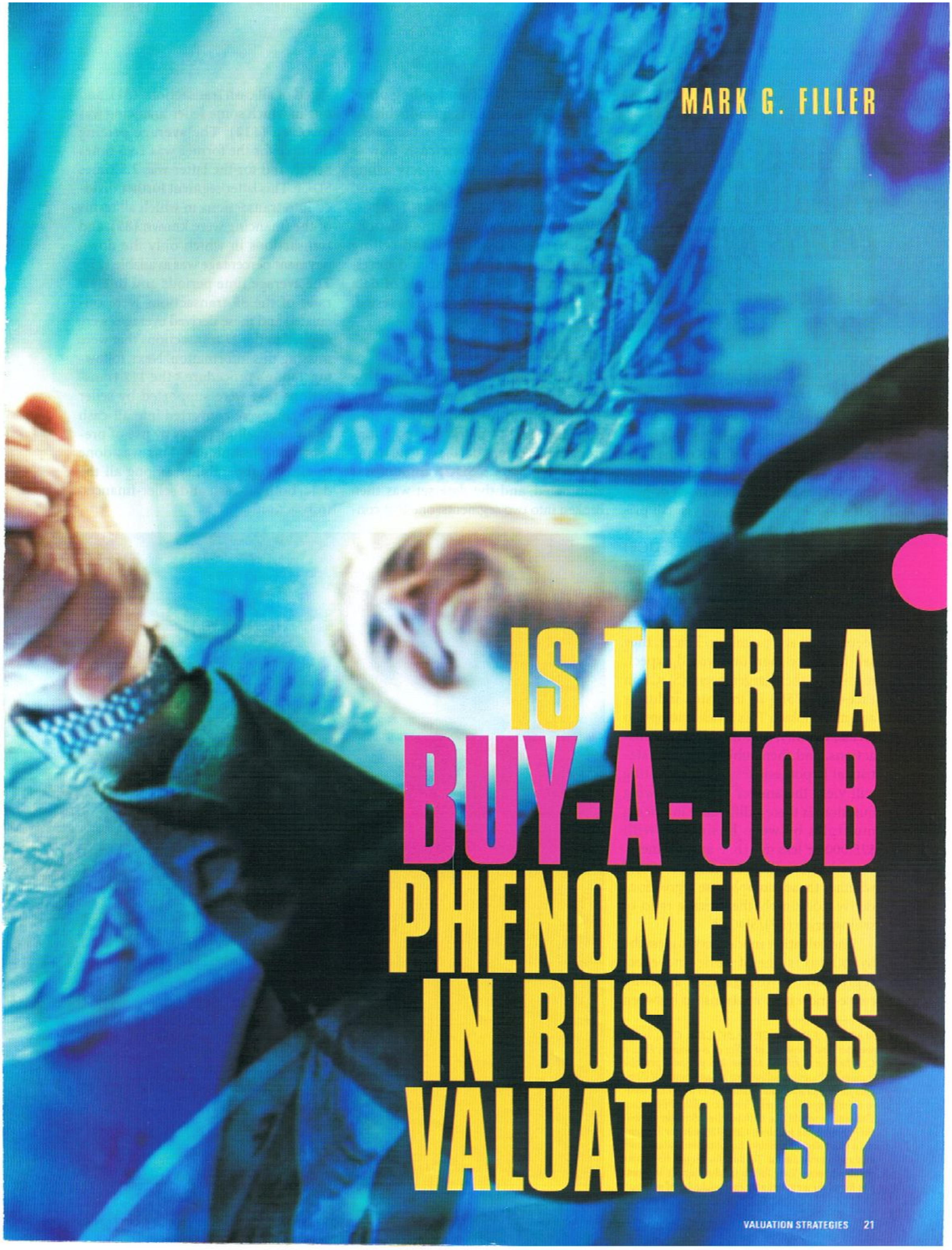
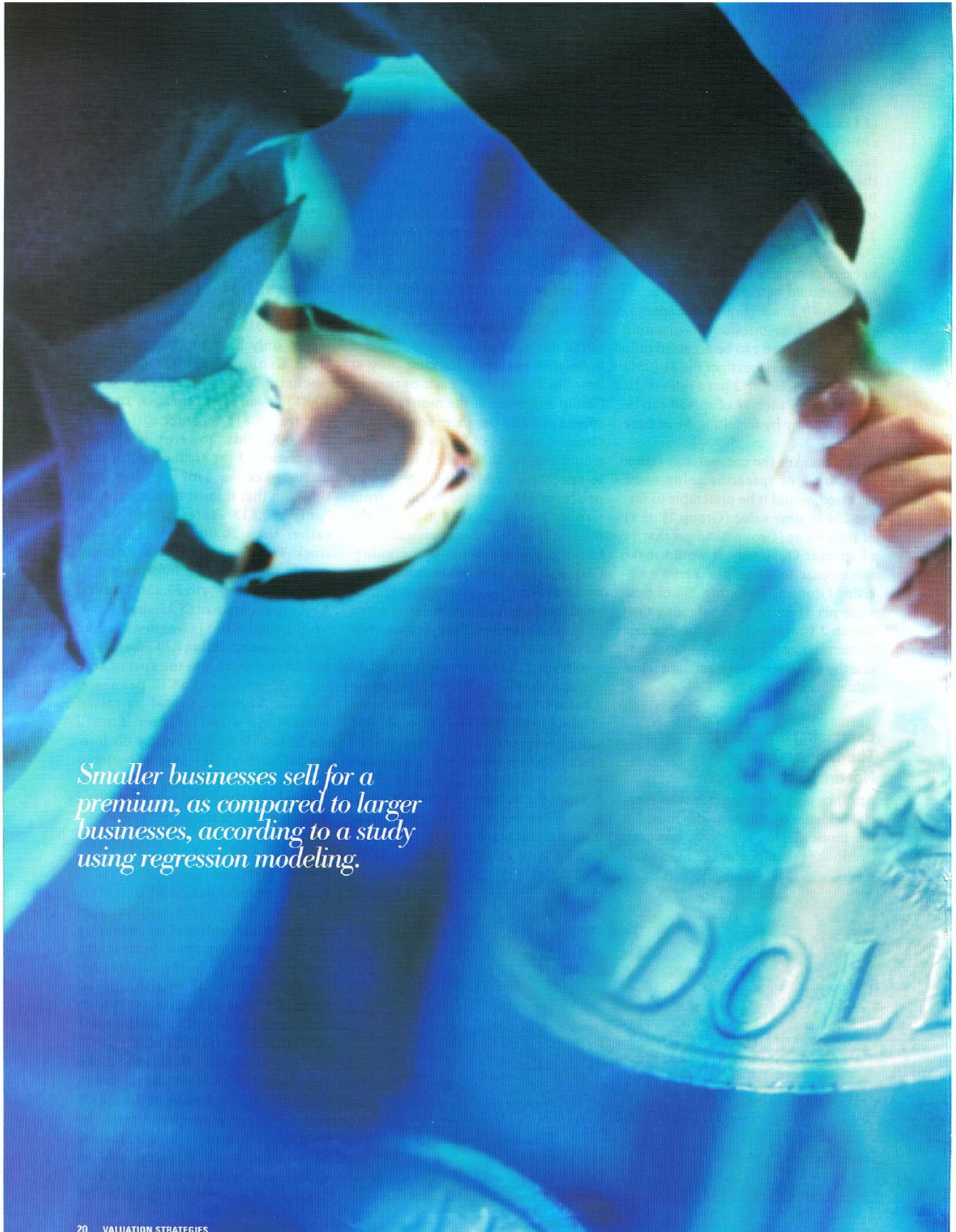


MARK G. FILLER

IS THERE A BUY-A-JOB PHENOMENON IN BUSINESS VALUATIONS?



Smaller businesses sell for a premium, as compared to larger businesses, according to a study using regression modeling.

A fundamental axiom of business valuation is that *ceteris paribus*, the greater the cash flow, the higher the selling price.

However, it has been suggested that this law is violated in a certain segment of the marketplace, that segment in which, in effect, the purchaser is buying himself or herself a job. In particular, very small privately held companies that generate seller's discretionary cash flow (SDCF) (net income + owner's compensation and perks + interest expense + depreciation) of less than \$75K, but with no cash flow available to a financial buyer, seem to sell at a premium. That is, they sell for more than one would expect, relative to their larger peers (SDCF in excess of \$75K) in the same industry and marketplace. This article attempts to locate, identify, and mark these transactions, and then subject them to statistical hypothesis testing. That testing will yield the answer to the following question: Is there a difference in pricing multiples between businesses with \$75,000 or less in SDCF and businesses with more than \$75,000 of SDCF, whether those multiples are regression-derived or simply the average ratio of selling price (SP)/SDCF?

The valuation model used to test the hypothesis is one of cause-and-effect regression, as there exists a strong cause-and-effect relationship between two variables, SDCF and selling price, and that relationship is quantifiable. As stated above, selling prices of businesses are a function of their cash flow—meaning that cash flow affects selling price. Cash flow will be the cause and selling price will be the effect. The postulated model expresses the relationship between cash flow and selling price. It is then specified and developed on the basis of a sample of data that allows the hypothesis to be tested.

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The author would like to thank Don Schaffer for initially posing the problem, Gene Dilmore for suggesting a most elegant solution, Ed Giardina, Susan Long, and especially Laura Tindall for suggestions and encouragement, Toby Tatum for showing the way, and Jim Rand for writing some real wicked cool macros!

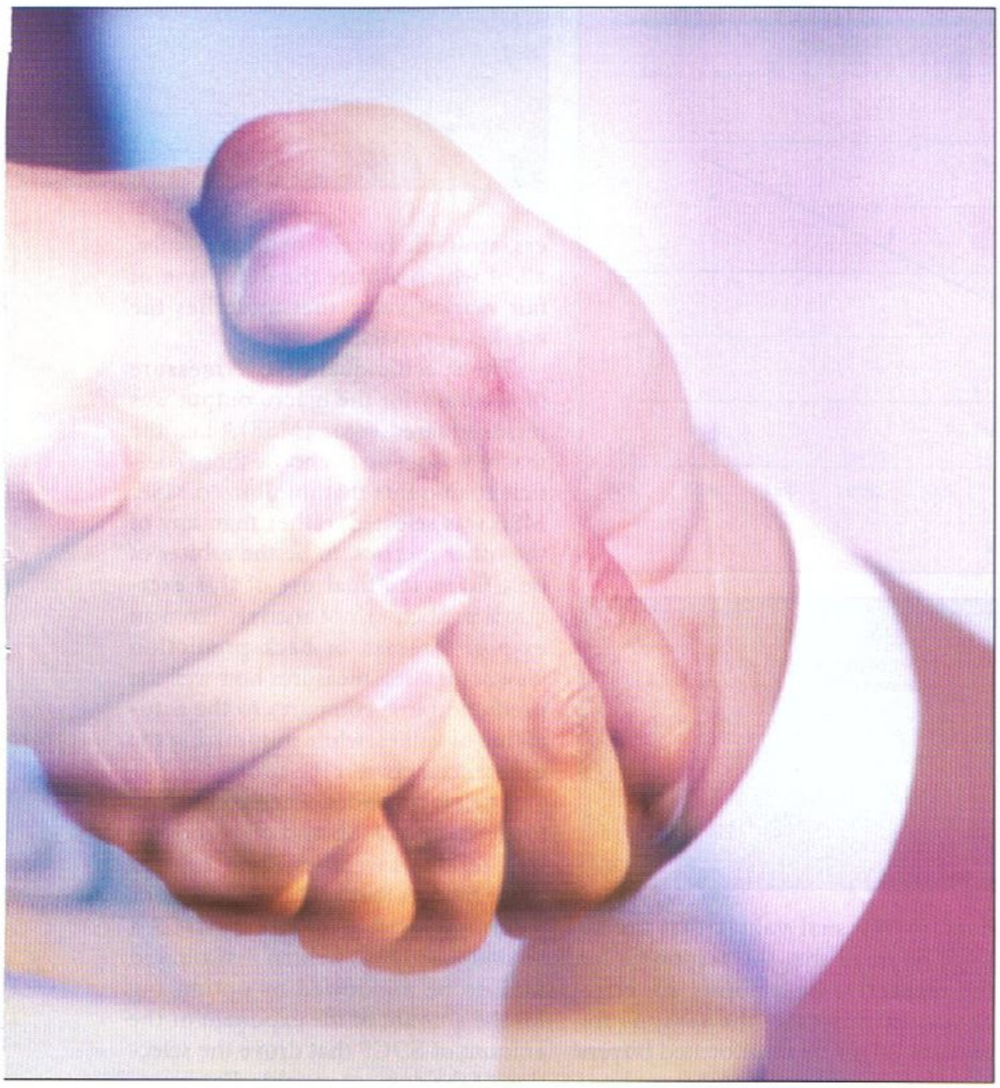
Marshalling the Data

The data sample from the printing industry follows the sample set out by Toby Tatum in his book.[1] The author downloaded 144 market transactions from the Bizcomps database. One transaction that had no SDCF amount was eliminated, and the data set was then broken into two segments: one that consisted of all cash transactions (31), and one in which some seller financing was involved (112). The average pricing multiple for the former was 1.95 times SDCF, and for the latter was 2.5 times SDCF. This latter segment further divided into transactions in which all terms of the financing were known (85), and transactions in which only the down payment percentage was available (27). The average time periods and interest rates of the 85 transactions were calculated and these derived averages were applied to the 27 transactions that were missing this information. Next, following Tatum's procedure,[2] the 112 transactions that were supported by seller financing were converted into all-cash equivalent selling prices by use of present value techniques. This was done to allow comparability among all the data, both all-cash and seller-financed transactions.

The discount rate used to present value the seller-financed sales is derived from a formula developed by Tatum.[3] Essentially, it starts with 14% and adds 1% for each 1/10th of the selling price that is seller-financed. Thus, if a transaction is 70% seller-financed, the discount rate is 21%. This makes sense for two reasons:

1. It is the formula that reduces the average SP/SDCF multiple for seller-financed transactions down to the average SP/SDCF multiple for all-cash transactions in the Bizcomps database.
2. Because seller paper is usually subordinate to bank debt, is not collateralized, will not be repaid on default, etc., it is essentially a very low-grade junk bond, and not a publicly traded junk bond, either.

These revised selling prices were substituted back into the Bizcomps worksheet, sorted by SDCF in ascending order, and used to produce Exhibit 1, a scattergram of selling price vs. SDCF for the 143 transactions. A review of this chart indicates that the transactions with the six largest SDCFs are, or will be, either outliers, influencers, or leverage points. A theoretical reason for removing them is that they violate the fair-market-value standard, in that they are most likely the result of transactions between ill-informed buyers or sellers, synergistic buyers, or distressed sellers. As such, these were removed, which, as a new scattergram in Exhibit 2 shows, reduces the standard error of the estimate (SEE)[4] from 243.6 to 86.3, a reduction in dispersion of 65%, as well as increasing r^2 from 70.65 to 81.23, an increase of 15%.[5] From this plot of raw data, one can visually determine how well the independent (cash flow) and dependent (selling price) variables are correlated. On the basis of this plot, it can be seen that a high degree of correlation exists between the two variables, and their relationship is linear. Given the fundamental axiom stated above, this is exactly what would be expected. The next step is to specify a model in equation form.



Building the Model

In regression modeling, different model forms require different coefficient estimation procedures, but the basic estimation procedure is the least squares method. This procedure attempts to minimize the distance between the actual observations (selling prices) and a fitted straight line that goes through the scattered data points. Regression modeling attempts to find estimates of the intercept and the slope, called coefficients, such that the sum of the squared differences between the actual data points and the fitted data points is minimized.

For this article, a regression model that provided the best fit for the 137 remaining observations in the sample set of market transactions was specified. Best fit means a model that meets more of the following criteria than any of its competing models:

- Lowest standard error of the estimate (SEE).
- Lowest coefficient of variation (COV).[6]
- Lowest mean absolute deviation (MAD).
- Lowest mean absolute percentage error (MAPE).
- Highest adjusted r^2.
- Highest F statistic.[7]
- Lowest Theil's U statistic.[8]
- Equal error variances—be homo-scedastic.

Fifty models were set up, including simple and multiple (quadratic) models; transformed predictor(s) and response variables; land ogarithmic, power, reciprocal transformations; and models with and without a dummy variable to account for the size of SDCF. An Excel macro was written that entered amounts into the particular regression equation for each model, computed the fitted Y response, removed from the data set

EXHIBIT 1
Print Shops—Selling Price vs. SDCF—Original 143 Data Points

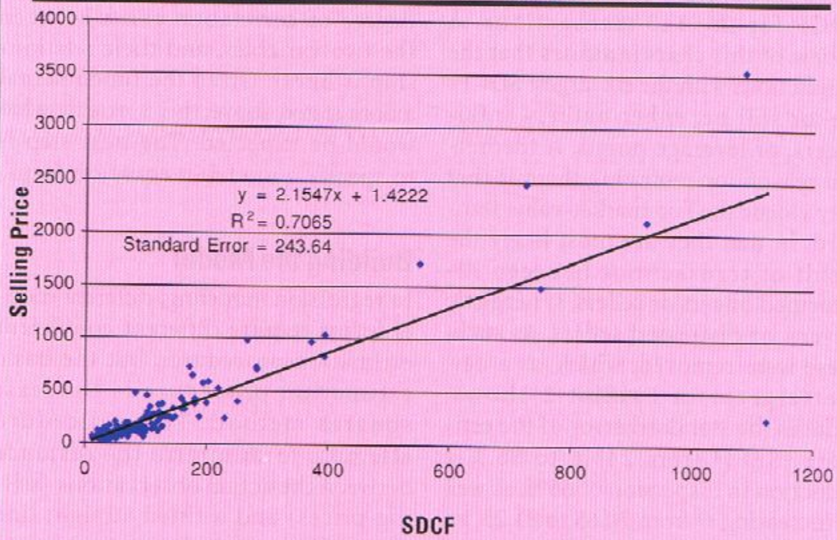


EXHIBIT 2
Print Shops—Selling Price vs. SDCF—Six Largest Data Points Removed

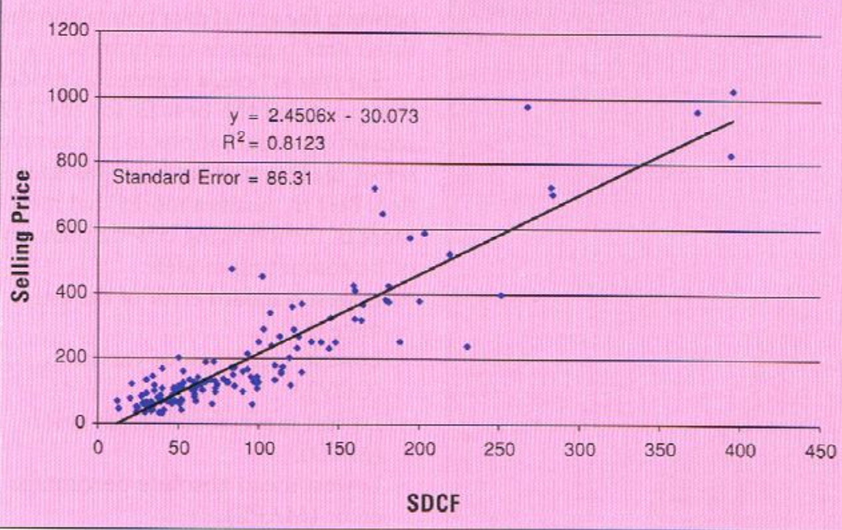


EXHIBIT 3
Relationship Between Data Point Removal and Decrease in COV

Residual Cutoff	Lowest COV	No. of Observations
2.0 Standard deviations	16.11%	90
2.5 Standard deviations	22.31%	118
3.0 Standard deviations	27.80%	128

any transaction that had a standardized residual greater than the cut-off value of 2.5, and then repeated the process until the model stabilized. Typically, standardized residuals greater than 3 are indicative of outliers, or unusual values that are so large or small that the responses for the respective data points are erroneous. In this case, the reasons for outliers might be uninformed buyers or sellers, irrationally exuberant buyers, strategic buyers, or forced sales, all of which violate the definition of fair market value that underlies the market approach.

The specific quantitative measure of accuracy for the macro output was mean squared error (MSE),[9] i.e., the macro was set up to choose those coefficient amounts that minimized MSE. MSE was selected, rather than any of the other metrics, to be the arbiter of best fit, as the final use of this exercise is prediction, not analysis. From an *ex-post* forecast, or back-prediction viewpoint, MSE measures how well the prediction line compares to the actual line of values, while minimizing the difference between the two.

The macro ended when it could no longer reduce MSE and all standardized residuals were less than 2.5. For those models that had an exponent or a dummy variable for size of SDCF, a second macro was written that allowed MSE to be minimized by optimizing for the amount of the exponent or the amount of SDCF that drove the selection of the dummy variable. For exam-

ple, if in a particular model, the predictor variable X was to take an exponent from .1 to 5, the macro would sort through all the integers in that range and select the one that minimized MSE. For the selection of the dummy variable for size, the macro would choose the amount of SDCF from between $20K and $80K that minimized MSE. That is, the model would assign a dummy variable of 1 to all transactions that had an SDCF equal to or lower than the amount chosen by the macro as it minimized MSE. In both situations, transactions with standardized residuals greater than 2.5 would be removed from the data set, and the process repeated until the model stabilized.

The cutoff of 2.5 standardized residuals was chosen as a compromise between the usual 3 and the Tatum-suggested 2. Using lowest coefficient of variation COV and observation count as metrics, running the 50 macro-driven models with the three different cutoff figures provides the results shown in Exhibit 3.

The decrease from 3 to 2.5 standard deviations results in a decrease in the COV of 24.6%, at a cost of an 8.4% decrease in the number of observations, for a ratio of 2.93 (24.6/8.4) to 1. On the other hand, a decrease from 3 to 2 standard deviations results in a decrease in the COV of 72%, at a cost of a 42% decrease in the number of observations, for a ratio of 1.71 (72/42) to 1. More than a third of the observations are given up to get that highly desirable low COV of 16.11%.

The regression model that came first in all but two of the test criteria listed above has the equation form:

$$\text{Y-hat} = 594.09 + 3.51X_1 - 386.0X_1^{.15} + 12.32X_2$$

where:

X_1 is SDCF

$X_1^{.15}$ is SDCF raised to the .15 power

X_2 is a dummy variable taking a value of 1 if SDCF is $58.01K or less, or 0 if SDCF is greater than $58.01K.

One of the reasons for selecting a power of .15 can be seen by viewing Exhibit 4, which shows the distribution of the raw-data form of the X variable, SDCF, being skewed positively to the right and non-normal in its shape. A superimposed normal distribution curve points out the discrepancy in shape between the two distributions. Because powers less than 1 can pull in the upper tail of a distribution and help make a skewed distribution more symmetrical, this technique was applied, with the results shown in Exhibit 5, in which the transformed data's histogram's outline now resembles that of the normal curve.

The second reason for selecting a model with a second-order power is that inspection of the scatter plot and an analysis of the selling price/SDCF ratios indicates a curvilinear relationship between X and Y, i.e., as SDCF increases, selling prices level off after a relatively steeper initial climb. This might be explained by having more sophisticated buyers at the upper end of the market. Including a second SDCF variable raised to the .15 power converts the curvilinear form to an intrinsically linear one, which better fits the data and allows the use of the least squares estimator. Thus, this

EXHIBIT 4
SCDF Histogram—Untransformed Data

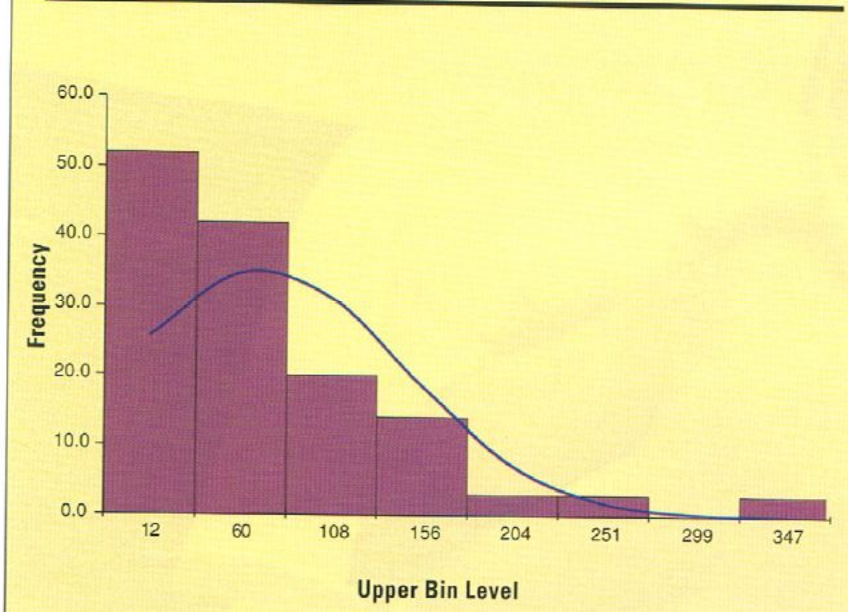
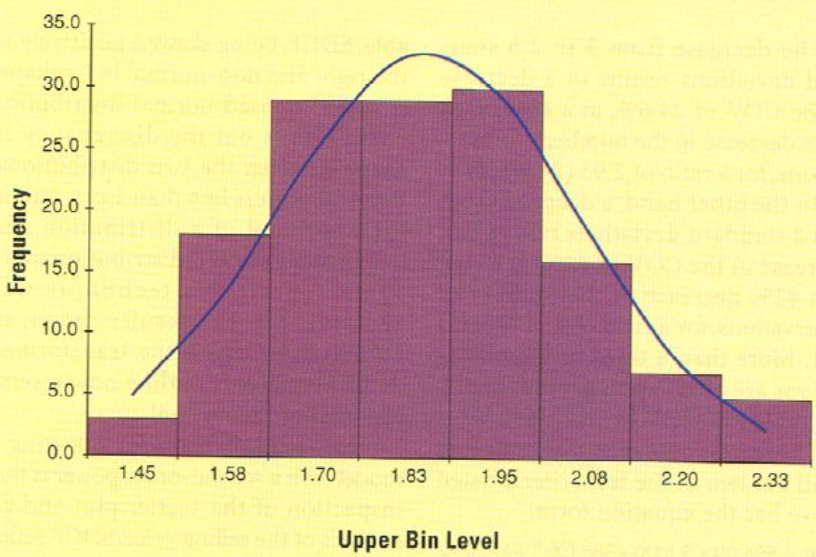


EXHIBIT 5
SCDF Histogram—Transformed Data to the .15 Power



transformation provides a simple way both to fix statistical problems (non-symmetrical distributions) and to fit curves to data (curvilinear regression).

Goodness of Fit

After building the model, the next step is to evaluate its quality by examining the statistics in the output table on how well the model fits the data. As previously mentioned, the $58.01K of SDCF is that amount which, in conjunction with an exponent of .15, minimizes MSE and optimizes the regression. The regression output is shown in Exhibit 6, and the very large adjusted r^2 of 94.9, the COV of 22.31% and the SEE of 36.8 should be noted, all indicating a very good fit given the high degree of dispersion in the data set (SDCF of between $90K and $100K has selling price coordinates of between $97K and $250K). The most important objective of regression modeling is to explain the changes in the dependent variable (selling price), by the change in the independent variables (amount of SDCF and its relative size). Here, 94.9% of the change in selling price is explained by some aspect of SDCF. While adjusted r^2 indicates that the regression model has explained a certain percentage of the total variation in the dependent variable, the SEE provides a measure of the closeness of fit of the scattered points about the fitted line. It is more informative to translate this absolute measure, 36.8, into a relative measure called coefficient of variation, i.e., as a percent of the average of Y, the dependent variable. The calculated COV reveals that, on average, actual Y observations differ from the predicted, or fitted, Y values by about 22.31%.

These goodness-of-fit metrics are demonstrated to useful advantage in Exhibit 7, a line chart plotting actual Y and predicted Y against the case. The goodness of fit is exemplified by the lack of bias (no predicted points are either higher or lower than any actual points) and the small degree of smoothing, indicating that the predicting ability of the model is very high. The residual plots contained in Exhibit 6 indicate that the residuals are normally distributed, that they have a constant variance, and that they are not corre-

1 Toby Tatum, *Transaction Patterns* (Toby Tatum, 2000).

2 *Id.*, pp. 17-29

3 *Id.*, see Chapter 3.

4 The square root of the mean squared error (MSE). (states the degree of dispersion in terms of the original response, or data set.)

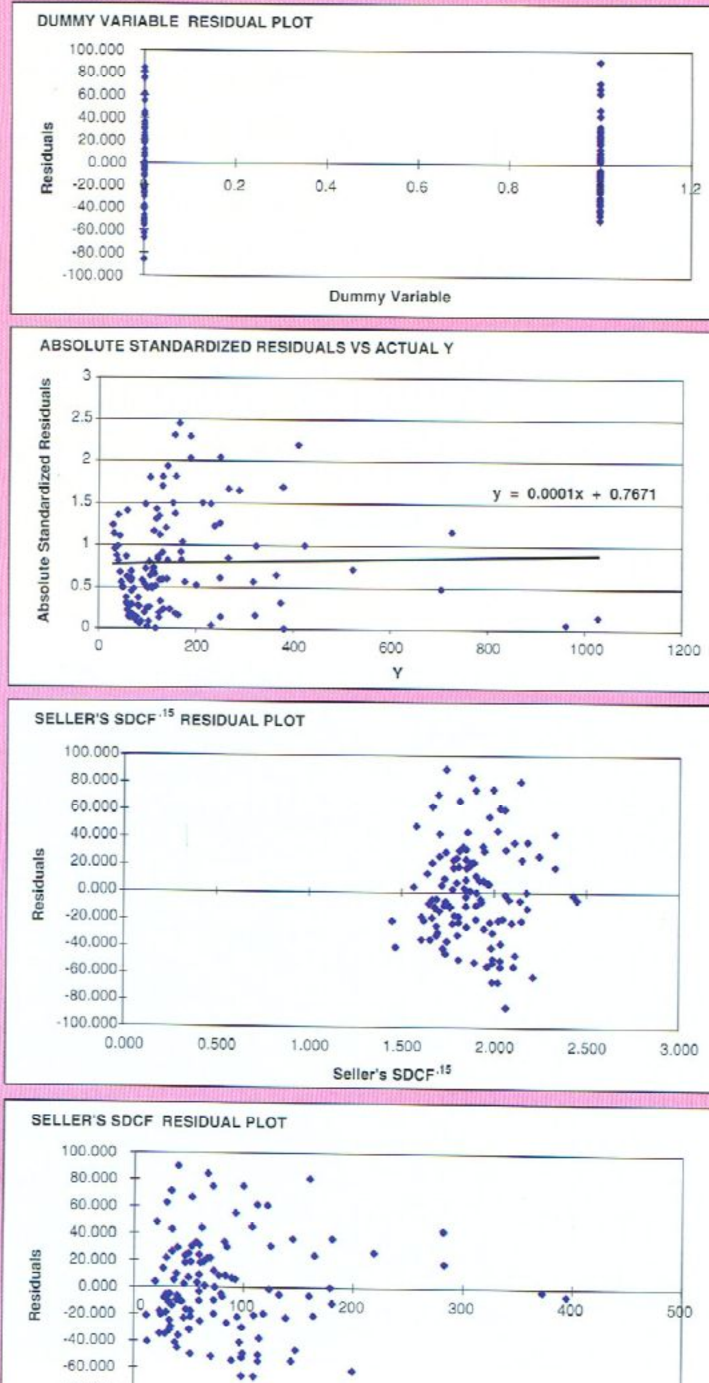
5 r^2 is the degree of explanatory power of the model. (takes a value between 0 and 1.)

6 The SEE divided by the average of the dependent variable. (allows for comparability of the degree of dispersion among differing data sets, models, etc.)

7 Indicates if the model as a whole is statistically significant.

8 A relative and unit free measure of predicition of accuracy. Like MAD and MAPE, it will be zero if the predicted outcome equals the actual data points.

EXHIBIT 6
Regression Output and Residual Plots



lated with each other. Various other tests were run indicating that the model produces normal, independent, and identically distributed residuals (results not shown). The only disappointment is the low t statistic[10] and high p-value[11] for the dummy variable, indicating its statistical non-significance. This problem will be addressed later in the article.

A typical graphical display of the regression results is shown in Exhibit 8, which provides the first indication of the phenomenon of businesses selling with no cash flow to a financial buyer in the bottom left quadrant of the chart, at the point where the trend line shifts upward and then curves leftward to better fit the data points through which it passes. This perhaps can be better seen in Exhibit 9, in which the data points have different indicators—squares for data points that take a dummy variable of 0 and diamonds for data points that take a dummy variable of 1. It should be obvious that the group of diamond data points, representing selling prices for companies with a SDCF of \$58.01K or less, are lined up on the chart very differently from their larger peers. Unlike the squares that continue their marked downward trend to the left, as SDCF gets smaller, the diamond cohort bunches up and strings out to the left.

Exhibit 10 continues the segmented presentation of the data set but with simple regression trend lines (not by the model at issue) drawn through them, along with the respective regression equation and r^2. These two lines have apparently different intercepts and slopes; this indicates that they might have different means as well. In fact, regressing selling price on the size dummy variable of the instant model yields the same result as a two-sample t test for a difference of means—the difference between means is statistically significant. Looking closely at the region where the two trend lines approach each other, one can see that a gap exists between them. In the preferred model, the dummy variable connects the two lines through an upward shift in order to account for the higher average selling prices relative to SDCF in that group. The coefficient of the intercept dummy variable produces an average increase in selling price of \$12.32K for all the transactions that have a SDCF equal to or less than \$58.01K, but keeps the angle of the two slopes equivalent. While \$12.32K is a substantial amount (adding approximately 15% to the selling prices), t tests (not shown) indicate that neither the two intercepts, nor the two slopes, differ significantly from each other.

Another way to look at the size phenomenon is to view it through the lens of a ratio, specifically the ratio of selling price to SDCF. By dividing each selling price by its corresponding SDCF, and then plotting the resulting ratios against SDCF, Exhibit 11 provides a more dra-

EXHIBIT 7
Line Chart—Actual vs. Predicted Sales Prices

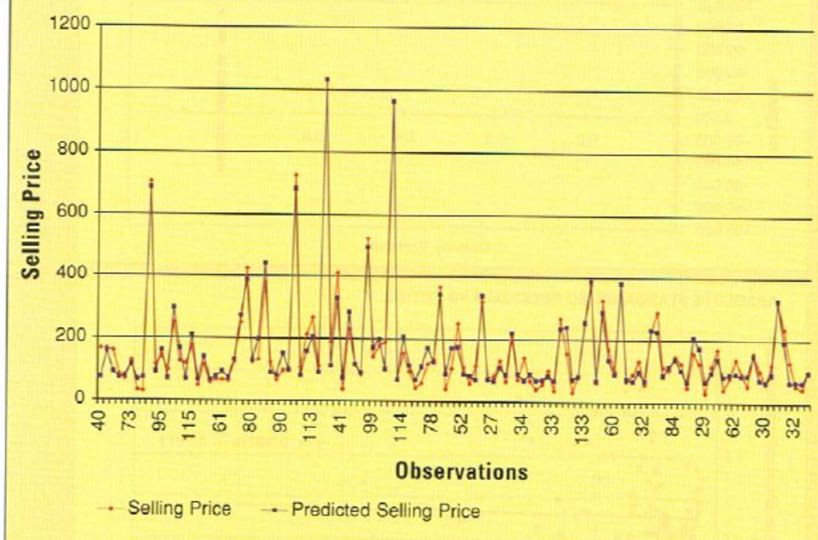
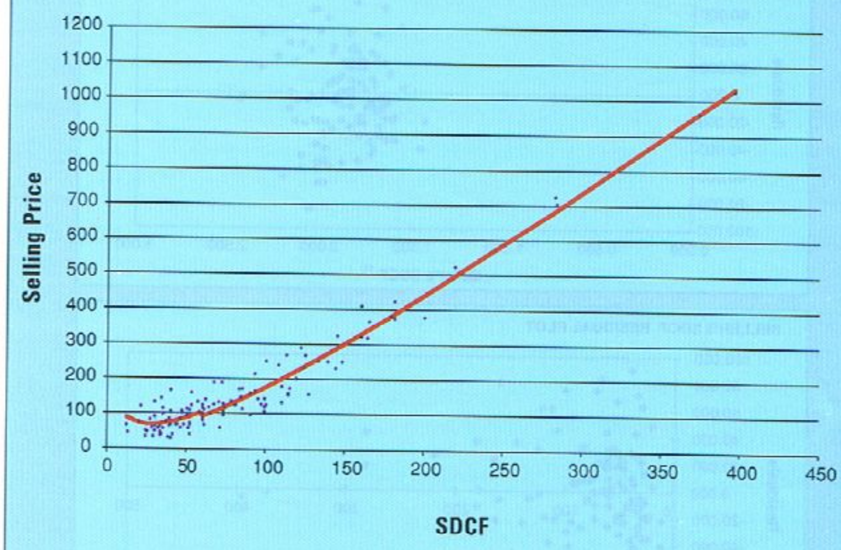


EXHIBIT 8
Scattergram w/ Trend Line—Selling Price vs. SCDF—Selected Model



matic presentation of the differences between the two transaction segments. What is expected, and what is actually shown, is a fairly flat line suggesting that the ratio of SP/SDCF is fairly constant across size, with perhaps a slightly larger multiple at the high end of SDCF, and a slightly smaller multiple at the low end of the X variable. However, when SDCF is \$58K or less, a striking change takes place—the multiples begin to rise! In fact, the squares do three things: a few continue the downward trend, more get exceedingly large, and the majority shift upward, above the average of the diamonds. The regression line goes backward, indicating that the smaller the SDCF, the higher the multiple. The average of the diamond and square multiples is 1.83 and 2.2, respectively, a 20.3% difference, which a two-sample t test for a difference of means indicates is significant. Outliers do not cause this; they were all removed in a prior exercise, leaving an inference that very small printing companies sell for an average premium of up to 20% relative to their larger peers, depending on the pricing mechanism—regression model or average ratio model. While working with and analyzing ratios is of some interest, regression analysis will be used, as regression has a much greater ability to reduce dispersion, which is its greatest advantage over using an average ratio to predict accurate selling prices.

The problem alluded to earlier—that of the low t statistic and high p-value for the dummy variable coefficient—indicates that the coefficient is statistically insignificant. What does this mean, how did it happen, and what remedial procedures might work in this situation? Our specified selling price model has three coefficients and a constant term. The F statistic, by being larger than 3, indicates that at least one of the three X coefficients is significantly different from zero. The individual t tests can tell us the significance of each of them. In the case of the dummy variable, dividing its coefficient by its standard error yields .981 (12.32/12.56). This indicates that the coefficient is less than one standard deviation from zero—so close to zero that there is a good chance of being zero. In fact, its p-value indicates that if there were no relationship between the SDCF cut-off value of \$58.01K and selling price, the probability of a sample having an estimated coefficient as different from zero as this one is 32.9%. This makes it statistically not significant—short for not significantly different from zero. Another way to view this is to see that the 95% confidence intervals of the coefficient, which range from -12.56 to +37.21, straddle zero. To be significant at the 5% level, its p-value would have to be less than .05, and its t statistic, with 114 degrees of freedom,[12] would have to be greater than 1.981. That the dummy variable has a relationship with selling prices of a certain amount is a conclusion that can be reached just by observing the scatterplots. It ought then to have a significant coefficient. The reason it does not is because of collinearity, detected by a combination of high adjusted r^2 and F statistic, coupled with a low t statistic for the dummy variable coefficient.

Multicollinearity

Collinearity, or multicollinearity, among the independent variables is one of the problems with multiple regression models. The existence of collinearity, or linear correlation among the independent variables, will cause the estimated coefficients to change when an independent variable is added or dropped from the model. Because all economic variables are correlated to some extent, the whole idea of model specification is to include the right number of variables in the model so that they can be properly accounted for. The fact that some or all of the independent variables are correlated among themselves generally does not inhibit the ability to obtain a good fit. Nor does it tend to affect inferences about mean responses or predictions of new observations, provided these inferences are made within the region of observations. However, the regression output cannot be used as an analytical tool to test for the validity of a relationship between certain variables, or to test the significance of a particular variable, as the separate effects of the variables cannot be generalized, even though their joint effects should still be valid. In sum, multicollinearity does not prevent solid predictions of selling prices, but it does prevent an analysis of the relationships between the independent variables and the dependent variable, as well as among the independent variables themselves.

Unfortunately, when multicollinearity is very high, it causes large variances in the estimated coefficients, making least squares estimation inefficient. As long as it is not too high, there is no need to worry. The degree of multicollinearity in the model can be ascertained with a correlation matrix, such as the one for this model shown in Exhibit 12. A rule of thumb is that any correlation less than .70 can be kept in the model—a test that one of the dummy variable correlations passes, and the other just fails. One would expect the second order version of SDCF, $SDCF^{.15}$, to be very highly correlated with SDCF. The dummy variable's moderately high correlation with SDCF and $SDCF^{.15}$ also comes as no surprise, as it changes value from 1 to 0 as the other two independent variables change size. However, because it is an abrupt shift change and not a trend change, the correlations are less severe than that between the SDCF variables.

EXHIBIT 9
Scattergram w/ Trend Line—Selling Price vs. SCDF—Highlighted Differences

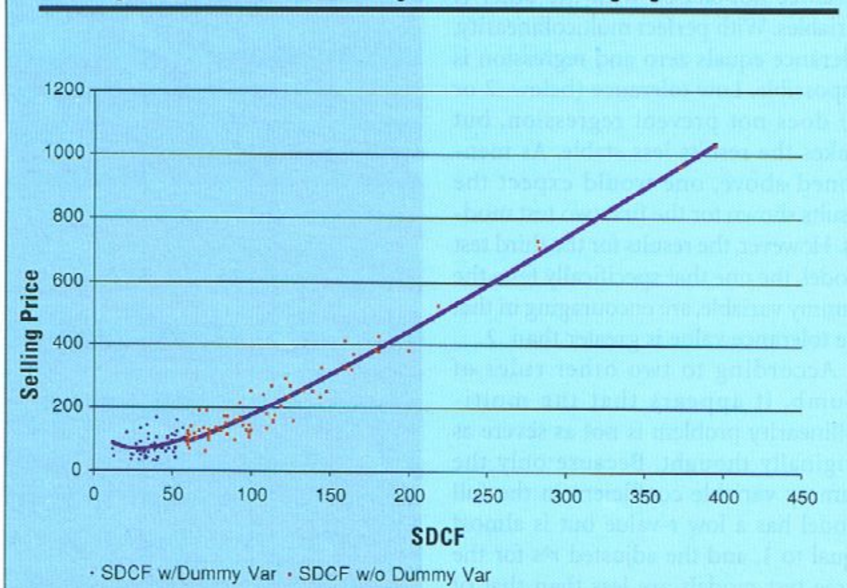
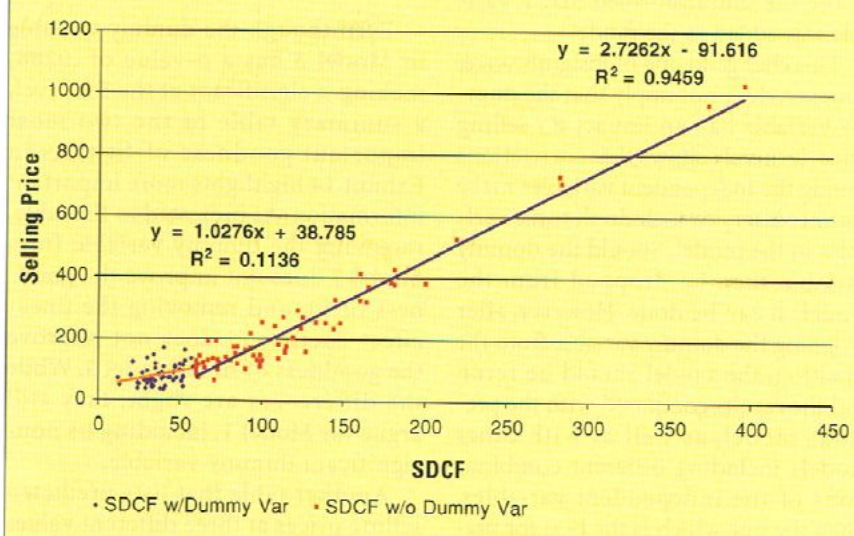


EXHIBIT 10
Scattergram w/ Trend Line—Selling Price vs. SCDF —Further Exploration of Differences



To test how severe the multicollinearity is in the model, three different test regressions (not shown) were performed, whereby each of the X variables were regressed on all the other X variables:

1. SDCF (X_1) was regressed on $SDCF^{.15}$ (X_2) and the dummy variable (X_3).
2. $SDCF^{.15}$ was regressed on SDCF and the dummy variable.
3. The dummy variable was regressed on SDCF and $SDCF^{.15}$.

Adjusted r^2 and tolerance values for these three regressions were compared with adjusted r^2 for the full model in

Exhibit 13. The tolerance of an X variable is the proportion of that variable's variance not shared with the other X variables. With perfect multicollinearity, tolerance equals zero and regression is impossible. Low tolerance (below .2 or .1) does not prevent regression, but makes the results less stable. As mentioned above, one would expect the results shown for the first two test models. However, the results for the third test model, the one that specifically tests the dummy variable, are encouraging in that the tolerance value is greater than .2.

According to two other rules of thumb, it appears that the multicollinearity problem is not as severe as originally thought. Because only the dummy variable coefficient in the full model has a low t-value but is almost equal to 1, and the adjusted r^2s for the three test models are less than that of the full model, predicting selling prices is not a serious problem. With all three variables in the model, the coefficient of the dummy variable is insignificant, even though r^2 is large and the SEE is relatively small. As shall be shown, the coefficient of the dummy variable was significant before the untransformed SDCF variable was added to the model.

This change to one of insignificance, however, does not imply that the dummy variable has no impact on selling price; it merely shows that correlations among the independent variables make it unnecessary to include all three variables in the model. Should the dummy variable then be dropped from the model? It can be done. However, after dropping the dummy variable from the equation, the model should be rerun and the results compared with the previous model, as well as with other models including different combinations of the independent variables. Then the one which is the best for predicting selling prices, i.e., the one that has the best fit, should be chosen. Dropping the dummy variable may not yield the best model.

The three different models tested include:

1. Model 1: Quadratic BAJ[13]—Exponent Model—the model at issue.
2. Model 2: Quadratic Model with No Dummy Variable.
3. Simple BAJ—Exponent Model with Dummy Variable.

Even though the dummy variable in Model 3 has a p-value of .0288, making it significant at the 5% level, a summary table of the two most important goodness-of-fit tests in Exhibit 14 highlights more important information. As indicated in the table, removing the dummy variable from Model 2 does not improve the goodness of fit, and removing the linear effect coefficient does not improve the goodness of fit of Model 3. While the differences are slight, they still argue for Model 1, including its nonsignificant dummy variable.

Another table that lists predicted selling prices at three different values for SDCF for each of the models is shown in Exhibit 15. It is obvious from the table that reasonably approximate results are obtained from all three models at the $100K and $40K levels, with an absolute spread of about $5K, but with increasing relative differences, as SDCF gets smaller. At the $10K level, however, there is a complete breakdown of comportment with the information contained in the scatter plots, as Models 2 and 3, both of which have significant t statistics for all independent variables, produce selling price values that are far lower than one would expect. Exhibit 16 demonstrates that Model 3 does not fully account for the upward and leftward sweep of the smallest SDCF transactions, i.e., it is a poorly specified model even though it has excellent goodness-of-fit metrics. Additionally, the percentage increase in value caused by the addition of the dummy variable is very much distorted in Model 3, as opposed to Model 1. Therefore, while a lack of significance for one or more of the parameters in a model may suggest that the model is unnecessarily complex, the dummy variable in the model will remain because: (1) of its r^2 and SEE values, (2) the multicollinearity problem appears to be marginal, (3) simpler models fail on a number of counts, and (4) the overall success of the model in predicting selling prices all argue against the effort of exploring simpler alternatives at this time.

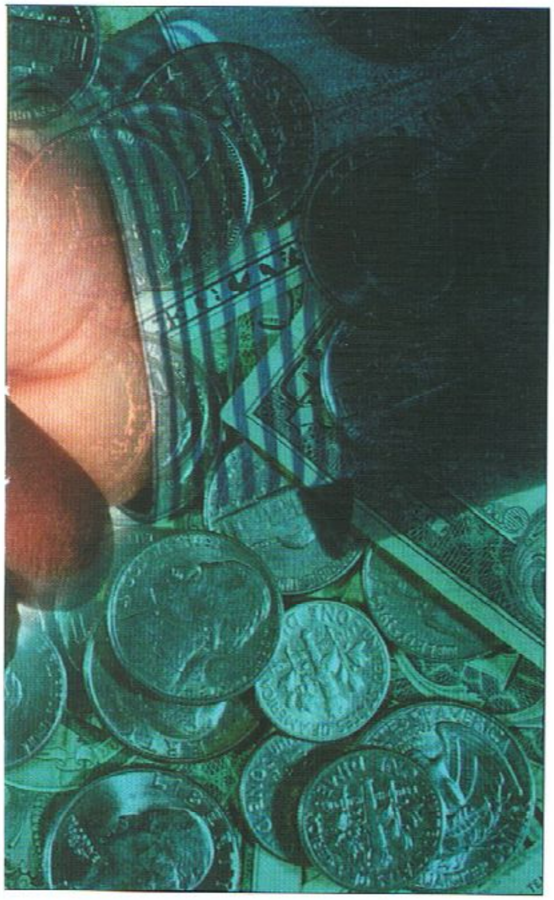


EXHIBIT 11
Scattergram w/ Trend Line—Price/SDCF Multiple vs. SDCF —Substituting Ratios for Selling Price

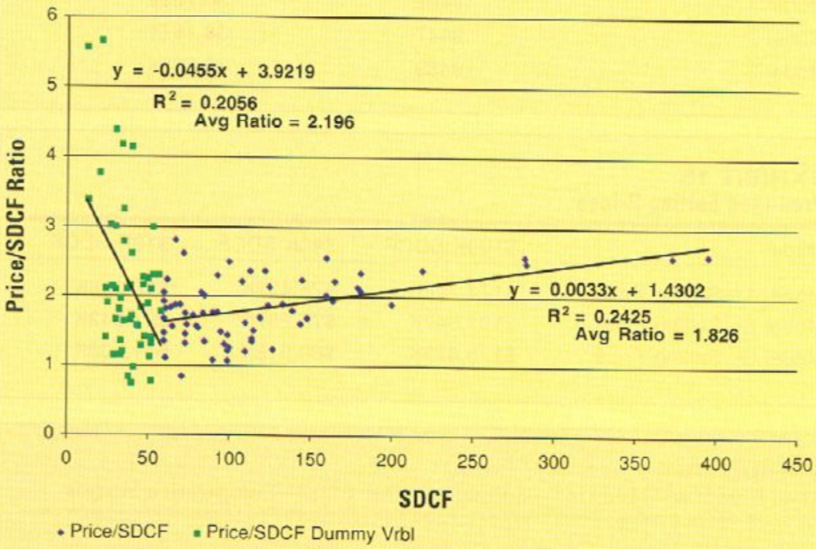


EXHIBIT 12
Correlation Matrix

	Seller's SDCF	Seller's SDCF.15	Dummy Variable
Seller's SDCF	1		
Seller's SDCF.15	0.927989219	1	
Dummy Variable	-0.615161201	-0.78339341	1
t stat	-8.403700543	-13.57530191	
p value	1.24919E-13	1.03229E-25	
Pearson Correlations			
Seller's SDCF	1.000	0.928	-0.615
Seller's SDCF.15		1.000	-0.783
Dummy Variable			1.000
Pearson Probabilities that there are No Correlations			
Seller's SDCF	-	1.4647517E-51	1.2491901E-13
Seller's SDCF.15		-	1.0322855E-25
Dummy Variable			-

EXHIBIT 13
Multicollinearity Test

Model	Adjusted r_2	Tolerance Values $(1 - r_2)$
Full - Y on X_1, X_2, and X_3	.9492	NA
X_1 on X_2 and X_3	.8917	.1083
X_2 on X_1 and X_3	.9327	.0673
X_3 on X_1 and X_2	.6972	.3028

Prediction Range

Prediction range is also an indicator of prediction accuracy. Assume the selected model has been used to predict a selling price given a particular value of SDCF. Now it is important to find out how accurate that prediction is, i.e., what is the interval range that encompasses the predicted selling price, given the SEE of the model. This can be accomplished with the use of a prediction interval formula, whose basic elements consist of the SEE, the number of observations, the degree of variability in the SDCF data, the confidence level, and how far the value of the SDCF variable is from the SDCF average. Because the predicted selling price is a random variable, its distribution is normal, with a mean of zero and a standard deviation of one. Therefore, the range of values that constitute its prediction interval will take the shape of a normal, or bell-shaped curve. With (1) an average SDCF of \$83.644, (2) an SEE of \$36.7892, (3) 117 observations minus three parameters that equal 114 degrees of freedom, and (4) a 95% confidence level,

EXHIBIT 14
Goodness-of-Fit Test

Model	Adjusted r_2	Standard Error (SEE)
Model 1	.9492	36.7892
Model 2	.9447	38.1671
Model 3	.9489	36.8684

EXHIBIT 15
Predicted Selling Prices

Model	$100K SDCF	$40K SDCF	$10K SDCF
Model 1—Selling Price	$174.798K	$75.492K	$96.256K
Model 2—Selling Price	$181.647K	$75.287K	$27.542K
Model 3—Selling Price	$175.873K	$80.018K	$41.508K

EXHIBIT 16
Scattergram w/ Trend Line—Selling Price vs. SCDF—Comparative Models

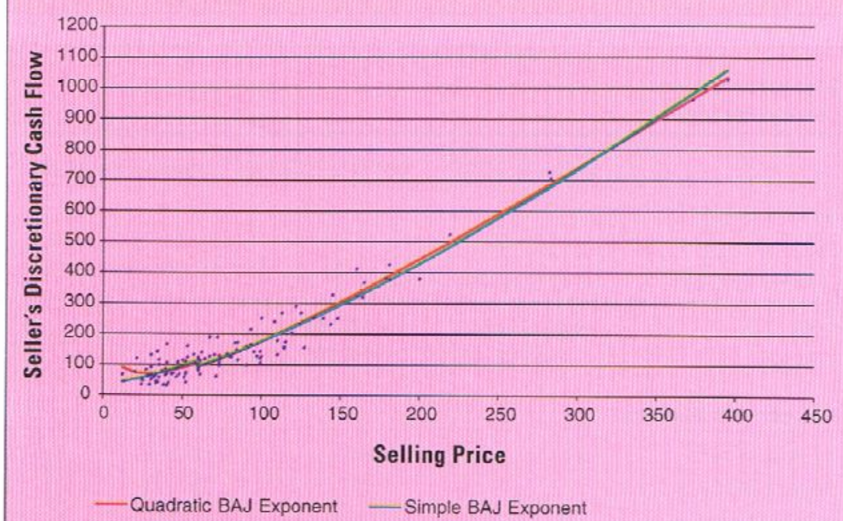


EXHIBIT 17
Predicted Selling Prices, Confidence Intervals, and Prediction Errors

SDCF	Predicted Selling Price	Prediction Interval	Range of Error
$200K	$441.30K	$74.27K	16.82%
$100K	$174.80K	$73.50K	42.04%
$40K	$75.49K	$73.64K	97.55%
$10K	$92.26K	$80.78K	83.92%

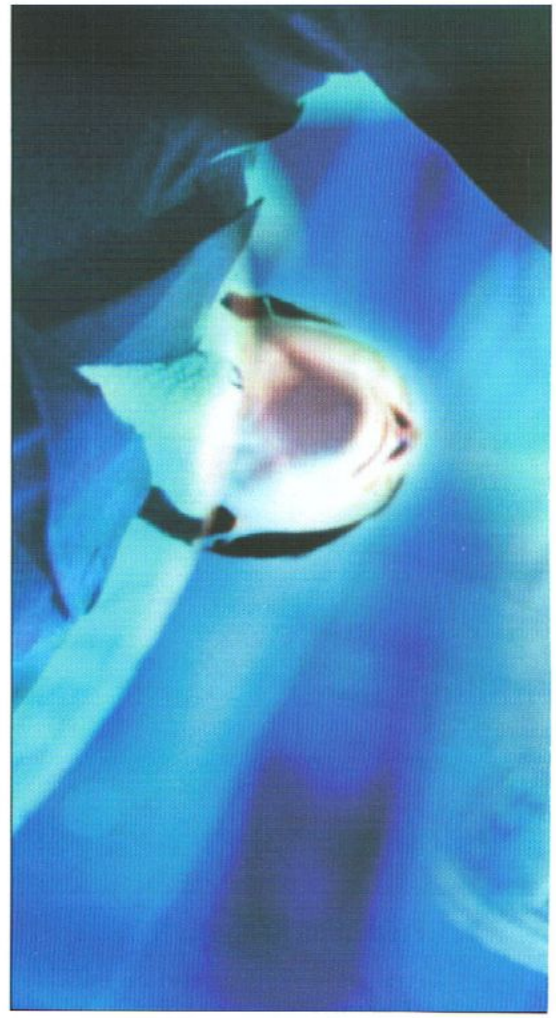
9 The sum of the squared difference between the actual response and the predicted response divided by the error degrees of freedom. (measures the degree of dispersion in the data set.)

10 The x coefficient value divided by its standard error. (indicates how many standard deviations the x coefficient is from zero.)

11 Indicates if the x coefficient is statistically significant at a particular level, i.e., if it is significantly different from zero.

12 Number of data points less the number of regression parameters, including the constant.

13 BAJ = Buy-a-Job.



selected SDCFs produce the selling prices, confidence intervals, and prediction errors contained in Exhibit 17.

The prediction interval tells the business appraiser the width of the forecast range—in other words, how large the forecast errors are expected to be. At the 95% confidence level, the absolute range of error is about the same for each amount of SDCF, but the resultant percentage error minimizes with increasing SDCF. However, this does not mean that the forecast error will be about $74K either way all the time, as if the prediction interval was a uniform distribution; it means that the forecast error can be anywhere from -$74K to +$74K. There is only a 2.5% chance that it will be greater than +$74K, and a 2.5% chance that it will be smaller than -$74K, and there is a 68.26% probability that the forecast error will range from about -$36.79K to +$36.79K.

Therefore, one can conclude that the null hypothesis is rejected, and that

there is a difference in pricing multiples between businesses with $75,000 or less in SDCF and businesses with more than $75,000 of SDCF, whether those multiples are regression-derived or simply the average ratio of selling price/SDCF.

Causes

Finally, what causes the phenomenon described in this article? Answers include:

- People will pay to buy themselves a job.
- People will pay more for the psychic benefits of being self-employed.
- Businesses for sale at the low end of the scale are relatively "cheap" (in absolute dollars), meaning that more people can afford to buy them. Thus, more demand for a limited supply means higher prices.
- Just the opposite is true at the high end, as the market is more efficient at that end, producing relatively lower prices, because buyers at the high end of the market are more sophisticated, knowledgeable, and better users of information. The end result is a curvilinear data set.
- The small business market, and not just the buy-a-job segment, is extremely thin. By this it is meant that for each business bought and sold, there are very few bidders—usually, only one or two at the most. With few bidders, information about the business is also very thin, i.e., the markets are inefficient. Few bidders who do not know much about the value of what they are buying tends to create SIC Code data sets that are widely dispersed, i.e., they have very large standard deviations, and in regression form, very large SEEs.

As this valuation method places a value only on the intangible assets, fixed assets, and inventory of the business under consideration, there are more items to be dealt with in order to come up with an equity value. For example, if SDCF does not capture the effects of all the value drivers, certain adjustments would be in order for conditions such as the immediate need to replace certain fixed assets, the fact that one customer accounts for 30% of sales volume, or the existence of a working capital deficiency or non-operating assets. In fact, these conditions, in conjunction with the reasons suggested immediately above, might explain the large SEEs obtained and the concomitant wide range of errors surrounding predicted values. Cash, accounts receivable, and inventory (if not already included in the price) need to be added to, and total liabilities deducted from, the value derived by the regression model to produce the final equity value. Consideration should be given, when the business is a C corporation and the interest being valued is one of control, to accounting for a built-in gains tax on the difference between market value of the assets and their tax bases.

Conclusion

Do all the SIC Code data sets in Bizcomps look like the one of the printing industry? Is the model presented in this article the model to use in all situations? The answer to both questions is: No! A large portion of the SIC Code data sets look just like the printing industry's, and others show no segmental variation, while a few demonstrate just the opposite effect—the low end of the market falls off the scale. Each data set needs to be charted on a scatter plot to determine visually how the variables are correlated over the entire continuum of X variables. As for which model to use, it must be noted that no model works in every situation. Each data set of SIC Code Numbers forms a certain pattern, and the right model captures most of the pattern inherent in the data set. The more a model captures a pattern, the less error will result. Therefore, it is highly likely that different best models will be appropriate for different sets of data. In regression modeling, it is a matter of marrying the right data with the right model. Like a real marriage, compatibility is everything! ●