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Demand, Recurring Costs, And Profitability

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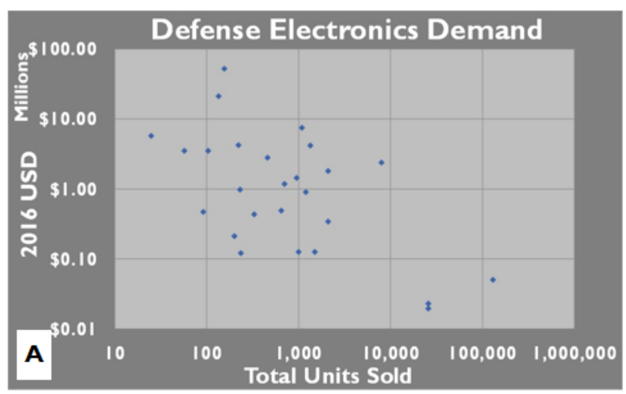
ABSTRACT:

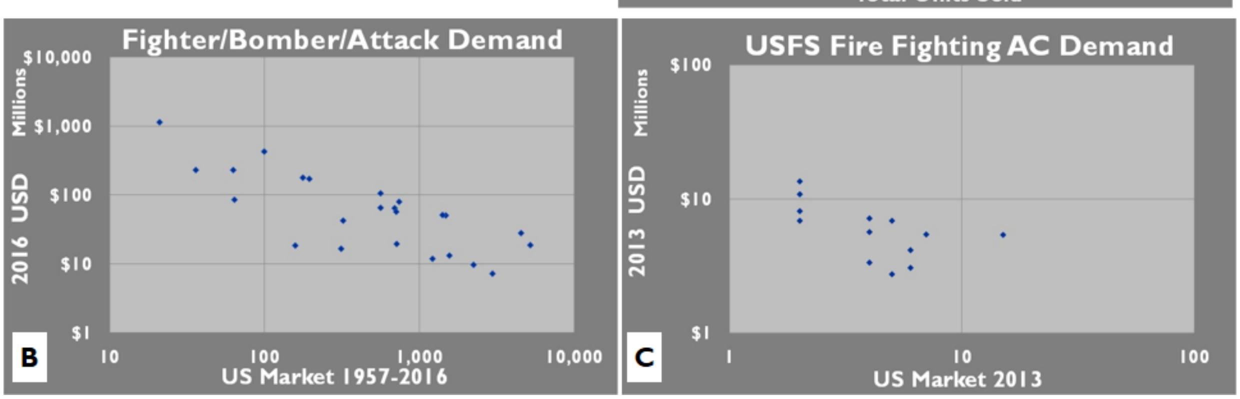
Customers in all markets collectively abide by their self-imposed demand curves, which dictate their responsiveness to changes in price and the maximum quantities of products they can absorb. Concurrently, producers in all markets face recurring costs, which typically fall over time due to a variety of factors. Producers can effectively model demand and recurring costs before product launch. Understanding how demand curves relate to recurring costs is key to enhancing profitability, which this paper examines.

1.0 Market Limits

Determining cost has been and continues to be the goal for the vast portion of the members of the estimating community. While costs will always be important, profits or earnings remain the ultimate target of any for-profit company. Estimators have given costs a great deal of thought, but comparatively little to profits. What if it were easier to estimate them than we knew?

Figure 1: Each of these markets have a general demand trend; quantities sold fall as prices rise. However, none of them appear to be well-correlated. More work must be done with the data to gain useful analyses. Initial forays into demand analysis almost always yield results such as these.





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While many factors come into play in studying marketplaces, one element that often escapes notice and need not is the observation and description of market limits. Too often, analysts ordered to study the costs of new programs receive no such direction concerning what markets can absorb and their responsiveness to changes in prices. Even if those same estimators were so directed, it is not clear that the data they will examine will portray instantly useful insights. Figure 1 reveals that simple plots of the quantities and prices for markets often yields only general trends, which are typically not very well-correlated.

There are numerous options estimators can use to overcome these obstacles. Let's consider the market addressed by Figure 1A, that for defense electronics (see Appendix A).[1] Instead of trying to consider the line of best fit through the data the way that it is, we can instead opt to characterize it in a couple of other ways. Suppose we created price bins for the data, summing up the total quantities sold and revenues in each bin, and dividing those bin revenues by those bin quantities, deriving a series of points representing total bin quantities and weighted average prices for each bin. Those aggregated points will represent aggregated market demand. If this is a viable method, with a potentially useful outcome, the question then becomes how to divide the bins.

The most obvious method would be to divide the bins in equal sizes according to price range, which we find implemented in Figure 2.[2] The red line in the right-hand part of that figure represents Aggregated Market Demand and has an R^2 of 92.6%. We use the bins to find the right-most and its nearest right-most model-observation in each bin to derive the Demand Frontier, as indicated by points with a yellow band about them, with the ability to include both points in each bin, one point in each bin, or neither of the points within a bin. With the points selected, we have a very satisfactory R^2 of 98.1%, but we find that our algorithm has managed to exclude a point beyond our Demand Frontier, which violates the central tenet of that concept. We wonder if we might do better with another method.

In Figure 3, we employ a binning technique which approximates a geometric progression concerning the number of observations in each Aggregate Demand bin. In this instance, the Aggregate Demand curve is more highly correlated than it was in Figure 2. However, in large measure, because we did not remove at least one and perhaps two outlying points, the Demand Frontier in Figure 3 has a lower correlation than that in Figure 2. And, even though the Aggregate Demand has a very good R^2, we once again speculate that we may get improved results with another technique.

We introduce an approximation of Fibonacci spacing in Figure 4. It has the best outcomes concerning both the market Aggregate Demand and the Demand Frontier. It is important to note, though, that while that this technique works best for this market, it won't necessarily describe all markets equally well. Hence, the use of the other methods for options to find the best possible outcome.

Note that the Demand Frontier and market Aggregate Demand, while closely related, work to portray different phenomena. The Demand Frontier, as the line of best fit through the rightmost and uppermost points in each bin, attempts to describe the limiting sales quantities along it. As such, there will necessarily be one or more points "beyond" the line or to the right of it, as the right- hand side of Figure 4 shows. The standard errors of Demand Frontiers yield the "fuzz" or potential dispersion of this Frontier; higher Demand Frontier standard errors reveal a fuzzier market limit than Demand Frontier equations with lower standard errors.

Figure 2: Regression of the points in **equally spaced** bins with respect to price results in this red market aggregate curve. With most of the points in lowest bin, the default "demand frontier" does not account for a pair of points beyond it, making us want to approach the same data with another method.

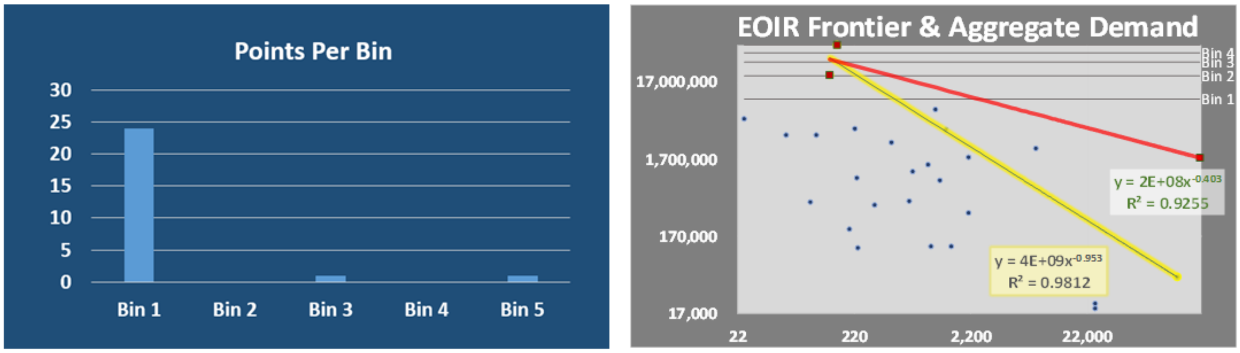


Figure 3: **Geometrically spaced** bins with respect to price form the red market aggregate curve. This method permits us to get representative points along what appears to be the demand frontier, but we might wonder if we can get a better correlation with yet another method.

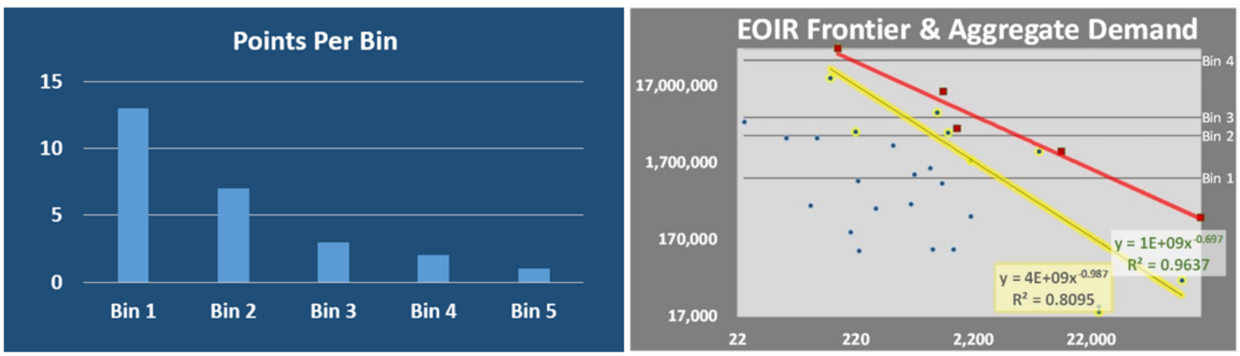
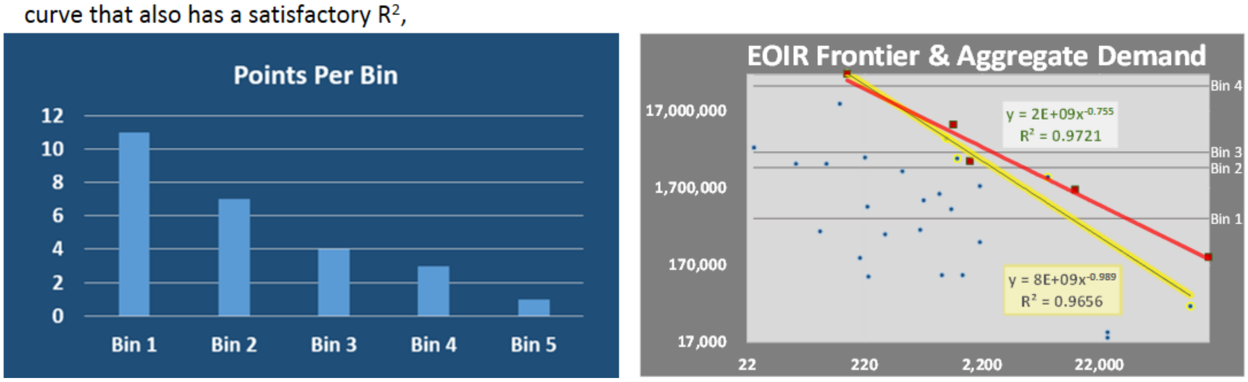


Figure 4: Bins created with **Fibonacci spacing** result in the red market aggregate curve. This method permits us to get representative points along a highly-correlated demand frontier, with an attendant aggregate demand curve that also has a satisfactory R^2,

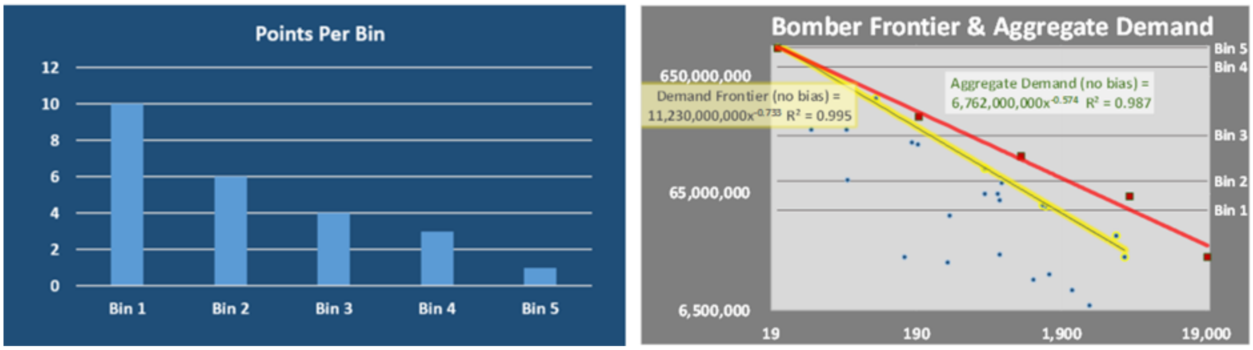


Market Aggregate Demand is different, in that it collects revenue from bins and compares them to one another. Markets with Aggregate Demand curves with slopes less than -1 have more revenue towards their upper ends, while those with exponents greater than -1 have more revenue in the lower priced regions. In government programs, where profits tie to revenues, both demand curves have important ramifications for profitability and sales potential, as we will observe presently.

2.0 Price Responsiveness and Limit Enforcement

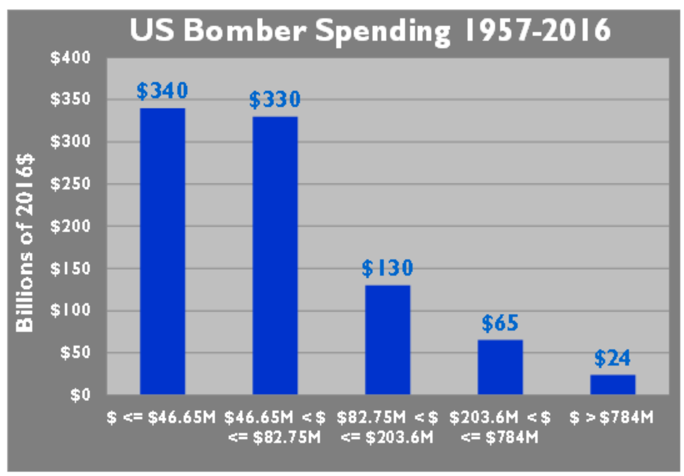
We can do some more work on the data supporting Figure 1B above in Figure 5 below (the market for fighters, bombers and attack aircraft, found in Appendix B). Here, using the Fibonacci method, we find a highly correlated market Aggregate Demand curve, one correlated to 98.7%, a standard error of $28.7 million and with a P-value of 0.07%. At the same time, we find the Demand Frontier correlated to 99.5%, with a standard error of $33.5 million and P-value of 6.79E-07. What do these curves have to say about price responsiveness and demand limits, respectively?

Figure 5: The market for fighters, bombers and attack aircraft responds well to bins created with **Fibonacci spacing** as displayed by the red market aggregate curve. The Demand Frontier has an even better correlation. Both curves had bias removed using the Ping Factor.[3]



We can see the ramifications of the relatively flat market Aggregate Demand curve from Figure 5 (with its exponent at -0.733) more clearly in Figure 6. Notice while the lowest priced bin has the most revenue, the next one up concerning price limits has nearly as much money in it. The two lowest-priced bins have over three times the revenue than the three highest-priced bins have. Those working for the United States Government in this market will find their profits largely tied directly to revenues. Based on this example, it makes sense to keep costs low, as it forces revenues and profits higher.

Figure 6: US spending on fighters, bombers and attack aircraft concentrates to the lower-priced vehicles, as it has for the last 60 years.



The full force of the Demand Frontier hit the B-2 bomber hard. Originally targeted to produce 165 units, the United States Air Force (USAF) eventually settled for 21.[4] Much the same phenomenon happened for them concerning their F-22 fighter: they originally thought they might be able to afford 750 of them but ended settling for less than 200 of them.[5] Now they seem to be headed down the same path with two ongoing programs, the Lockheed Martin F-35A fighter and the Northrop Grumman B-21 bomber, as we can see in Figures 7 and 8.

Figure 7: The USAF had an untenable F-35A position in 1996. It is only slightly better now.

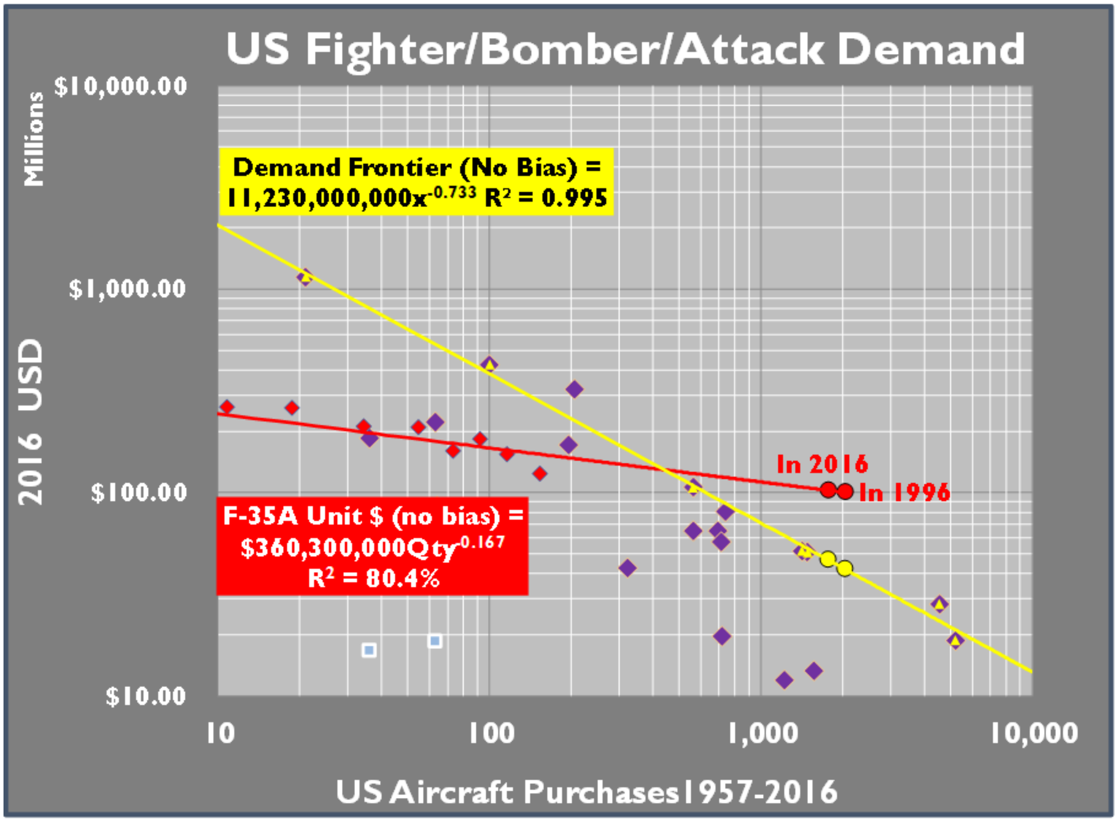


Figure 8: The USAF targets 100 B-21s at a price not supported by the Demand Frontier.

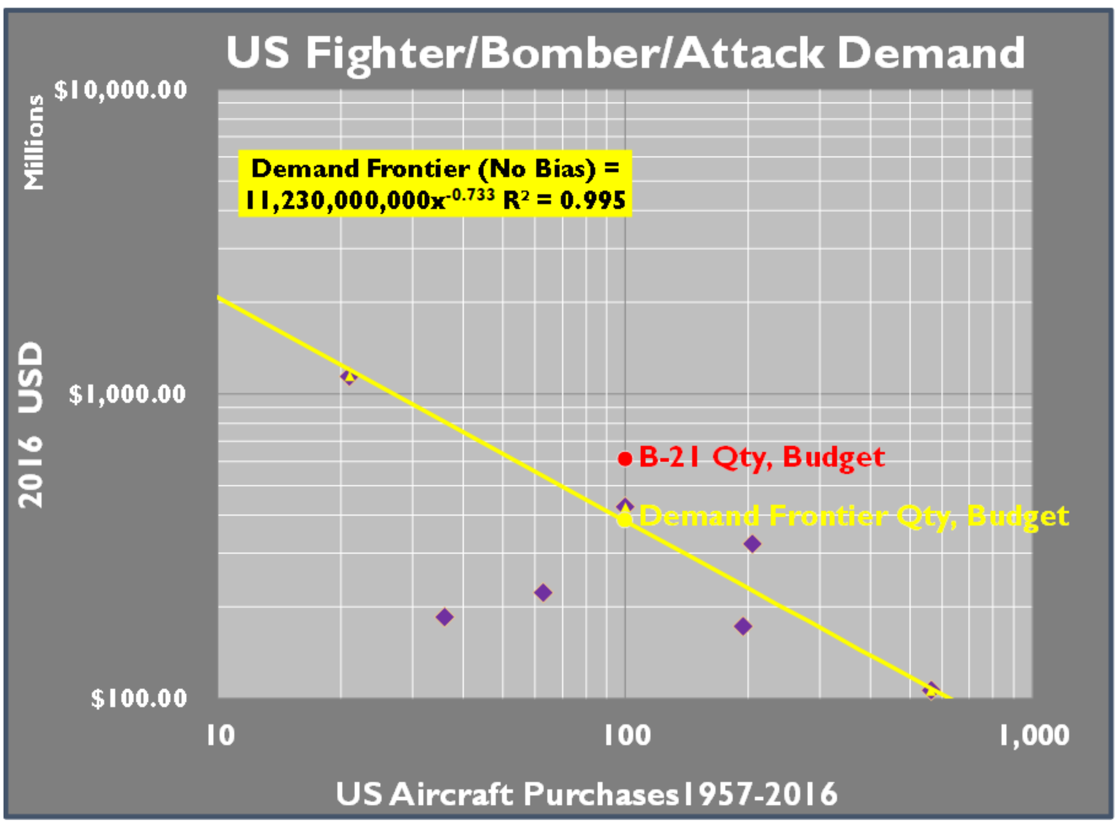


Figure 7 reveals the F-35A production history as a series red diamonds, representing the lot midpoints and average prices. The best fit curve through it, indicated in Figure 7, has an R^2 of 80.4%, a standard error of $28.5 million and a P-value of 0.04%. We solve for where the Demand Frontier intersects the F-35A learning curve:

$$360{,}300{,}000 * Qty^{-0.167} = 11{,}230{,}000{,}000 * Qty^{-0.733}$$
$$0.0320837 = Qty^{-0.566}$$
$$\ln(0.0320837) = -0.566 * \ln(Qty)$$
$$6.07669 = \ln(Qty)$$
$$436 = Qty$$

The quantity above represents where the two lines cross. However, note we derive the Demand Frontier from points on either side of it. Thus, there is a probability that the F-35A can meet its production goals. As shown in Figure 7, the program goals for it were 2036 in 1996, and 1763 in 2016. Recalling that the standard error for the Demand Frontier is $33.5 million, solving for the projected F-35A costs and the attendant Demand Frontier values at those points, we find this:

Table 1: The USAF's chances of making its revised F-35A sales goal have improved slightly.

Year	Sales Goal	Frontier $	F-35A $	Difference	Std. Devs.
1996	2036	$42,200,000	$100,900,000	$58,700,000	1.8
2016	1763	$46,900,000	$103,400,000	$56,500,000	1.7

By similar analysis, in Figure 8, using the Demand Frontier, we can find that supportable price for 100 units of the B-21 is $384 million, meaning that the USAF is 6.7 standard deviations away from its true target price. Using the same process as above, one can find that despite the USAF's stated need for 100 B-21s[7], the market limiting quantity of B-21s[7] at $610 million in 2016$[8] is 53.

Thus, the barrier formed by the Demand Frontier has deep meaning for military planners and new aircraft designers alike. If a program manager wanted to have as few as ten units and were willing to spend the Demand Frontier limiting price for it, that price would be $2.08 billion a copy, while the recurring unit revenue would be $20.8 billion as shown in Figure 9. Conversely, as revealed in Figure 10, a program wanting 5,000 units could at the Demand Frontier afford a price of $21.8 million each, with a resulting revenue of $109 billion. There is more money at the lower end of this market that at the upper end. Also, on the left-hand side of Figure 5 points out, there are many more models in the lowest price bin (ten) as compared to the highest price bin (one).

In discovering the Demand Frontier, some may bristle at the use of the B-2, as it lies well beyond the rest of the range of the data. As Figure 10 depicts, though, we still get a highly correlated Demand Frontier without it, one not dramatically different than the one with it. It seems more useful to keep the B-2 in the analysis from a couple of standpoints. First, it was built and well-documented; few analysts dispute the costs associated with it. Second, with the advent of the B-21, the B-2 data serves as a useful metric to bound the problem of estimating it. Without the B-2 data, estimates of the B-21 may consist of extrapolations, which we would like to avoid.

Figure 9: The Demand Frontier limits affect total possible revenue and profits.

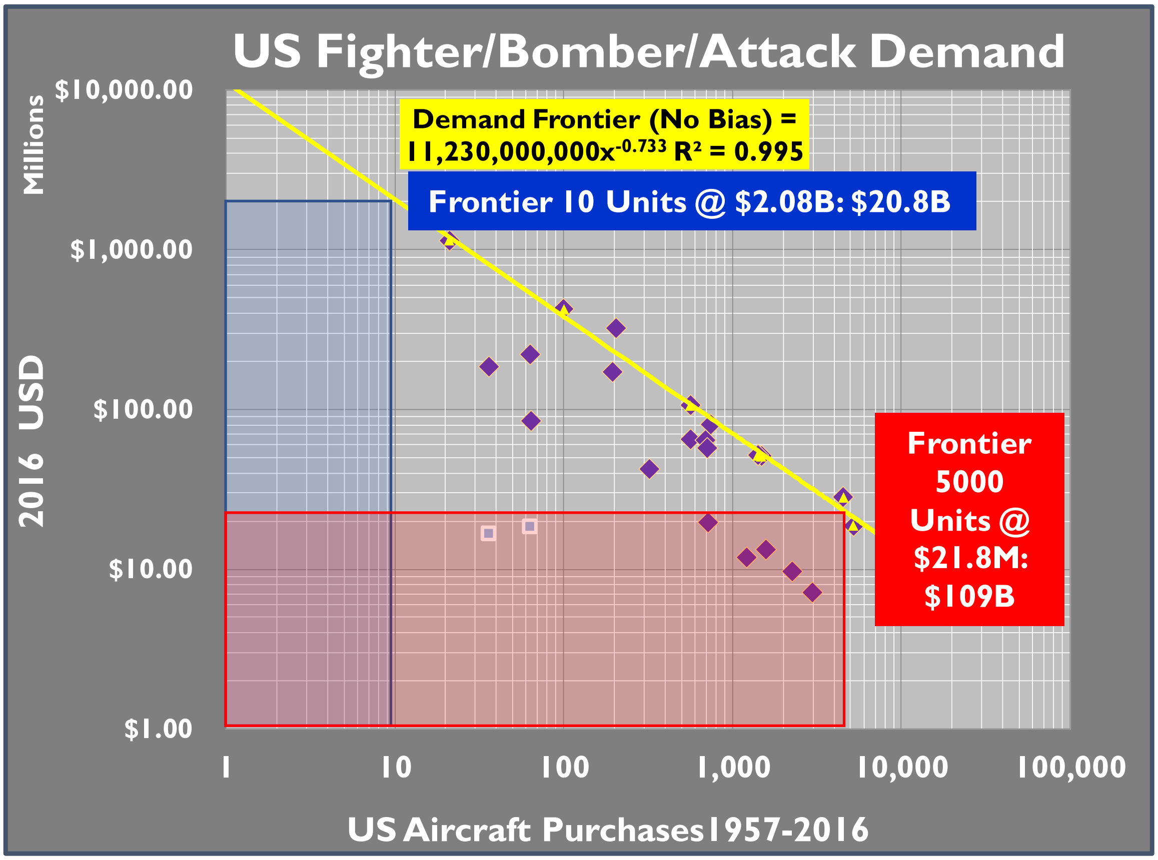
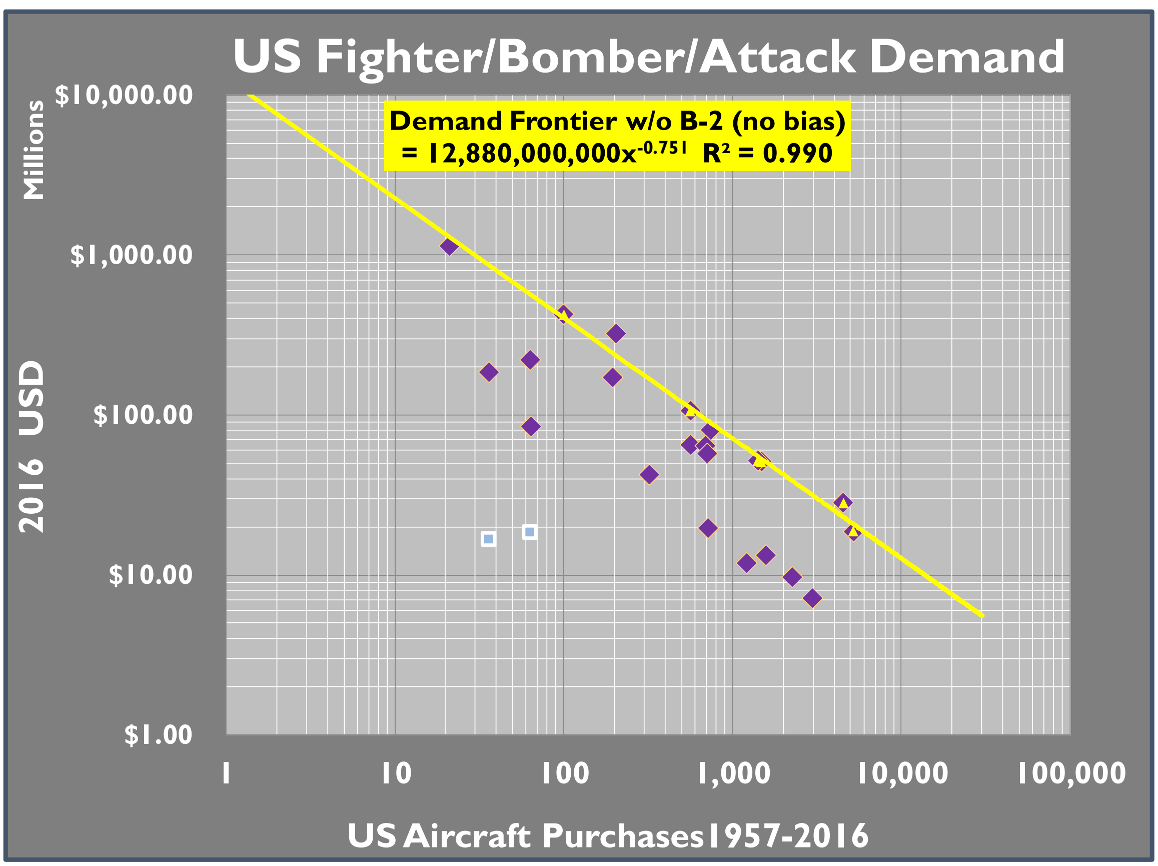


Figure 10: Removing the B-2 from the mix still produces a similar and highly significant curve.



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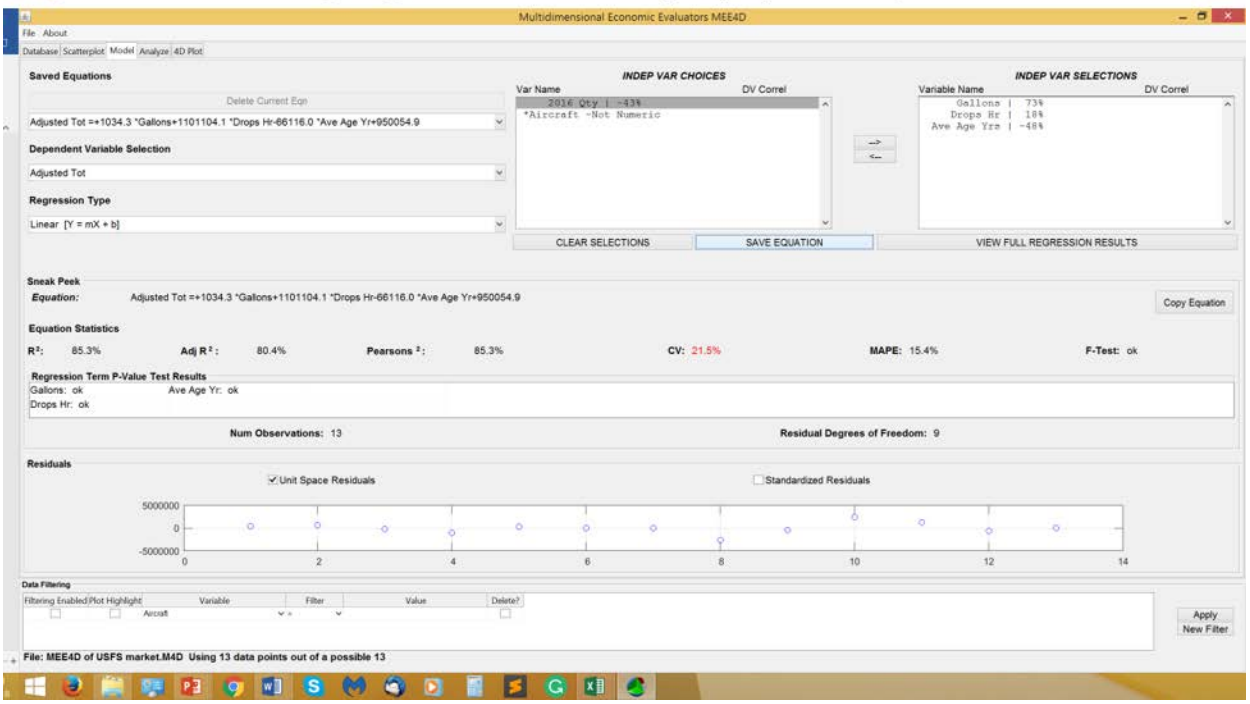
3.0 Working with the Demand Frontier

The United States Forest Service (USFS) pays several contractors annually to fight fires from the air, as shown in Appendix C.[9] Even though collectively they form a small database, they offer some statistically significant observations that may be used to optimize profits.

If we use annual price for a firefighting aircraft model to the USFS as a dependent variable, we find that the price is a linear function as shown in Figure 11. Figure 11 reveals that after paying an initial price of $950,000 per aircraft (the constant), the USFS paid $1,034 for each gallon (a measure of capacity). It also paid $1.1 million for each drop a model could do from a water source ten nautical miles away (a speed variable). Also, it reduced how it would pay for a given model $66K for each added year the models had been in service (a measure of reliability, older planes are less reliable).

Figure 11: Value in fire fighting aircraft is based on capacity, speed and age.



Suppose now that we have a new model to bring to USFS. With a capacity of 2,500 gallons, the ability to perform 6.9 drops per hour from water sources ten nautical miles from the fire and given that they are very new (0.1 years old), each model in service is worth $11.1 million to the USFS for one year, as we see in Figure 12.

Figure 13 shows the value of new firefighting aircraft at left, those that are 40 years old at right. Note the value surface in the left-hand part of Figure 13 is higher, further up the currency axis, meaning newer planes are worth more than older ones, due to their reliability.

As we see in Figure 14, this becomes a very good deal for the USFS. They get to have this highly capable, new model at over $3.5 million less than its demonstrated value. But what does this mean to the seller?

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Figure 12: At least three independent variables figure into the value of firefighting aircraft.

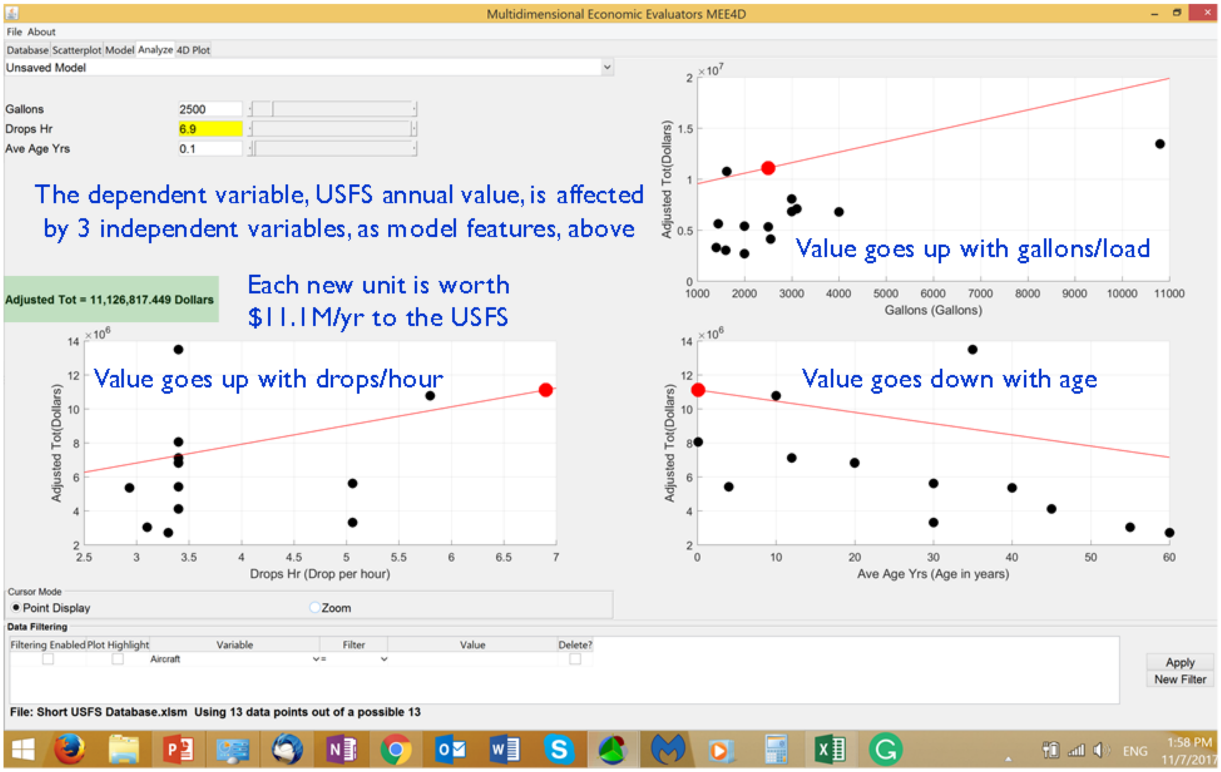


Figure 13: We can portray firefighting aircraft in two views of a 3D Value Space.

This is the value of a new model

Here's the value of a 40 yr old model

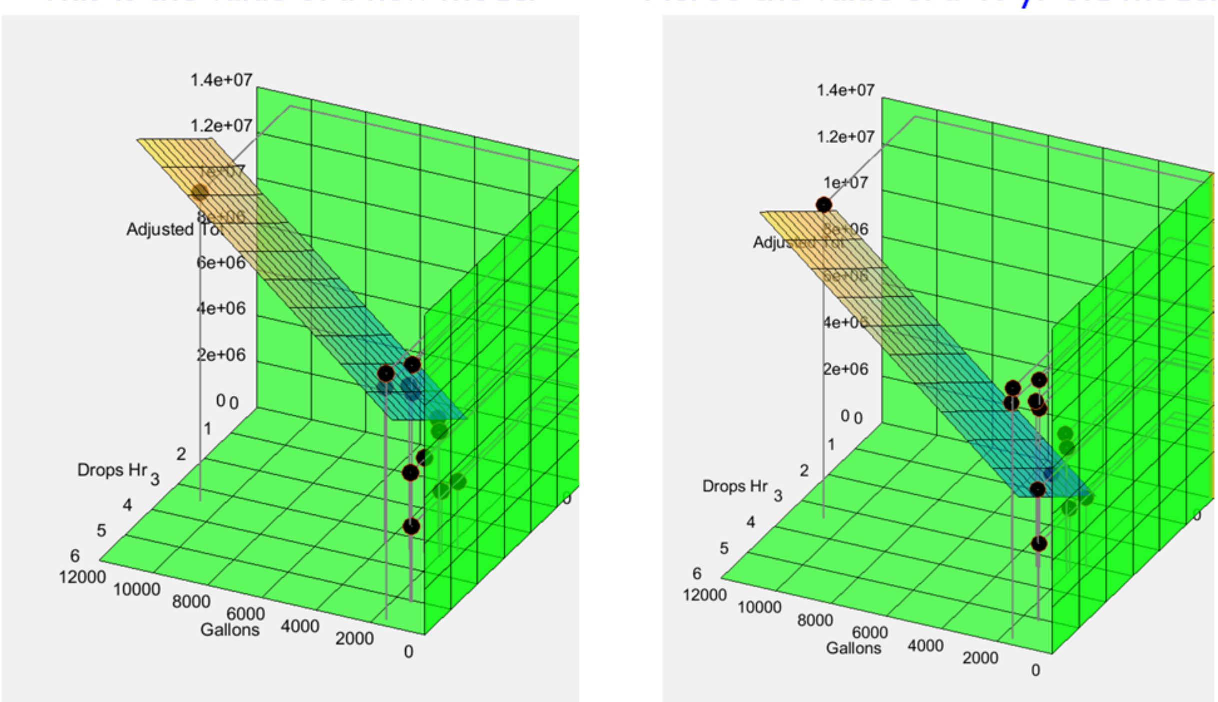


Figure 14: Selling a service for less than its value makes it more attractive to its buyers.

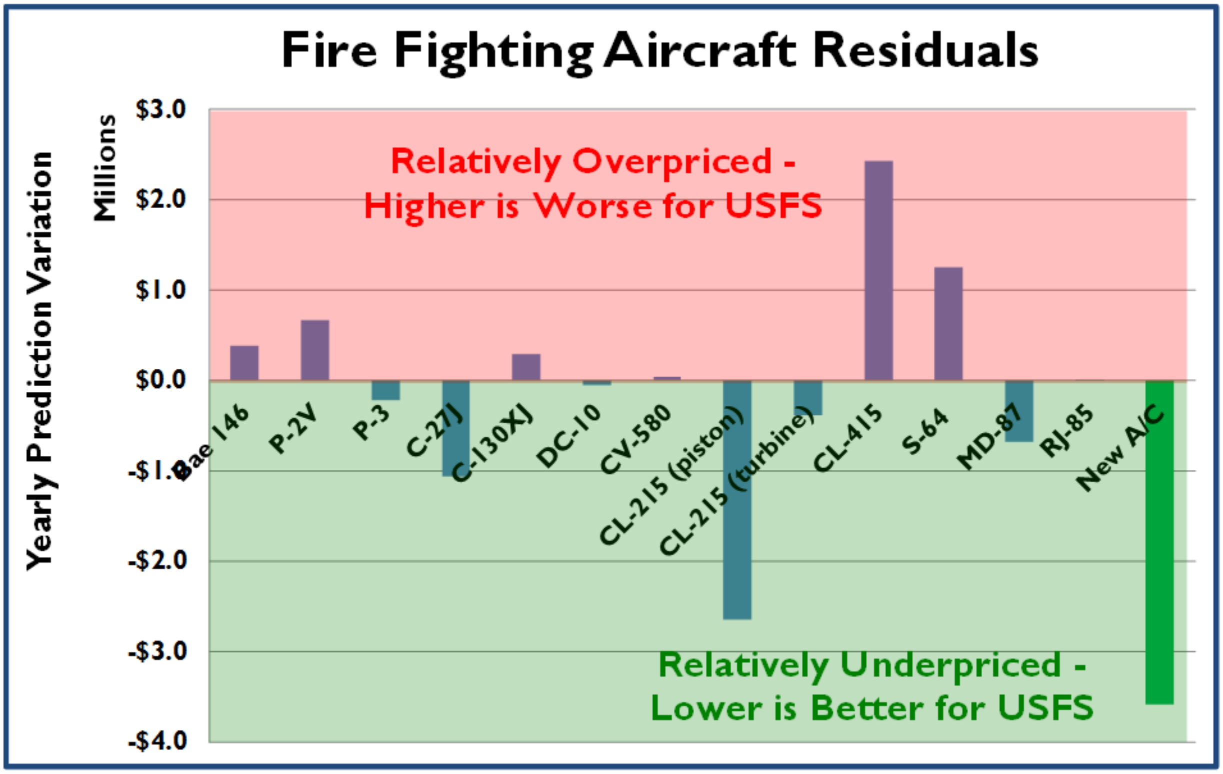


Figure 15: The seller makes more revenue at the lower price, profits depend on his marginal costs.

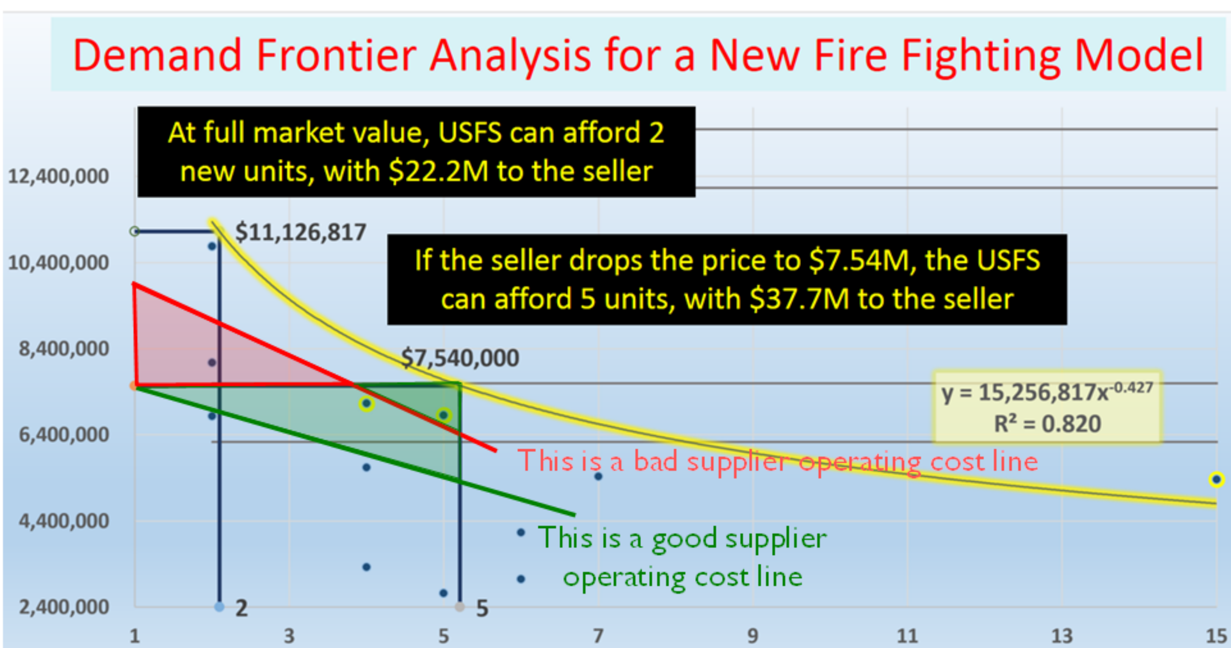
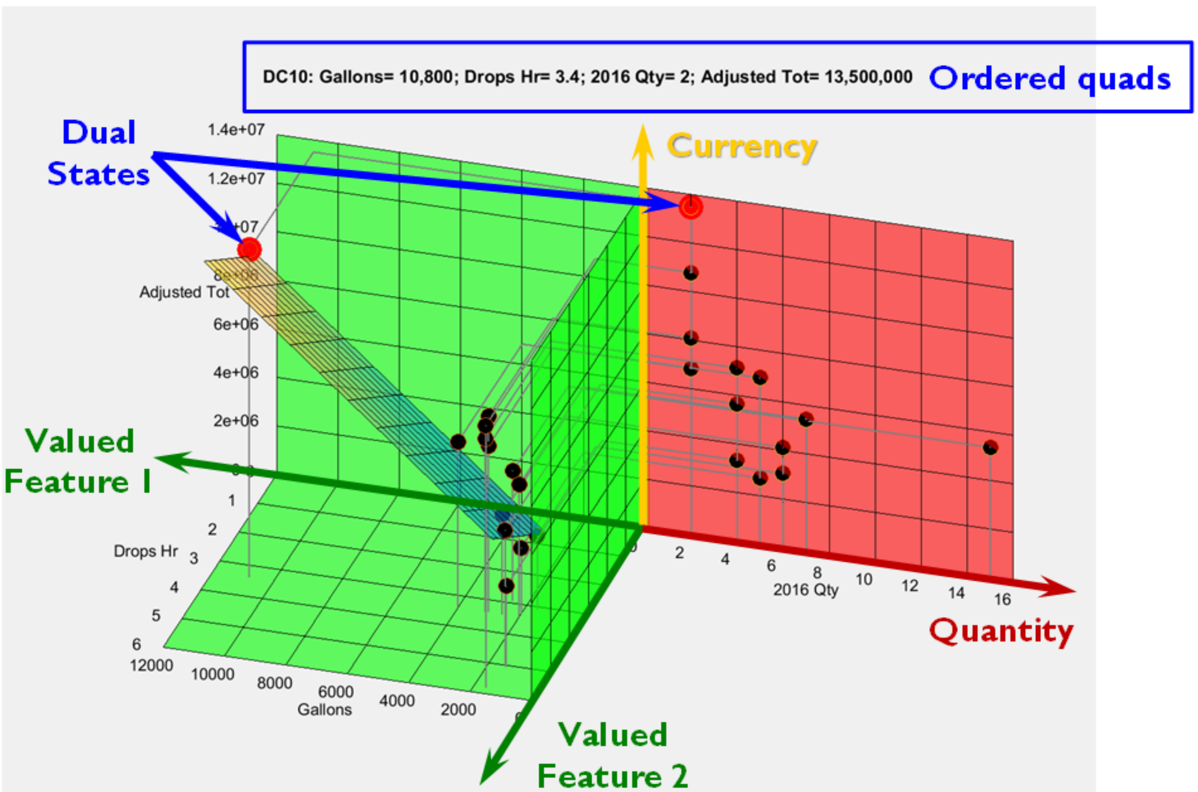


Figure 15 shows us that the seller can make much more revenue by dropping the price, selling the services of five units instead of two. The profits to the seller thus become a function of the seller's marginal costs, which might add profits with additional units. The seller must test for this. If the seller's costs match the red line, he or she loses money on the first four aircraft he puts in service, only making money on the last one, but experiences a net loss. If instead, the supplier found that the green line matched costs, the program becomes profitable on balance.

Since the 2D Demand Plane and the 3D Value Space share a common currency axis, that means they abut one another to form a 4D system as shown in Figure 16. All markets work in this way.

Figure 16: All markets work with Value Spaces abutting Demand Planes, in linked dual states.



4.0 Summary

Demand limits exist for military and other government programs. Studying the properties of the market Aggregate Demand and the associated Demand Frontier is especially important for estimators. Too often suppliers have made little or no attempt to understand these limits and have lost money in the process. For US government projects, the government makes the data required to do such analyses available to the public; as such estimators can acquire and decode it to provide important market relationships at every level in every program. Consistent application of the techniques offered above will help reduce large quantity reductions which, despite their regularity, seem to come as a surprise to all concerned parties every time.

References:

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9. USFS data provided by the customer, who will go unnamed here.

Appendix A: Defense Electronics (Electro-Optical/Infrared, or EO/IR) Database (flyaway cost, in 2016$)

Model	Price	Qty		Model	Price	Qty
AN/ALE-55	$19,500	25,682		AN/AES-1	$3,500,000	57
AN/ALQ-214	$4,230,000	222		ADM-141	$211,000	200
AN/USQ-113	$470,000	92		AN/APR-48A	$430,000	330
AN/ALQ-212	$1,800,000	2,103		BOL 510	$120,000	236
AN/ALE-47	$50,000	130,000		ADM-160B	$125,000	1,500
AN/ALQ-144	$2,370,000	8,000		ADM-160C	$125,000	1,000
AN/AAR-57	$340,000	2,100		AN/ALE-50	$22,800	25,682
AN/ALR-56	$900,000	1,200		ALQ-184	$1,440,000	950
AN/ALQ-218	$21,190,000	135		AN/ALR-67	$1,180,000	700
AAQ-24(V)	$52,000,000	156		AN/ALR-69	$980,000	231
AN/ALQ-131	$4,140,000	1,350		AN/AQS-22	$3,500,000	104
AN/ALQ-135	$7,510,000	1,092		AN/APG-79	$2,800,000	461
AN/ALQ-162	$490,000	650		AN/AQS-20	$5,700,000	25

Appendix B: Bombers, Fighters and Attack Aircraft (flyaway cost, in 2016$)

Model	16 Unit Fly $	TQty		Model	16 Unit Fly $	TQty
B-52H	80,200,000	740		F-14	57,100,000	712
B-1B	424,600,000	100		F-111	106,000,000	563
AV-8B	42,400,000	323		F-4	18,700,000	5,195
F/A-18A-D	50,900,000	1,480		A-7	13,300,000	1,569
F/A-18E/F	64,900,000	563		F-8	11,900,000	1,219
F-15A-E	51,600,000	1,415		A-4	7,200,000	2,960
F-117A	85,300,000	64		F-5	9,700,000	2,246
F-16C/D	28,200,000	4,540		F-35A	177,347,691	177
F-22	171,900,000	195		F-35B	229,726,553	36
B-2	1,143,400,000	21		F-35C	229,726,553	63
A-6	64,600,000	693		MQ-9	16,700,000	313
A-10	19,600,000	716		MQ-1	18,600,000	158

Appendix C: United States Forest Service Large Airtankers (annual cost per plane, in 2013$)

Model	$/season/unit	Gallons/drop	Drops/hr from 10	Ave. Age (Years)	2013 Qty
Bae 146	$6,855,000	3,000	3.4	20	5
P2V	$3,050,000	1,600	3.1	55	6
P3	$4,134,000	2,550	3.4	45	6
C27J	$5,432,000	2,000	3.4	4	7
C130XJ	$8,078,000	3,000	3.4	0.1	2
DC10	$13,500,000	10,800	3.4	35	2
CV580	$2,725,000	2,000	3.3	60	5
CL215 piston	$3,331,000	1,400	5.1	30	4
CL215 turbine	$5,640,000	1,440	5.1	30	4
CL415	$10,780,000	1,620	5.8	10	2
S64	$5,365,000	2,500	2.9	40	15
MD87	$6,831,000	4,000	3.4	20	2
RJ85	$7,126,000	3,110	3.4	12	4