

Variance explained by IQ

Claim:

[IQ] explains at best between 2 and 13% of the performance in some tasks

I already have prepared the <u>WLS</u> data set <u>here</u>, and it has a good IQ test, so I will use that. Lets look at the regression of grades on IQ.

- imports
- regression

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-0.0053	0.00818	-0.648	0.517	
iq_std	0.595	0.00816	73	0	

Fitting linear model: grades_std ~ ig_std

Observations	Residual Std. Error	R^2	Adjusted R^2
9624	0.802	0.356	0.356

The adjusted R^2 is 0.356, so IQ explains ~35% of the variance of grades in this data set. Taleb defenders may say that things such as school grades don't matter in real life. But whatever your position on this, the situation is that he made a specific claim about how much IQ explains *at best*, which was off by a large factor.

IQ selection vs random selection

Claim:

Turns out IQ beats random selection in the best of applications by less than 6%

He hasn't specified what exactly he means by this. But I'm pretty sure he is thinking of a comparison like the one he talks about in this tweet:



QUIZ DU JOUR (very very simple)

IQ is said to correlate at .5 with performance. You hire an employee with above average IQ. What is the probability of above average performance?

What is the probability if there were 0 correlation with performance?

Assume Normal distr. 7:57 AM · 09 Jan 19

So I will analyze something this, a stylized example with assumptions similar to these. In the real world, you will likely have other information that complicates this picture, such as education credentials; but we ignore that for now.

I create two normally distributed variables, with correlation 0.5, and call them IQ and performance.

create variables

cor	n	mean_IQ	sd_IQ	mean_performance	sd_performance
0.5	1e+08	3.16e-06	1	0.000102	1

The probability of hiring an employee with above average performance, if you hire an employee with above average IQ is:

above_average_iq <- df %>% filter(IQ > 0)

nrow(above_average_iq %>% filter(performance > 0)) / nrow(above_average_iq)

0.667

The probability if there was 0 correlation is of course 0.5. So using IQ as a criteria beats random selection by 16.67% (as Taleb also found). This is a little more than 6%, but that is a detail. More importantly, this example is a theoretical use case where using IQ testing is not so useful. To look at something a little more realistic, let's say a company wants to avoid people with a performance more than 2 standard deviations below the mean. (Perhaps such employees have a risk of causing large harm, which could for instance be an issue in <u>the military</u>.) And we again compare admitting people at random vs only taking applicants with above average IQ.

If the company admits people at random, we get this proportion of people with a performance more than 2 SD below the mean:

```
bad_performance_w_random_selection <-
nrow(filter(df, performance < -2)) / n</pre>
```

bad_performance_w_random_selection

0.0228

And if the company only takes applicants with above average IQ, we get this proportion of people with a performance more than 2 SD below the mean:

```
bad_performance_w_iq_criteria <-
nrow(filter(above_average_iq, performance < -2)) /
nrow(above_average_iq)</pre>
```

```
bad_performance_w_iq_criteria
```

0.00406

This is an improvement by a factor of:

bad_performance_w_random_selection / bad_performance_w_iq_criteria

5.6

jsmp: Taleb is wrong about IQ

In other words, using IQ selection criteria in this case beats random selection by more than 450%. Quite different than the claimed 6%.

IQ and income

Claim:

There is no correlation IQ/Income above 45K

He makes this claim based on this image:



There is no correlation IQ/Income above 45K (Assume 2007 \$s). Even in situations

The image is from <u>this paper</u>, which gets its data from <u>NLSY79</u>. This data is also public, so we can again check for ourselves. Description of the preprocessing I perform is described here.

▶ read nlsy

n 8232

The plot looks similar to the one from the paper, but somewhat different, because I use the average income values for a period of 10 years, instead of that from a single year.

▶ plot



As in the plot used by Taleb it's quite hard to see whats going on with all the overlying points. Reducing the transparency helps somewhat.



plot with reduced transparency

If we look at only incomes above \$45.000 per year, there is still a clear correlation of about 0.3.

▶ plot



Another way to make the relationship clearer is to plot the distribution of income for seperate IQ groups. Plotting the distribution avoids the issue of the plot becoming unclear and confusing due to overlapping points.

The plot below again plots only people with income above \$45k per year. The difference IQ makes is clear, both in the median value, and the length of the tails.



▶ plot

IQ and fat tails

[The income data] truncates the big upside, so we not even seeing the effect of fat tails

It is correct that in the presence of fat tails the correlation is uninformational in predicting expected income. And the data from these studies does not give good information about such tails. However, it is highly possible that the effect of IQ is even more impactful in the tails, rather than less. For example, Bill Gates and Paul Allen scores 1590/1600 on their SATs, which for SATs at that time meant extremely high IQs. Since Bill Gates is also in the tail of wealth and income, this indicates that the overall impact of people in the tails is to accentuate rather than diminish the importance of IQ.

Correlation only for low IQ

IQ mostly measures extreme unintelligence

He claims that IQ has high correlation with traits at low IQ, but that this correlation falls drastically at above median IQ, as illustrated in this figure from the post:



(Edit: In case this is not clear, Taleb uses the above figure as an illustration, not as a precise empirical claim.) It's quite easy to look into the data to see whether this actually is the case. We can use the same two data sets used above.

If we plot IQ vs log(income), that will tell us how large a percentage increase in income each extra IQ point gives. Then we can plot a local regression (loess) and compare that to a linear regression. If the relationship between IQ and income radically diminished at above average IQ, then we would expect the loess regression line to approach horizontal. However, this is not what we see - instead the two regression lines follow each other quite closely. It is true that the percentage increase in income per IQ point is a little higher for lower IQs, but it never stagnates.



The regression results show that each IQ point increases log(income) by about 0.025

▶ regression

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	7.8	0.0606	129	0	
iq	0.0254	0.000603	42.1	0	

Fitting linear model: log_income ~ iq

Observations	Residual Std. Error	R^2	Adjusted R^2
8232	0.831	0.177	0.177

which means an increase in income of:

- ► calculation
- 2.57

percent for each IQ point.

An alternative illustration is shown below, using the WLS grade-IQ relationship:



We see clearly that the above 100 IQ line has a slope that is not horizontal, meaning IQ correlates with grades even at higher than median IQ. In fact the slope is about the same as that for the regression line of students with below median IQ.

In a third illustration, we can look at the distributions of incomes for high, low and median IQs. Both increases in IQ moves the median of the income distribution and enlarges the tail.



▶ plot

Conclusion

All the claims from the article that I looked at, that can be interpreted as something specific and tested in a real data set, turned out not to be correct. If Taleb hadn't blocked everyone who disagrees with him, perhaps he would have found out about this, and not published a post with all these incorrect claims.