VALUATION

The Transaction Databases: Some Statistical Questions and Concerns

By Mark G. Filler, CPA, ABV, CVA, AM, CBA

In life in general and in the world of valuation in particular, we often take as an article of faith those ideas that should always be testable hypotheses. For example, we always assume that there is a causal, or at least a highly correlative, linear relationship between price and earnings (however defined) or between price and market share or between price and relative profitability. We also assume that the coefficient of variation is a valid selection tool to choose among valuation metrics. And lastly, we assume that when we regress price against earnings, market share, or relative profitability that a high R-square, a low standard error of the estimate, and a p-value of less than 0.05 tell us all we need to know about the validity of the model. I recently explored the use of the Bizcomps, IBA, and DealStats transaction databases for the used car industry (NAICS code 441120 and SIC Code 5521) and found that testing these three assumptions led to some surprising results for all three databases. What follows is an exploration of those results along with some statistical rules of thumb to follow when using the databases.

Before a valuation analyst can predict price based on sales, seller's discretionary earnings (SDE), gross profit, etc., the analyst needs to answer two basic questions: Is there a statistically significant linear relationship between the two variables? And even if there is, does it have any explanatory power? In other words, is the coefficient of determination, r^2, greater than 0.50 so that the valuation analyst can opine to a concluded value with a reasonable degree of certainty that the opinion will pass the "more likely than not" test?

The Coefficient of Correlation

When performing a valuation using the direct market data method, a basic requirement is that there be not only a logical relationship between price and sales (or EBITDA or SDE, etc.) but also that it be, at a minimum, a statistically significant linear correlated relationship, as the same basic assumptions for linear regression also apply to correlation. Of course, linearity is a necessity for a useful linear regression model, but it is also essential for ratio models, no matter the measure of central tendency used—mean, median, or weighted harmonic mean of the chosen ratio. And hand-in-hand with linearity is the idea that price, the dependent variable, ought to be, at a minimum, symmetrical about its mean.

Since most of the sample sizes we derive from the transactional databases are small, we cannot assume that the central limit theorem will overcome the infirmity of nonsymmetrical samples as it does when sample size is at least 30, and even better, when it exceeds 50. Therefore, we need to test for symmetry for the dependent variable (the independent variable need not be symmetrical) before doing a correlation test. If the dependent variable, price, is at least symmetrical, if not near-bell-shaped, and at best, normally distributed, we can use Pearson's product-moment correlation coefficient, denoted as Pearson's r, to test for correlation, and by substitution, also test for linearity. Defaulting to Spearman's[1] rank correlation coefficient, denoted as s, is not a solution, as it does not measure linearity, but association.

Assuming the dependent variable passes the symmetry tests, the results of the Pearson correlation test will tell us to what degree the variables are either positively or negatively linearly correlated with each other, using a scale from -1 to +1, where absolute 1 is perfect correlation. If we wish to make inferences about the population or test the hypothesis that there is no linear relationship between the two variables, we can then assess the coefficient of correlation for statistical significance with a t-test. If our null hypothesis is that there is no linear relationship between price and SDE,

1 All statistical calculations were made using either Excel's built-in functions, or the functions and tools of StatPlus, the Excel add-in that comes with Berk and Carey's introductory text, *Data Analysis with Microsoft Excel*, or the functions or tools of Real Statistics, the Excel add-in available for free at www.real-statistics.com.

for example, then our rejection of the null hypothesis will depend on the size of the correlation coefficient, the number of observations in the sample, and the percentage of test results we are willing to accept as incorrect, e.g., 10 percent, 5 percent, or 1 percent or less.

The resulting p-value of the t-test is just the first step. If the p-value is less than, say 0.05, then we have a statistically significant linear correlation coefficient. We next have to inquire about the explanatory power of the correlation model. If, for example, we have a correlation coefficient of 0.625 with a p-value of 0.021, indicating a linear relationship, we can test explanatory power by calculating an r^2, or coefficient of determination, of 0.391. This means that the variation in the independent variable, sales or SDE, explains only 39.1 percent of the variation in the dependent variable, price. This leaves 60.9 percent of the variation unexplained, and puts the valuation analyst, as a testifying expert, in an untenable situation.

The Coefficient of Variation

To use the unitless measure of dispersion called the coefficient of variation (standard deviation ÷ mean), two criteria must be met. First, the distribution of price-to-sales, etc., must be at least symmetrical, if not near-bell-shaped, and at best, normally distributed. Second, the coefficient of variation must be statistically significantly different from zero, which can be calculated using a t-test.

As the test for symmetry is the more important of the two tests (in the valuation context, we are always looking for coefficients of variation that are closer to zero than not), how do we determine that the distribution meets the minimum requirement of symmetry? The following are indicative of such:

- A box plot that is relatively symmetrical; i.e., the median is in the center of the box and the whiskers extend equally in each direction
- A histogram that looks symmetrical
- A mean that is approximately equal to the median, which is approximately equal to the weighted harmonic mean
- A coefficient of skewness that is relatively small; i.e., between -1.25 and +1.25, where perfect skewness is zero[2]

If the distribution is classified as normal by the Shapiro-Wilk, D'Agostino-Pearson, and Lilliefors tests, then it is, by definition, symmetrical and no further analysis is required.

Even if the distribution of valuation ratios meets these two criteria, a broader question is whether the coefficient of variation conveys any useful information if the numerator and denominator of the valuation ratio are either not significantly correlated or lack any explanatory power.

Masking in Linear Regression

Frequently in regression analysis applications, the data set contains some cases that are outlying or extreme; that is, the observations for these cases are well separated from the remainder of the data. These outlying cases may involve large residuals and often have dramatic effects on the fitted least squares regression function. It is therefore important to study the outlying cases carefully by means of visual tests, such as scatter plots and residual plots, and computational tests, such as standardized residuals, and decide whether they should be retained or eliminated. I have written previously about removing outliers whose residuals are more than 2.5 standard deviations from the mean as these transactions are, by their nature, dissimilar from and not relevant to the subject company.[3]

But what about those extreme cases that are not outliers as defined in the previous paragraph, as they lie on the plane of the regression line and therefore have small residuals, but instead are potential influencers and/or leverage points as they are separated from the range of all the other observations? These cases mask, or cover up, the effects of the bulk of observations, such as outliers described above, and hence, have a great deal of influence on the totality of the regression output. In fact, as we shall see, a leverage point can turn a poorly performing regression model into one that appears to have great promise. We can test for influence or leverage with statistical tools or we can simply look at a scatter plot to identify them. Once identified, they can be removed from the model inputs to see to what extent the regression output changes.

2 For a small sample of n = 15, the standard error of skewness is 0.6325, and the critical value is 1.96 × 0.6325 = 1.24. Hence, if the absolute skewness value is less than 1.25, we can assume symmetry. As the sample size increases—and, per the central limit theorem, the sampling distribution of the mean becomes more normally distributed—the critical value decreases to compensate.

3 Mark G. Filler, "Is There a Buy-a-Job Phenomenon in Business Valuations?," *Valuation Strategies* 7, no. 6 (July/August 2004): 20-33.

Applications and Examples

Ratio Models

Valuation analysts typically select a particular array of ratios, assume that it is not symmetrical, and select the median as their measure of central tendency. Or, they will remove the outliers from the ratio array, thereby making it symmetrical, and use either the arithmetic mean or the weighted harmonic mean as their measure of central tendency. In either case, the analyst has assumed what he or she needs to prove—that the numerator and denominator of the ratio are linearly correlated and have sufficient explanatory power. In the balance of this article, we will walk through an outline of the exploratory steps necessary to test these two assumptions.

Using the aforementioned used car dealer transaction data, we will start with the price-to-sales ratio, with input data and descriptive statistics shown on Exhibit A.[4] We began with 53 asset sale transactions from the three databases: 24 from DealStats, 17 from IBA, and 12 from Bizcomps. Of the 53 transactions, there were eight duplicates, or 15.1 percent of the total, and of those eight, three were in each of the databases, while five were in only two. Since we were not combining the databases, this low level of duplication should not distort the results of our inquiry.

Then we tested for outliers greater than 2.5 standard deviations from the mean and removed one transaction each from the DealStats and IBA databases. Next, we tested the ratio arrays for symmetry, using the coefficient of skewness and the Shapiro-Wilk, D'Agostino-Pearson, and Lilliefors tests. Only the IBA ratio array passed this test.

Table 1

Price to Sales	DealStats	Bizcomps	IBA
Ratios			
Symmetrical	No	No	**Yes**
Near-Bell-Shaped	No	No	**Yes**
Normal	No	No	**No**
Price			
Symmetrical	No	Yes	No
Near-Bell-Shaped	No	Yes	No
Normal	No	Yes	No
Pearson's r	93.81%	41.85%	64.91%
p-value	.0000	.1757	.0065
r^2	.880	.175	.421

4 Exhibits A through J may be found online at https://www.nacva.com/20so-exhibits.

While symmetry,[5] at a minimum, is required for correlation testing, and two of the databases fail this basic test, even if we impute symmetry,[6] we can see from Table 1 that the Bizcomps data set is not statistically significant, with a p-value greater than 0.05. Nor does it have any explanatory power, even with a normally distributed dependent value, with an r^2 of 0.175. The IBA data set is near-bell-shaped and statistically significant, with a p-value less than 0.05, but it too lacks explanatory power with an r^2 of 0.421. Again, ignoring lack of symmetry, only the DealStats data set demonstrates both statistical significance and strong explanatory power. These results appear to be too good to be true for nonsymmetrical data, and in fact they are a consequence of masking, which we will explore later in the regression section of this article.

Ignoring lack of symmetry, only the DealStats data set demonstrates both statistical significance and strong explanatory power.

But for now, as the DealStats and Bizcomps ratio data sets are not symmetrical, we cannot use average measures of central tendency from either of them. The IBA ratio data set is symmetrical, which would allow us to use the average or the weighted harmonic mean as a valuation metric if the price-to-sales relationship had any explanatory power. If the Bizcomps data set had a low enough p-value and a high enough r^2, the median would be available as a measure of central tendency. But it does not. Therefore, we are left, for now, with the DealStats median price-to-sales ratio as our default measure of central tendency, which is shown on Exhibit A in the DealStats ratio column as 0.141.

Now, let us turn our attention to the price-to-SDE data sets, with input data and descriptive statistics shown on Exhibit B[7] for the Bizcomps and IBA databases (DealStats only had nine SDE transactions, a number deemed insufficient for this exercise). Initially, we tested for outliers greater than 2.5 standard deviations from the mean, and removed one and two transactions, respectively, from the IBA and Bizcomps databases. Next, we tested for symmetry using the coefficient of skewness and the Shapiro-Wilk, D'Agostino-Pearson, and Lilliefors tests. For this model, both the price and ratio arrays are more than just symmetrical, they are normally distributed, allowing us to utilize Pearson's correlation coefficient, which results are shown in Table 2 along with the r^2 statistic.

5 As Shapiro-Wilk is the more powerful test for normality, if the data array shows normality under it, the data array will be deemed to be normal. If the coefficient of skewness is between -1.25 and +1.25, and the data array passes none of the normality tests, it will be deemed to be only symmetrical. If the data array is symmetrical and passes one or both of the weaker D'Agostino-Pearson and Lilliefors normality tests, it will be deemed to be near-bell-shaped.

6 Many statistical tests require that the data be normally distributed. However, most of these tests are quite robust to violations of normality, especially when the data is at least symmetrically distributed. Being symmetrical about the mean allows the empirical rule to be invoked, which explains that approximately 68 percent of the data points will lie within one standard deviation of the mean, about 95 percent within two standard deviations of the mean, and about 99.7 percent within three standard deviations of the mean.

7 *See* https://www.nacva.com/20so-exhibits.

For these three models, the dependent variable (price) is not even symmetrical, never mind normally distributed, which will have an impact on the regression models.

Table 2

Price to SDE	Bizcomps	IBA
Ratios		
Symmetrical	Yes	Yes
Near-Bell-Shaped	Yes	Yes
Normal	Yes	Yes
Price		
Symmetrical	Yes	Yes
Near-Bell-Shaped	Yes	Yes
Normal	Yes	Yes
Pearson's r	54.01%	78.96%
p-value	.0863	.0066
r^2	.292	.623

Even though the array of price-to-SDE ratios is normal for both databases and the dependent variable (price) is normally distributed, the Bizcomps relationship between price and SDE is neither statistically significant at the 0.05 level, nor does it meet the threshold level of explanatory power, leaving us unable to use any of the price-to-SDE measures of central tendency to formulate a price for a subject company. The IBA price-to-SDE relationship is both statistically significant and above the threshold of explanatory power, as we would expect with the ratio array and the dependent variable both normally distributed. But, as we shall later demonstrate, the IBA r^2 of 0.623 and the p-value of 0.0066 for Pearson's r are artifacts of masking.

Finally, let us investigate three valuation metrics exclusive to the DealStats database: price-to-gross profit, price-to-EBIT, and price-to-EBITDA, with input data and descriptive statistics shown on Exhibit C.[8] Initially, we tested for negative earnings and outliers greater than 2.5 standard deviations from the mean and removed one EBITDA transaction and two transactions each from the EBIT and gross profit arrays. Next, we tested for symmetry using the coefficient of skewness and the Shapiro-Wilk, D'Agostino-Pearson, and Lilliefors tests. For these three models, the dependent variable (price) is not even symmetrical, never mind normally distributed, which will have an impact on the regression models that we will inspect shortly. However, all three models have symmetrical ratio arrays, allowing us to utilize Pearson's correlation coefficient, which results are shown in Table 3 along with the r^2 statistic.

8 *See* https://www.nacva.com/20so-exhibits.

Table 3

DealStats	Price to Gross Profit	Price to EBIT	Price to EBITDA
Ratios			
Symmetrical	Yes	Yes	Yes
Near-Bell-Shaped	Yes	Yes	Yes
Normal	Yes	No	Yes
Price			
Symmetrical	No	No	No
Near-Bell-Shaped	No	No	No
Normal	No	No	No
Pearson's r	99.91%	22.04%	-1.46%
p-value	.0000	.3243	.9572
r^2	.998	.049	.000

Once again, even though the array of price-to-earnings ratios is symmetrical for all three databases, the relationships between price and EBIT and EBITDA are not statistically significant and neither meets the threshold level of explanatory power, leaving us unable to use any of the price-to-EBIT or price-to-EBITDA measures of central tendency to formulate a price for a subject company. Price-to-gross profit appears to tell a different story: the array of ratios is normally distributed but the dependent variable price is not even symmetrical. However, the dependent and independent variables are correlated with a high degree of statistical significance, and with an r^2 of 0.998 the model has much in the way of explanatory power. But as we shall see, this too is an artifact of masking.

Regression Models

We will now turn our attention to the masking issue that is presented in matched pairs of scatterplots: Exhibits D and E, F and G, and H and I.[9] Each of the masked charts—D, F, and H—show an observation that, while lying on the plane of the trend line, is at a great distance from the central group of observations and, therefore, is a leverage point. As the trendline lies close to the leverage point, it has a small residual and therefore does not show up as an outlier. The question is: Is the leverage observation news or noise? Does it tell us anything about a pricing multiple that we should consider for our subject company? Before we answer that question, let's examine the unmasked charts—Exhibits E, G, and I—to see if the regression outputs have changed significantly after removing the leverage point from the data set. To that end, let us compare regression output metrics for the paired data sets.

For Exhibits D and E

DealStats—Price to Sales	r^2	t statistic	CoV	Median Sales Value
Masked	.880	16.4	134.7%	($155,272)
Unmasked	.097	00.0	74.2%	$193,000

9 *See* https://www.nacva.com/20so-exhibits.

The changes between D and E are so major, as the masked model produces a negative value and the unmasked model so lacks significance that we would reject both models. Even if our subject company was as large as the leverage case, we would still decline using the masked model as we would be relying essentially on a sample of n = 1.

For Exhibits F and G

IBA—Price to SDE	r^2	t statistic	CoV	Median Sales Value
Masked	.623	3.64	38.5%	$132,576
Unmasked	.154	1.13	44.7%	$134,306

These results, while similar to those of D and E, are not as extreme. But they are still problematic, as using the masked model brings forth the concern of sample size n = 1, and the unmasked model is not statistically significant. The approximately equal values obtained using the median sales value does not hold at the extremes, with disparate values that are 20 percent apart.

For Exhibits H and I

DealStats—Price to Gross Profit	r^2	t statistic	CoV	Median Sales Value
Masked	.998	105.9	16.3%	$156,656
Unmasked	.396	3.53	63.1%	$181,028

These results present a new problem: The unmasked model is statistically significant, but its explanatory power does not meet the greater-than-0.50 threshold. The masked model suffers from the sample size n = 1 deficiency, while the 95 percent confidence interval of the unmasked model is ±126.2 percent. We would reject both models.

Conclusion

We have examined eight regression models and for one reason or another, they have all failed to make the cut. Exhibit J, DealStats' price-to-EBITDA model, best exemplifies the inherent problem with all eight models. If the regression models fail, because of either lack of statistical significance or lack of explanatory power, then the ratios derived from the same dependent and independent variables will also prove to be unreliable. This is not to claim that selling prices are not dependent on market share (sales) or cash flow (SDE or EBITDA), but that the quality of some transaction data may be less than required.

So, what to do? If you use the transaction databases, perform some exploratory data analysis by graphing your data in a scatterplot, running tests for outliers, symmetry, correlation, statistical significance, and explanatory power. Hopefully, the NAICS or SIC code you will be working with will be more amenable to developing a value using the market approach than was the one utilized for used car dealers. VE

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Exhibit A
Price to Sales

DealStats			Bizcomps			IBA		
Price	**Sales**	**Ratio**	**Price**	**Sales**	**Ratio**	**Price**	**Sales**	**Ratio**
30,000	199,000	0.151	375,000	645,000	0.581	98,000	240,000	0.408
60,000	207,000	0.290	260,000	830,000	0.313	65,000	297,000	0.219
83,000	348,958	0.238	175,000	1,401,000	0.125	60,000	456,859	0.131
60,000	456,859	0.131	75,000	955,000	0.079	225,000	501,000	0.449
375,000	645,339	0.581	250,000	720,000	0.347	65,000	520,461	0.125
295,000	704,949	0.418	78,000	525,000	0.149	125,000	546,000	0.229
435,000	916,195	0.475	247,000	1,700,000	0.145	95,000	720,000	0.132
75,000	955,423	0.078	70,000	1,518,000	0.046	220,000	872,000	0.252
80,000	1,518,299	0.053	70,000	1,518,000	0.046	225,000	918,000	0.245
355,300	1,552,221	0.229	60,000	457,000	0.131	75,000	955,000	0.079
150,000	1,778,108	0.084	385,000	8,270,000	0.047	240,000	1,395,000	0.172
45,500	1,913,196	0.024	195,000	7,028,000	0.028	175,000	1,401,434	0.125
190,000	2,429,728	0.078				282,000	2,133,000	0.132
450,000	2,878,396	0.156				200,000	2,458,000	0.081
170,000	3,371,511	0.050				720,000	3,870,000	0.186
75,000	3,522,097	0.021				385,000	8,270,257	0.047
185,000	3,755,689	0.049						
98,000	4,323,630	0.023						
588,510	4,902,427	0.120						
150,000	7,028,439	0.021						
385,000	8,270,257	0.047						
300,000	10,276,919	0.029						
18,600,000	36,546,000	0.509						

Descriptive Statistics

	Price	*Sales*	*Ratio*	*Price*	*Sales*	*Ratio*	*Price*	*Sales*	*Ratio*
Mean	1,010,231	4,282,637	0.168	186,667	2,130,583	0.170	203,438	1,597,126	0.188
Median	170,000	1,913,196	0.084	185,000	1,178,000	0.128	187,500	895,000	0.152
Standard Deviation	3,837,647	7,527,488	0.172	118,929	2,624,956	0.165	166,085	2,021,066	0.112
WHM			0.236			0.088			0.127
Kurtosis	22.912	16.767	0.525	(1.051)	2.686	2.586	5.989	8.375	1.215
Skewness	4.783	3.896	1.299	0.484	1.986	1.665	2.179	2.752	1.224
Range	18,570,000	36,347,000	0.560	325,000	7,813,000	0.554	660,000	8,030,257	0.403
Maximum	18,600,000	36,546,000	0.581	385,000	8,270,000	0.581	720,000	8,270,257	0.449
Minimum	30,000	199,000	0.021	60,000	457,000	0.028	60,000	240,000	0.047
Count	23	23	23	12	12	12	16	16	16
CoV	3.799	1.758	1.029	0.637	1.232	0.973	0.816	1.265	0.594

Normality Tests

Shapiro-Wilk Test

	Price	*Sales*	*Ratio*	*Price*	*Sales*	*Ratio*	*Price*	*Sales*	*Ratio*
W-stat	0.247	0.508	0.800	0.870	0.627	0.794	0.767	0.645	0.879
p-value	0.000	0.000	0.000	0.066	0.000	0.008	0.001	0.000	0.038
alpha	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
normal	no	no	no	yes	no	no	no	no	no

d'Agostino-Pearson

DA-stat	57.813	47.909	7.000	1.490	11.583	9.346	19.947	27.149	5.877
p-value	0.000	0.000	0.030	0.475	0.003	0.009	0.000	0.000	0.053
alpha	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
normal	no	no	no	yes	no	no	no	no	yes

Lilliefors Test

D-stat	0.5003	0.2933	0.2219	0.2362	0.3985	0.3010	0.2254	0.2886	0.1918
p-value	0.0000	0.0000	0.0041	0.0605	0.0000	0.0030	0.0286	0.0000	0.1135
alpha	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
normal	no	no	no	yes	no	no	no	no	yes

Symmetrical	no	no	no	yes	no	no	no	no	yes
Near-bell-shaped	no	no	no	yes	no	no	no	no	yes
Normal	no	no	no	yes	no	no	no	no	no

Exhibit B

Price to SDE

Bizcomps			IBA		
Price	SDE	Ratio	Price	SDE	Ratio
70,000	40,000	1.750	98,000	75,000	1.307
60,000	85,000	0.706	60,000	85,129	0.705
75,000	94,000	0.798	125,000	119,000	1.050
78,000	125,000	0.624	95,000	142,000	0.669
250,000	142,000	1.761	220,000	201,000	1.095
260,000	150,000	1.733	225,000	122,000	1.844
195,000	182,000	1.071	75,000	212,000	0.354
175,000	319,000	0.549	175,000	318,692	0.549
70,000	443,000	0.158	200,000	199,000	1.005
247,000	500,000	0.494	385,000	511,432	0.753
385,000	511,000	0.753			

Descriptive Statistics

	Price	*SDE*	*Ratio*	*Price*	*SDE*	*Ratio*
Mean	169,545	235,545	0.945	165,800	198,525	0.933
Median	175,000	150,000	0.753	150,000	170,500	0.879
Standard Deviation	108,116	175,473	0.561	98,012	131,669	0.428
WHM			0.720			0.835
Kurtosis	(0.42)	(1.22)	(0.999)	1.75	3.12	1.183
Skewness	0.66	0.73	0.592	1.22	1.70	0.932
Range	325,000	471,000	1.603	325,000	436,432	1.490
Maximum	385,000	511,000	1.761	385,000	511,432	1.844
Minimum	60,000	40,000	0.158	60,000	75,000	0.354
Count	11	11	11	10	10	10
CoV	0.638	0.745	0.594	0.591	0.663	0.459

Normality Tests

Shapiro-Wilk Test

	Price	*SDE*	*Ratio*	*Price*	*SDE*	*Ratio*
W-stat	0.868	0.847	0.867	0.888	0.827	0.943
p-value	0.073	0.039	0.070	0.162	0.030	0.585
alpha	0.050	0.050	0.050	0.050	0.050	0.050
normal	yes	no	yes	yes	no	yes

d'Agostino-Pearson

DA-stat	1.091	2.494	1.503	4.841	9.359	2.889
p-value	0.580	0.287	0.472	0.089	0.009	0.236
alpha	0.050	0.050	0.050	0.050	0.050	0.050
normal	yes	yes	yes	yes	no	yes
Lilliefors Test						
D-stat	0.2560	0.2562	0.2399	0.1729	0.2592	0.1630
p-value	0.0414	0.0410	0.0730	0.5330	0.0535	0.6281
alpha	0.05	0.05	0.05	0.05	0.05	0.05
normal	no	no	yes	yes	yes	yes
Symmetrical	yes	yes	yes	yes	no	yes
Near-bell-shaped	yes	yes	yes	yes	no	yes
Normal	yes	no	yes	yes	no	yes

Exhibit C
DealStats
Price to Gross Profit, Price to EBIT, Price to EBITDA

Price to Gross Profit			Price to EBIT			Price to EBITDA		
Price	GP	Ratio	Price	EBIT	Ratio	Price	EBITDA	Ratio
83,000	71,310	1.164	60,000	49,800	1.205	60,000	49,800	1.205
60,000	87,000	0.690	185,000	131,407	1.408	185,000	134,591	1.375
30,000	113,454	0.264	45,500	150,749	0.302	45,500	150,749	0.302
60,000	183,689	0.327	150,000	87,309	1.718	150,000	182,268	0.823
75,000	211,783	0.354	150,000	182,268	0.823	75,000	41,471	1.808
375,000	283,897	1.321	1,391,140	226,199	6.150	75,000	84,772	0.885
45,500	295,805	0.154	75,000	39,821	1.883	295,000	162,327	1.817
295,000	296,522	0.995	450,000	253,241	1.777	80,000	443,114	0.181
150,000	316,426	0.474	75,000	84,772	0.885	170,000	46,914	3.624
170,000	353,481	0.481	295,000	162,327	1.817	385,000	81,588	4.719
75,000	356,417	0.210	80,000	443,114	0.181	60,000	84,315	0.712
185,000	369,108	0.501	170,000	40,590	4.188	30,000	12,886	2.328
190,000	401,732	0.473	385,000	74,646	5.158	83,000	30,549	2.717
385,000	432,315	0.891	60,000	80,296	0.747	588,510	104,224	5.647
450,000	436,009	1.032	30,000	11,657	2.574	190,000	69,745	2.724
300,000	539,537	0.556	83,000	29,411	2.822	355,300	92,113	3.857
98,000	559,368	0.175	588,510	104,224	5.647			
80,000	585,208	0.137	190,000	68,384	2.778			
150,000	833,916	0.180	435,000	201,065	2.163			
435,000	916,195	0.475	300,000	239,167	1.254			
588,510	1,112,809	0.529	355,300	92,002	3.862			
18,600,000	23,374,000	0.796	98,000	320,900	0.305			

Descriptive Statistics

	Price	*GP*	*Ratio*	*Price*	*EBIT*	*Ratio*	*Price*	*EBITDA*	*Ratio*
Mean	1,040,000	1,460,454	0.554	256,884	139,698	2.257	176,707	110,714	2.170
Median	160,000	362,763	0.478	160,000	98,113	1.797	116,500	84,544	1.813
Standard Deviation	3,925,237	4,901,535	0.346	297,737	106,910	1.745	155,919	101,095	1.613
WHM			0.712			1.839			1.596
Kurtosis	21.919	21.854	(0.321)	10.097	1.687	0.057	1.916	8.152	(0.167)
Skewness	4.678	4.668	0.761	2.867	1.280	0.968	1.483	2.574	0.784

Range	18,570,000	23,302,690	1.184	1,361,140	431,457	5.970	558,510	430,228	5.466
Maximum	18,600,000	23,374,000	1.321	1,391,140	443,114	6.150	588,510	443,114	5.647
Minimum	30,000	71,310	0.137	30,000	11,657	0.181	30,000	12,886	0.181
Count	22	22	22	22	22	22	16	16	16
CoV	3.774	3.356	0.625	1.159	0.765	0.773	0.882	0.913	0.743

Normality Tests

Shapiro-Wilk Test

	Price	*GP*	*Ratio*	*Price*	*EBIT*	*Ratio*	*Price*	*EBITDA*	*Ratio*
W-stat	0.252	0.264	0.915	0.677	0.893	0.897	0.825	0.729	0.931
p-value	0.000	0.000	0.061	0.000	0.021	0.026	0.006	0.000	0.252
alpha	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
normal	no	no	yes	no	no	no	no	no	yes

d'Agostino-Pearson

DA-stat	55.740	55.640	2.489	33.709	8.598	3.870	8.682	25.584	2.014
p-value	0.000	0.000	0.288	0.000	0.014	0.144	0.013	0.000	0.365
alpha	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050	0.050
normal	no	no	yes	no	no	yes	no	no	yes

Lilliefors Test

D-stat	0.5003	0.4828	0.1789	0.2252	0.1754	0.1756	0.2261	0.2131	0.1491
p-value	0.0000	0.0000	0.0625	0.0046	0.0736	0.0730	0.0278	0.0486	0.4370
alpha	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
normal	no	no	yes	no	yes	yes	no	no	yes

Symmetrical	no	no	yes	no	no	yes	no	no	yes
Near-bell-shaped	no	no	yes	no	yes	yes	no	no	yes
Normal	no	no	yes	no	no	no	no	no	yes

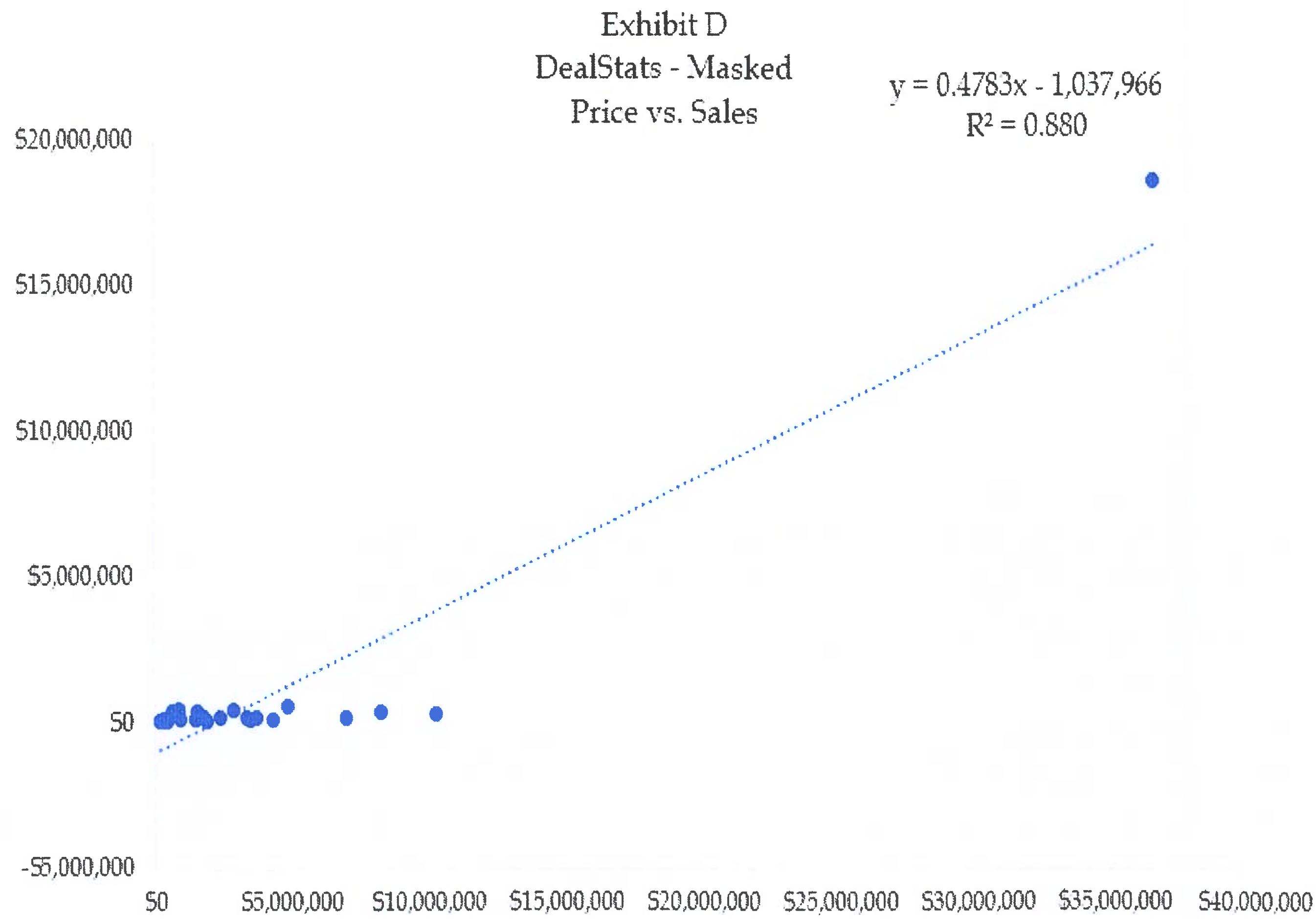


Exhibit D
DealStats - Masked
Price vs. Sales
y = 0.4783x - 1,037,966
R^2 = 0.880
$20,000,000
$15,000,000
$10,000,000
$5,000,000
$0
-$5,000,000
$0
$5,000,000
$10,000,000
$15,000,000
$20,000,000
$25,000,000
$30,000,000
$35,000,000
$40,000,000

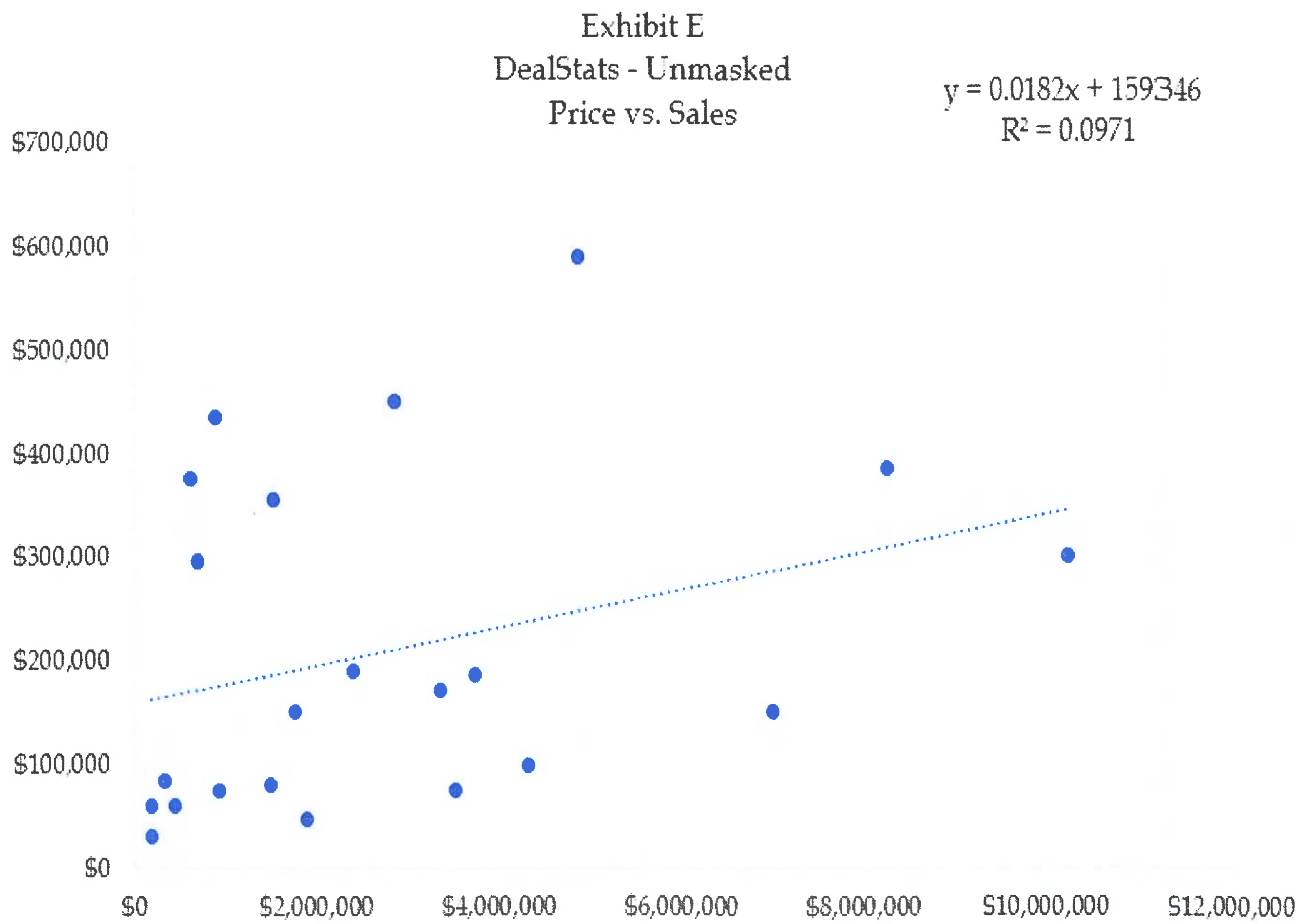


Exhibit E
DealStats - Unmasked
Price vs. Sales
y = 0.0182x + 159346
R² = 0.0971
$700,000
$600,000
$500,000
$400,000
$300,000
$200,000
$100,000
$0
$0
$2,000,000
$4,000,000
$6,000,000
$8,000,000
$10,000,000
$12,000,000

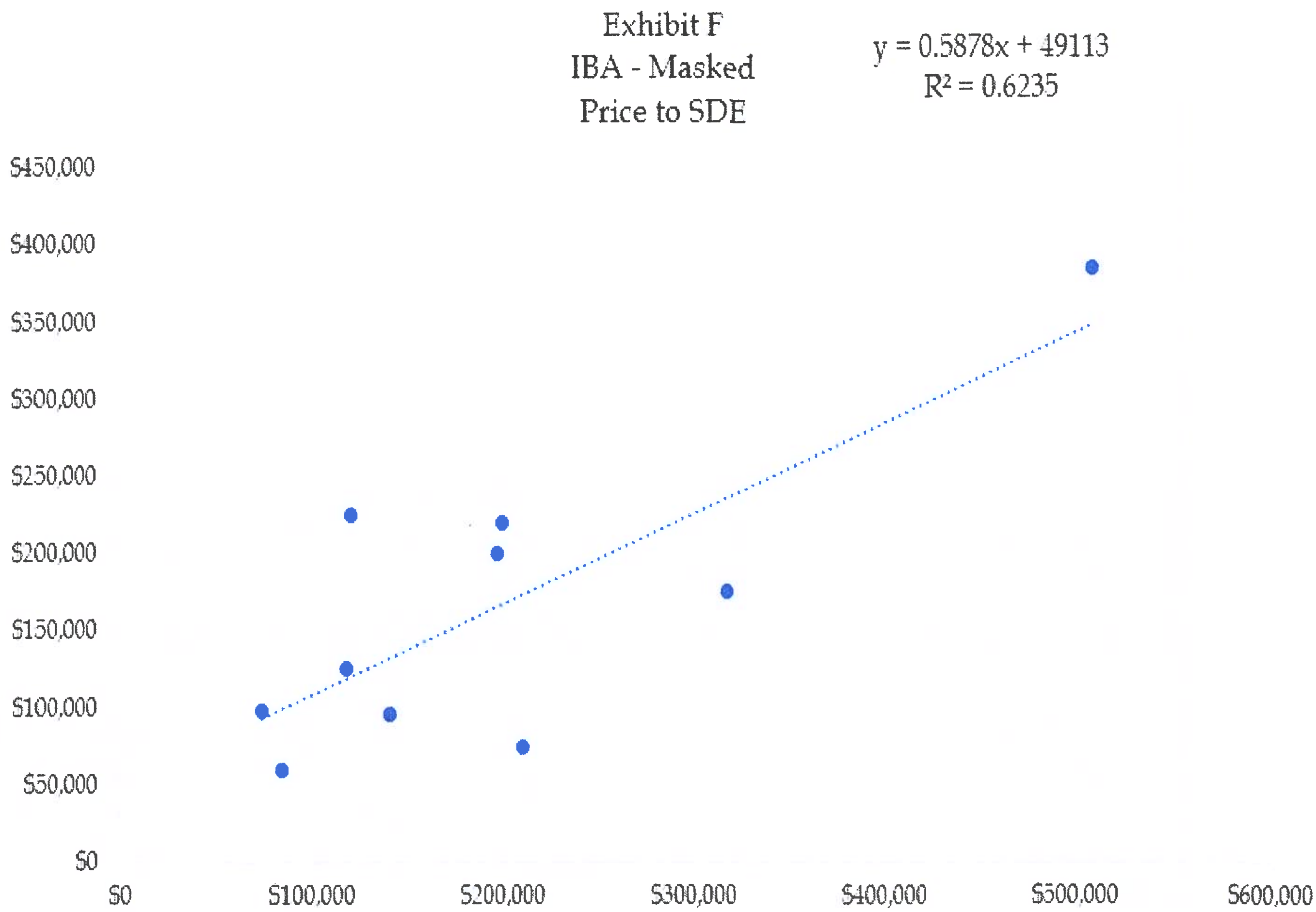


Exhibit F
IBA - Masked
Price to SDE
y = 0.5878x + 49113
R² = 0.6235
$450,000
$400,000
$350,000
$300,000
$250,000
$200,000
$150,000
$100,000
$50,000
$0
$0
$100,000
$200,000
$300,000
$400,000
$500,000
$600,000

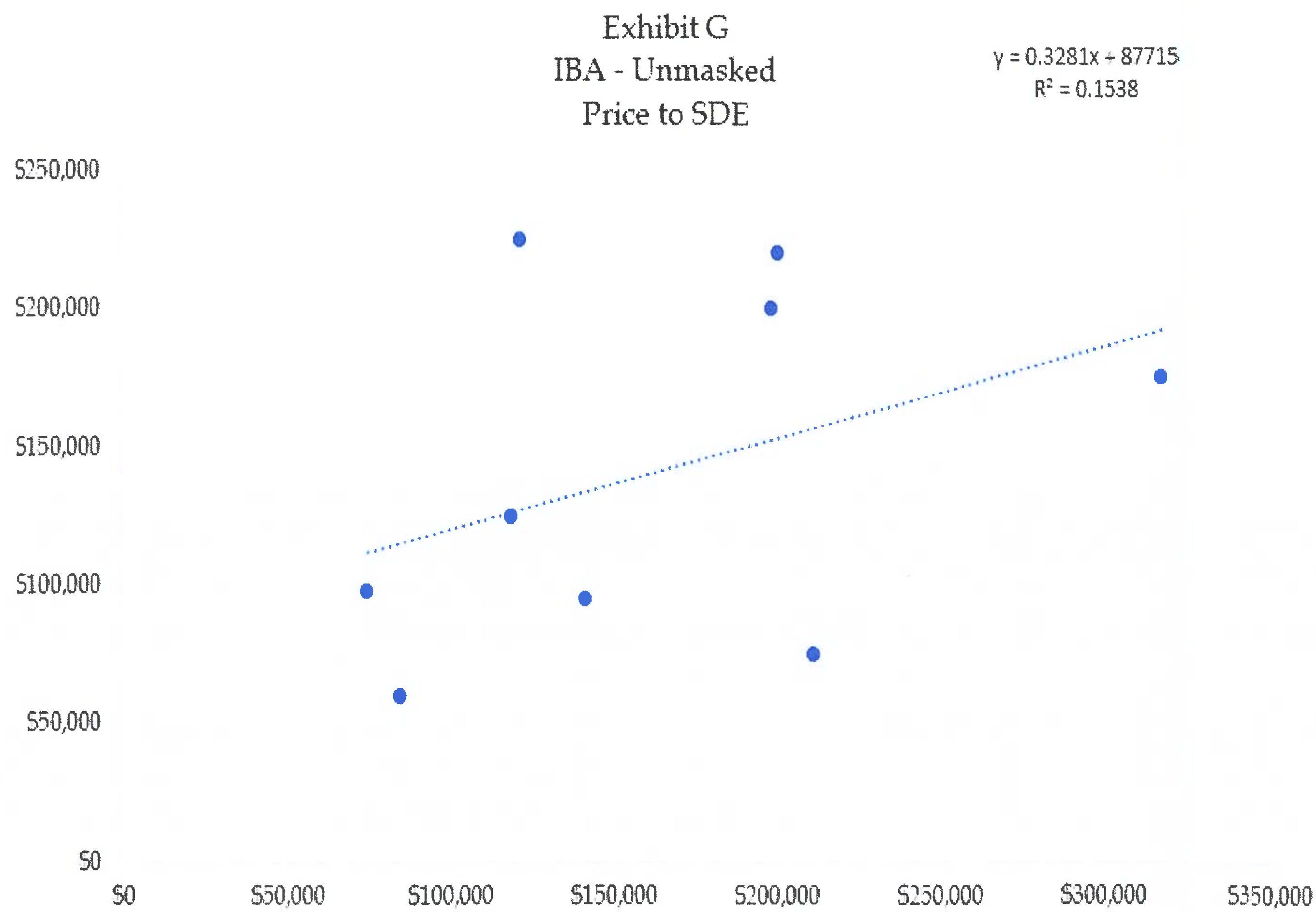


Exhibit G
IBA - Unmasked
Price to SDE
y = 0.3281x + 87715
R² = 0.1538
$250,000
$200,000
$150,000
$100,000
$50,000
$0
$0
$50,000
$100,000
$150,000
$200,000
$250,000
$300,000
$350,000

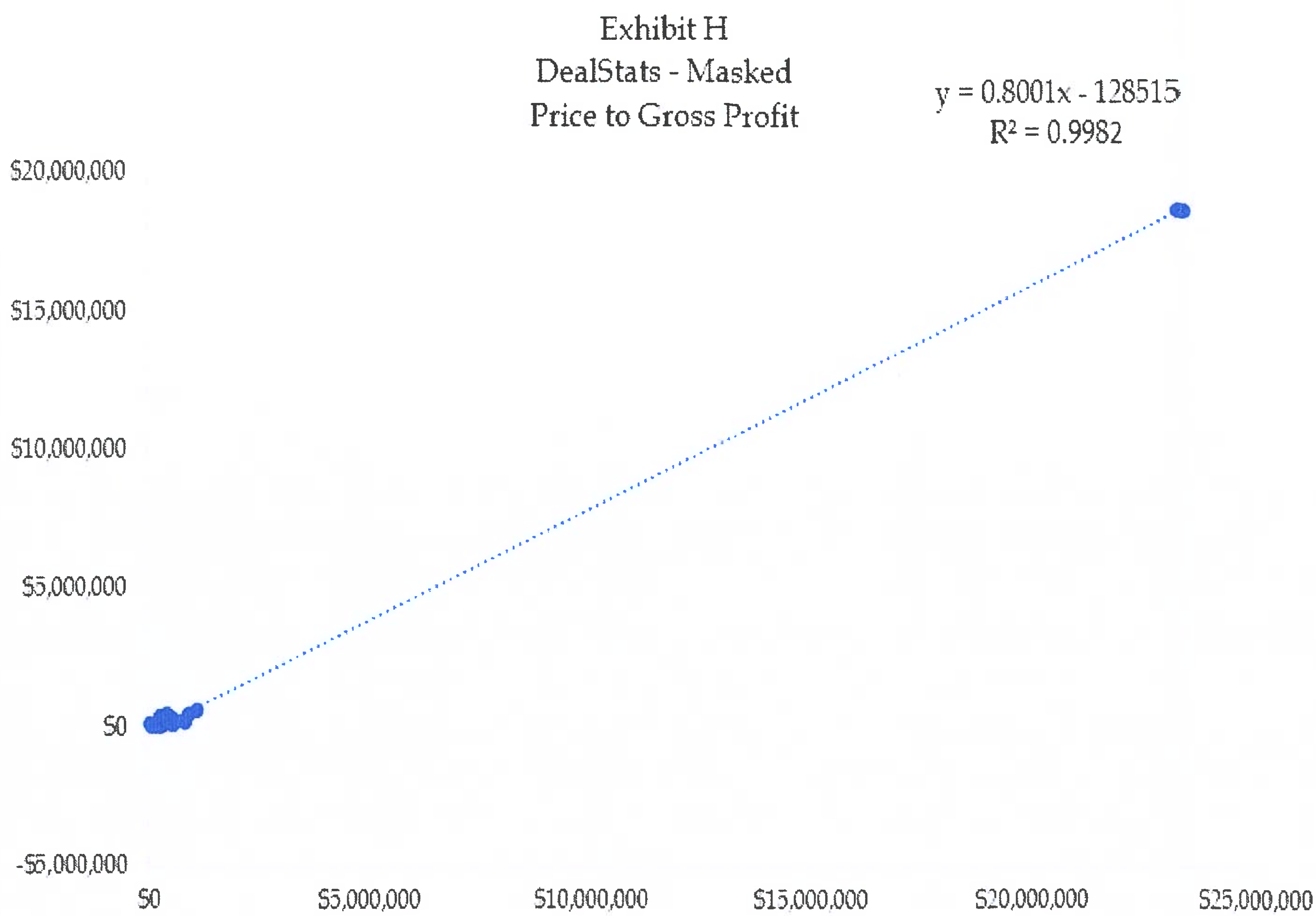
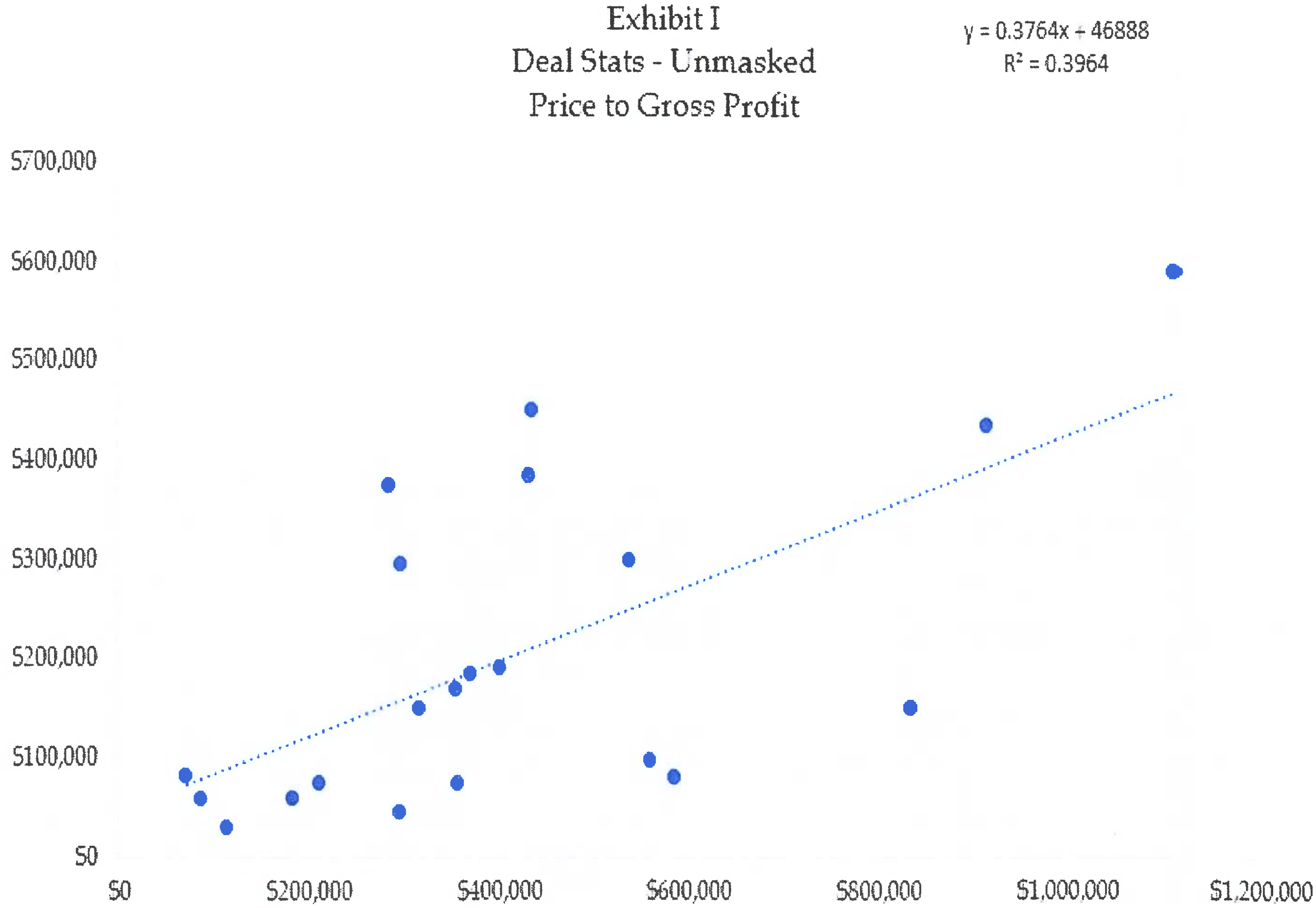


Exhibit H
DealStats - Masked
Price to Gross Profit
y = 0.8001x - 128515
R² = 0.9982
$20,000,000
$15,000,000
$10,000,000
$5,000,000
$0
-$5,000,000
$0
$5,000,000
$10,000,000
$15,000,000
$20,000,000
$25,000,000

Exhibit I
Deal Stats - Unmasked
Price to Gross Profit



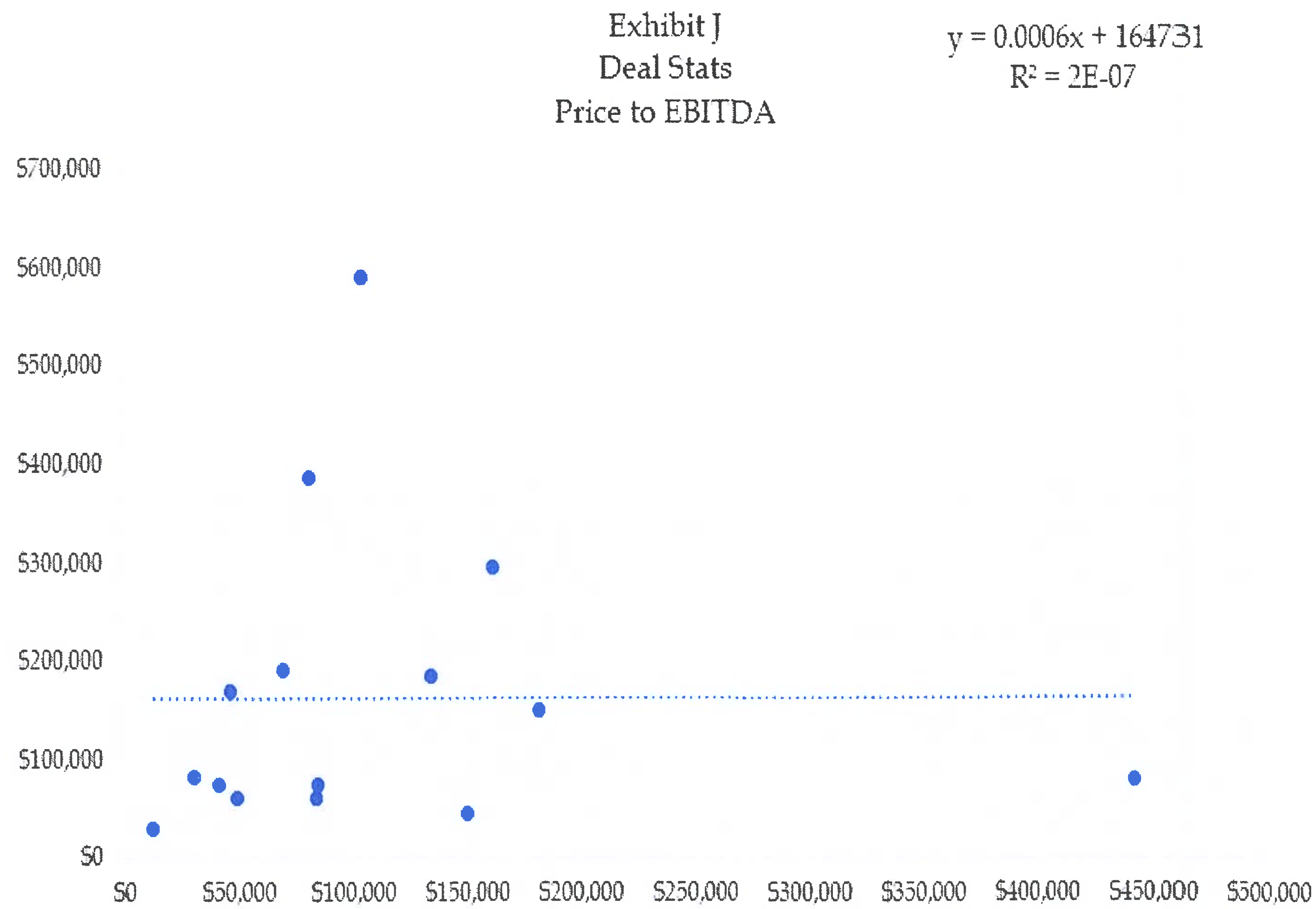


Exhibit J
Deal Stats
Price to EBITDA
y = 0.0006x + 164731
R² = 2E-07
$700,000
$600,000
$500,000
$400,000
$300,000
$200,000
$100,000
$0
$0
$50,000
$100,000
$150,000
$200,000
$250,000
$300,000
$350,000
$400,000
$450,000
$500,000