Examining the Blavatskyy Hypothesis:
Obesity and Corruption in the Former USSR

Logan Cooper

ECON 627: Soviet Economic History

Professor Charlie Becker

December 8, 2021

1. Introduction

Corruption is a tricky thing to quantify. Most studies of corruption (including this one) rely at least to some extent on subjective surveys of how corrupt people think their country is. These surveys are almost always conducted by foreign experts, and are vulnerable to a variety of problems. There may be a gap between the average person's perception of corruption and the actual incidence of it (Donchev & Ujhelyi, 2014). Additionally, if corruption is thought of as a vector of many different factors, aggregated measures of corruption may abstract away large differences in the corruption of individual institutions, e.g., corrupt police but strong courts (Reinikka & Svenson, 2006). Even cultural differences over what *exactly* constitutes corruption can play a role in distorting the accuracy of subjective measures (Bardhan 2006; Wei 1999).

These problems have led to a literature around alternative methods to measure corruption. At the micro level, this has included things like comparing records of earnings to self-reported assets (Gorodnichenko & Peter 2007). For larger scale corruption at the level of major officials, we have seen attempts to use observations of the leaders themselves: for example identifying expensive Swiss watches on the wrists of Chinese Communist Party officials (Lan & Li 2018).

One attempt in the same vein of Lan and Li comes from Blavatskyy (2021) and has gained some notoriety. His idea is that the average Body Mass Index (BMI) of cabinet-level officials could be a way to measure corruption in a country. The (implied) causal pathway there is that ministers lining their own pockets with government money or taking bribes to make make or ignore laws will have more money to spend on fattening things like banquets, high-class restaurants, and alcohol. The BMI of ministers can be estimated from photographs with the help of a computer vision algorithm developed by Kocabey et al. (2017). Blavatskyy's paper does end up concluding that there is a positive correlation between subjective corruption indices and the median BMI of cabinet ministers in countries of the former Soviet Union.

As intriguing of an idea as this is, Blavatskyy's paper is far from perfect. It lacks controls for several attributes of leaders which are known to correlate with BMI, such as age and gender (Masood & Reidpath, 2017; Reas et al., 2001). Without these controls, it is impossible to determine whether we are actually seeing more corrupt countries having heavier leaders, or whether some other variable is

at play. For example, it could easily be that the leaders of more corrupt countries tend to stay in power for longer, leading to older – and possibly heavier – leaders.
Despite this risk of omitted variable bias, a follow-up study (Blavatskyy, 2021 b.) suggests that this model does have some external validity, as the median BMI of Ukrainian leaders tracks the subjective corruption indices closely from 2000-2020.

In short, the goal of this paper is to examine the internal validity of "Obesity of politicians and corruption in post-Soviet countries." This will involve reproducing Blavatskyy's results, examining the correlation of several possible omitted variables, and finally constructing a model to try and correct for those variables. We will do this over the course of the following sections. Section two describes the data sets, both those used in the original paper and those that I have gathered independently. Section three details the methodology used to test Blavatskyy's hypothesis. Section four examines the results of those tests, and section five concludes.

2. Data

As there are several steps to this process, there are also several datasets which will be used to accomplish this paper's goal. First of all, I will be using Blavatskyy's original set of "frontal face images of cabinet ministers from 15 post-Soviet states who were in office in 2017" (2021 a.) and running them through his exact code (based on Kocabey et al. 2017) to derive their BMI estimates.

For both sets of images, we also gather some additional information about the leaders pictured for controls. We hand-classify the leaders as male or female, and find as many of their dates of birth as possible to determine their ages as of 2017. This means that we have age data for most politicians in all of the countries except Tajikistan, where only two politicians had publicly available dates of birth.

We will also be bringing in three of the five corruption indicators used in the original paper:
1. Transparency International Corruption Perceptions Index
2. World Bank worldwide governance indicator 'Control of Corruption'
3. The sub-attribute 'Absence of Corruption' of Global State of Democracy Index
4. European Research Centre for Anti-Corruption and State-Building Index of Public Integrity
5. Basel Anti-Money Laundering Index

However, most of our results will only rely on the first three. For one, they are the only measures which include all the countries in the sample. Additionally, Blavatskyy's results focus on 1 and 2, so we will focus there as well.

One note on these measures: With the exception of the Basel Anti-Money Laundering Index, lower values on these measures mean more corruption. However, higher numbers on Basel indicate more corruption. While this is an odd quirk of the data, it makes sense that a lower ranking on the Index of Public Integrity would mean more corruption, while a lower ranking on an anti money laundering index would indicate less money laundering, and by extension less corruption. This is mentioned primarily for the interpretation of later results.

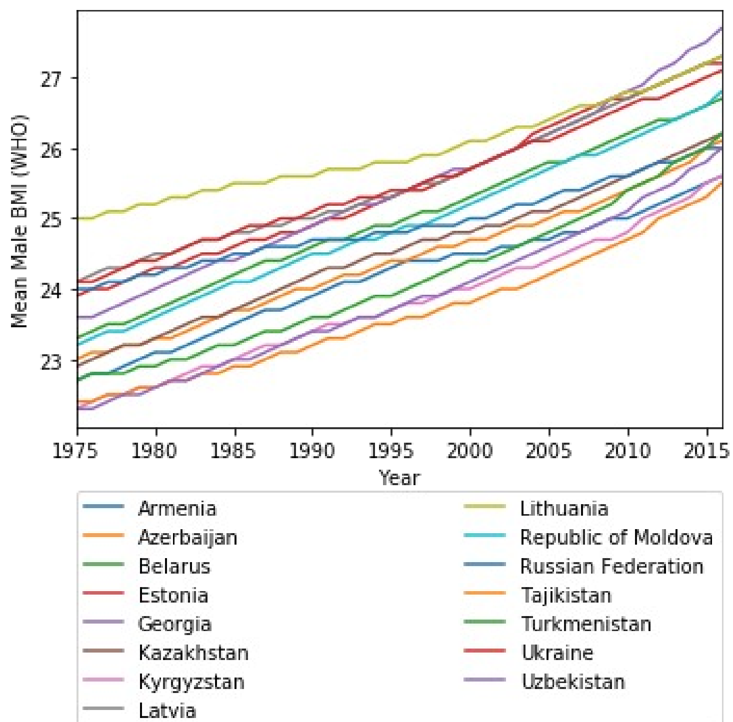

Figure 2.1: Mean Male BMI by country 1975-2016

For the first round of controls for sex, I will be using BMI data from the World Health Organization's Global Health Observatory which give us the mean BMI of each country in the sample, as well as the means for men and women. It is not available for 2017, so I am using 2016's data. For our first round of age controls, I am using mean age from the UN World Population Prospects. Once again, the data are not available for 2017, so I am using data from 2015. While these differences in year may introduce a slight distortion to our results, it is not likely to invalidate them. As we can see in figures 2.1 and 2.2, although BMI rises over time in each country in the sample, we do not see dramatic upticks in BMI from year to year in any country in the sample.

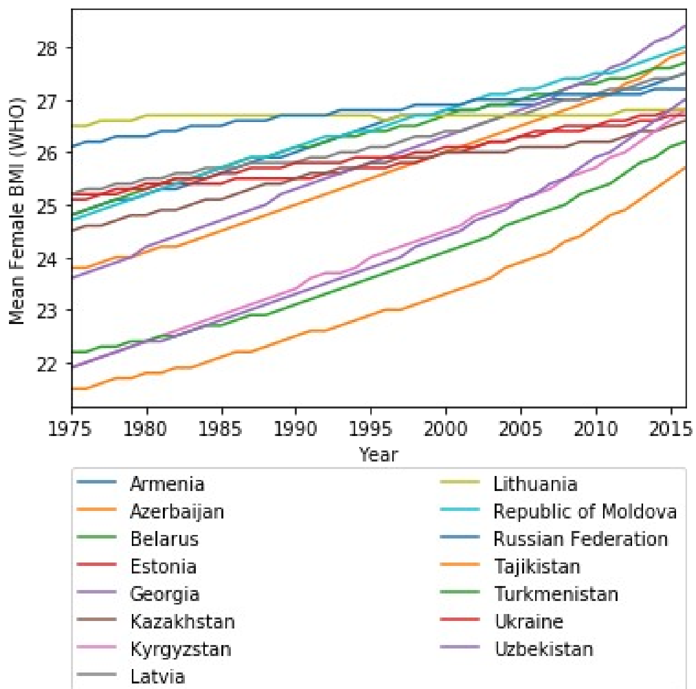

Fig. 2.2: Mean Female BMI by country 1975-2016

For our more advanced controls, I will be using data from the survey "Health in Times of Transition: Trends in Population Health and Health Policies in CIS countries" (HITT-CIS, or HITT for short). From here, I will be using data on the (self-reported) height, weight, sex, and age of 18,000 (16,943 after removing those with missing data) individuals from a subset of the former Soviet Union: Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, and Ukraine (Wallace & Haerpfer, 2010). Although this data set is somewhat older than our sample data, and from only part of the USSR (notably omitting the Baltic States), it will allow us to construct a rough picture of the relationship between age, sex, and BMI in the former USSR.

3. Methodology

The methodology for replicating Blavatskyy's work is the same as he puts forward in his paper:

> For each image in the dataset, the minister's body-mass index is estimated using the computer vision algorithm recently developed by Kocabey et al. (2017).4 This algorithm is a two-stage procedure. The first stage is a deep convolutional neural network VGG-Face developed by Parkhi, Vedaldi, and Zisserman (2015). This neural network extracts the features from a deep fully connected neuron layer *fc6* for the input image. The second stage is an epsilon support vector regression (Smola & Vapnik, 1997) of the extracted features to predict body-mass

> indexes of 3,368 training images (with known body-mass index values) collected by Kocabey et al. (2017).
> (2021)

Where this paper will differ is primarialy in the controls. Much of Blavatskyy's argument comes down to his observation that "[r]elatively less corrupt countries have slimmer politicians but more overweight voters." (2021) That is to say: the BMI of a country's people and that of its leaders are negatively correlated. However, the body mass indices of these leaders does not exist in a vacuum: it is affected by a variety of factors, notably their sex and age.

To initially control for sex differences, I will determine the sex ratio of leaders in each country and use those ratios to create a weighted average BMI for each country. I calculate this as follows:

$$(MenRatio \times MenBMI) + ((1 - MenRatio) \times WomenBMI)$$

I will then use linear regression to test whether or not the negative correlation holds up when I regress the median BMI of a country's leaders on our sex-adjusted BMI.

There is also evidence linking age and BMI (Masood & Reidpath, 2017; Reas et al., 2001), so controlling for age would also give us some insight into whether or not any link between BMI and corruption actually exists. It may be that more corrupt countries have older leaders. On a surface level, I will be checking if leader age is correlated with leader BMI and with the subjective corruption measures.

On a more advanced level, I will be using the HITT-CIS data to 'correct' leader BMI. To do this, I will be constructing a model for the effects of age and sex on BMI. After calculating the BMI of each person in the sample, I remove outliers. Here that means the handful of observations with a BMI > 50. These are relatively spread out across the age spectrum, but with a slight clustering in younger ages (< 30). The rationale behind removing these people is that these people are far outside the typical BMI range, so including them will distort our estimates away from what is typical. More specifically, the clustering of these people in younger ages will underestimate the effect of age on BMI.

After removing those outliers, I construct two models to attempt to correct leader BMI for age and sex. The simpler of these models is a two-variable OLS regression using age and sex (IsFemale is a binary variable 1 for female, 0 for male):

$$BMI = \alpha + \beta_0 Age + \beta_1 IsFemale + \epsilon$$

Our second model introduces an interaction effect: multiplying the dummy IsFemale variable by Age to account for any differences in how BMI varies with age between men and women. This regression will result in the following equation:

$$BMI = \alpha + \beta_0 Age + \beta_1 IsFemale + \beta_2 IsFemale \times Age + \epsilon$$

Once I have the regression coefficients from the HITT data, I will use them to normalize the BMI of each leader according to their sex and age. I will then attempt to reproduce Blavatskyy's results with both normalized BMIs.

There is one other difference in between this approach and that of Blavatskyy, and that is our choice of summary statistic. Blavatskyy's paper used the median of the ministers' estimated BMI. While we will use this approach to reproduce his results, most of the work in this paper will use the mean. The primary motivation for this is the fact that the WHO only reports mean BMI in its data, so using the mean instead of the median will sidestep a small weakness in Blavatskyy. However, as noted in the next section, these values are very close.

4. Results

4a. Reproducing Blavatskyy

In a nutshell, we can reliably reproduce Blavatskyy's results. While there are some minor discrepancies between the results we obtained from the BMI estimation process, those appear to be either the result of minor differences between the running environments, or rounding errors. In either case, they do not change the results (see fig. 3.1). While Blavatskyy does not report the exact coefficients for the correlations between BMI and the five corruption indicators, our results in fig. 3.2 match his graphs in both sign and (visually) in magnitude. It should be noted that the Basel Anti-Money Laundering Index is missing Belarus and Turkmenistan. The Index of Public Integrity is missing those two, as well as Armenia and Uzbekistan.

	Our Median BMI	Our Mean BMI	Blavatskyy's Median BMI
Estonia	28.8	30.4	28.7
Lithuania	30.3	31.8	30.3
Latvia	30.7	31.2	30.7
Georgia	31.0	32.2	30.9
Armenia	32.2	31.7	32.1
Russia	32.5	32.5	32.5
Moldova	32.8	33.2	32.7
Belarus	32.8	33,5	32.9
Azerbaijan	33.3	32.9	33.3
Kyrgyzstan	33.4	34.9	33.3
Tajikistan	33.5	33.1	33.6
Kazakhstan	33.7	34.3	33.8
Ukraine	34.5	33.6	34.4
Turkmenistan	34.6	34.9	34.7
Uzbekistan	35.5	35.0	35.5

Fig. 4.1: Our BMI results against Blavatskyy's

Measure	Coefficient	P-Value	R-Squared	Observations

World Bank Control of Corruption 2017	-0.4244	<0.001	0.835	15
Corruption Perceptions Index	-8.2239	<0.001	0.860	15
Basel Anti Money Laundering Index 2017	0.6202	0.011	0.612	13
IDEA Absence of Corruption 2017	-0.0948	<0.001	0.653	15
Index of Public Integrity 2017	-0.6270	<0.001	0.850	11

Fig. 4.2: Our regression coefficients of BMI on five corruption measures

4b. Sex

Our first control is for sex. As mentioned above, we construct a weighted BMI and use linear regression to get a more rigorous measure of correlation than Blavatskyy uses. Redoing Blavatskyy's regression using median estimated minister BMI as an independent variable and mean country BMI as a dependent variable, we get a regression coefficient of -0.1743. Although this does turn out to be just barely statistically significant (p=0.046), due to the small sample size and lack of causal pathway between the two variables, we can think of this coefficient as less of a predictor and more as vindication of Blavatskyy's claims that minister BMI and population BMI are negatively correlated (see fig. 4.3).

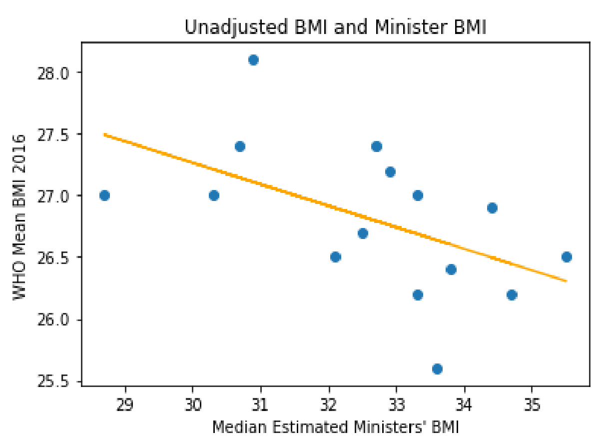

Fig. 4.3: Unadjusted BMI and Minister BMI

This relationship holds up when we control for sex. The regression coefficient of median estimated minister BMI on sex-adjusted BMI is -0.212109 (p=0.027). Once again, this coefficient should not be taken as explanatory, but it does vindicate Blavatskyy's hypothesis (see fig. 4.3). If this negative relationship remains after controlling for sex, we cannot reject the claim that "[r]elatively less corrupt countries have slimmer politicians but more overweight voters" (Blavatskyy 2021) with the claim that relatively less corrupt countries may have more women in government. This makes sense when we look at data from the WHO: despite women being shorter and lighter on average, many of the countries in our sample actually have higher BMIs for women then men. In Armenia, to bring out the most extreme of the examples, the mean BMI for women is 1.8 points higher than it is for men.

This is not a totally robust test, and there are possible confounding factors. Most notably, BMI may be correlated with sex among the ministers in the following way: thinner, more conventionally-attractive women may be more likely to succeed in politics. Although there is no literature on this from the Soviet Union, a paper by Roehling et al finds that "[o]verweight women, but not overweight men, were … underrepresented" in US Senate elections (2014). This may bias our results in the following way: lighter-than-average female politicians will bring down the BMI of the politicians in general, leading to a less negative relationship than we currently observe.

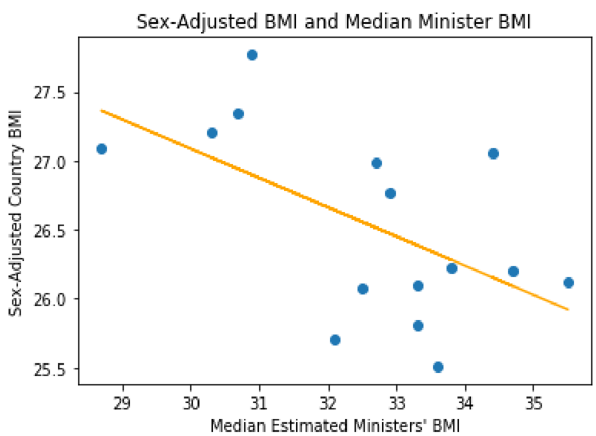

Fig. 4.4: Adjusted BMI and Minister BMI

4c. Age

A second factor that could influence BMI is age. The leaders of all fifteen countries in the sample are notably older than the average citizen, and BMI tends to be positively correlated with age (Masood & Reidpath, 2017; Reas et al., 2001). In short: people tend to put on weight as they age, but don't grow taller after a certain point. Before continuing, it should be noted that Tajikistan is omitted from this section, as we were unable to find data for the ages of almost all Tajik politicians.

The first question that arises here is if there is a correlation between the median minister BMI and their mean age, and there is. Regressing mean age on median minister BMI results in a coefficient of 1.3176, albeit with a p-value of 0.054. This means we cannot generalize this age-BMI effect, but it does tell us that the countries in the sample with older leaders are also those with heavier leaders (see fig. 4.5

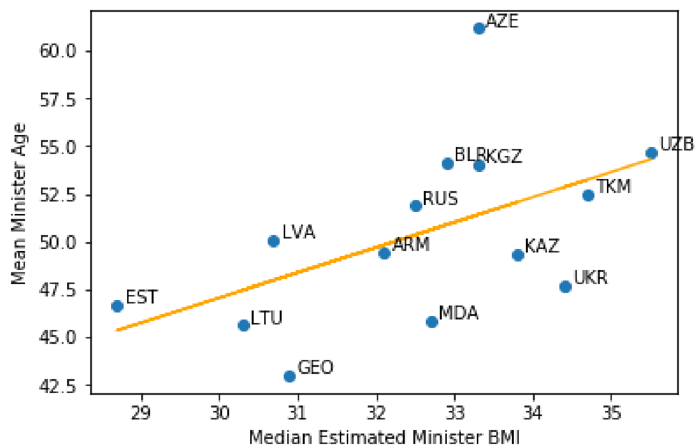

Fig. 4.5: Minister BMI and Age

Additionally, we find that the three measures of corruption encompassing every country in the sample are also correlated with leader age. The Corruption Perceptions Index (1.7456, p=0.057), Control of Corruption Index (-0.1010 p=0.032), and IDEA Absence of Corruption Index (-0.0297 p=0.007) are all correlated with the mean age of the leaders. If we can link age and BMI, this would cast major doubt on Blavatskyy's hypothesis, as there would be no way to tell apart countries with leaders who are heavy because they are old, and those who are heavy because they are corrupt.

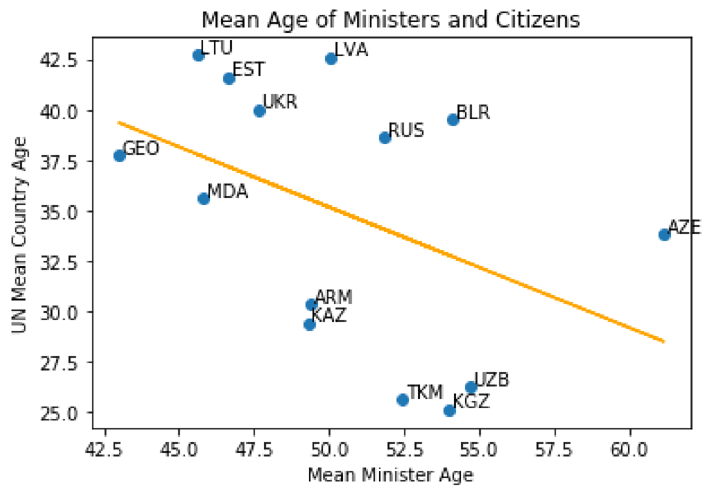

Fig. 4.6: Mean Minister BMI and Mean Country Age

To take another page from Blavatskyy, we will also regress the mean age in each of the countries against the mean age of the ministers, as it could be that older ministers come from older countries. This turns out not to be the case. Mean age within a country and mean age of its ministers are negatively correlated (-0.3181, p=0.119). While that is a weak correlation, examining the data reveals that there appear to be two clusters of ages: one group of older ministers from older countries, and another of younger ministers from younger countries (see fig. 4.6), a possible avenue for further study.

4d. Normalized BMI

Running our first linear regression on the HITT data first regression gives us the following results:

	Coefficient	P-Value
Intercept	21.0016	<0.01
Age	0.1027	<0.01
IsFemale	-0.1625	0.016
R-Squared: 0.139	Observations: 16,932	

Normalizing the BMI of each minister with this formula, and taking the mean for each county allows us to compare our new results to each of the three corruption indices that we are using. The normalized results are reasonable. Although they are compressed into a much smaller range of values, the corrected and estimated BMIs are positively correlated (see fig.4.7). All three continue to have negative correlations, the coefficients of which are reported in the table below.

Measure	Coefficient	P-Value	R-Squared	Observations
Control of Corruption	-0.9865	0.029	0.338	14
Corruption Perception Index	-17.118	0.052	0.280	14
Absence of Corruption	-0.2902	0.006	0.486	14

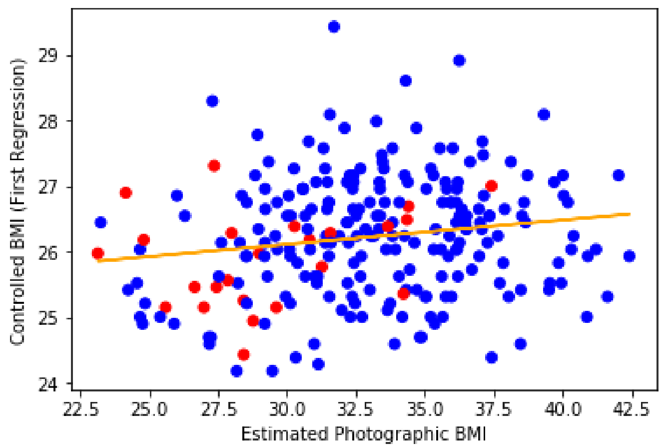

Fig. 4.7: Estimated Minister BMI from Photographs and First Controlled BMI

Note: Red observations are women

However, the relationship between mean BMI in a country and mean BMI of its leaders begins to break down. On the surface, they are negatively correlated (-0.4943, see fig. 4.8), however with a p-value of 0.1, this correlation is not statistically significant.

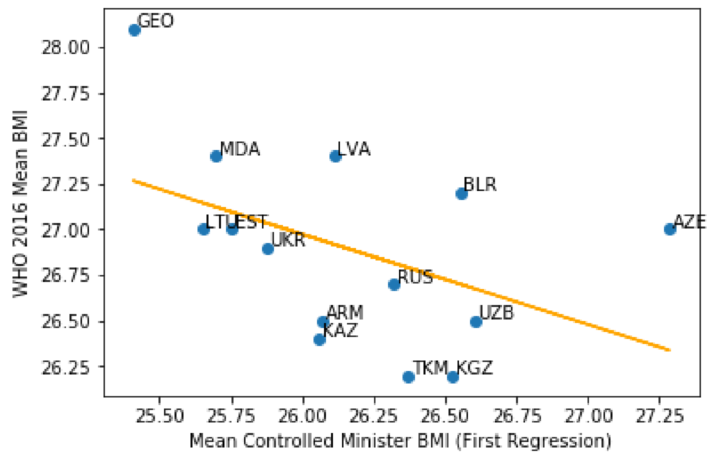

Fig 4.8: Mean Controlled Minister BMI and 2016 Mean BMI

Our second regression yields results similar to the first. It still yields a positive correlation between our normalized BMI and the BMI estimated from photographs. However, it also 'squishes' the estimates for men, making them much more closely clustered while spreading out the estimates for women much more (see fig. 4.12). The coefficients of this regression are reported in the table below.

	Coefficient	P-Value
Intercept	22.4773	<0.01
Age	0.0672	<0.01
IsFemale	-2.8593	<0.01
Age*IsFemale	0.0643	<0.01
R-Squared: 0.153	Observations: 16,932	

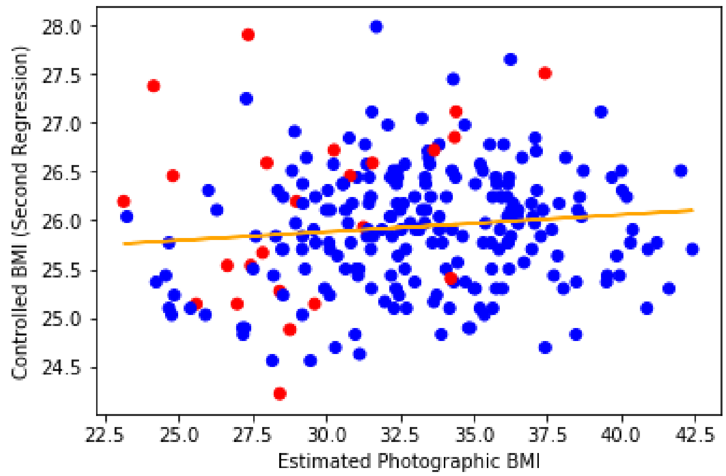

Fig. 4.9: Estimated Minister BMI from Photographs and Controlled BMI

Regressing this new normalized BMI on the corruption measures also results in similar results. The main difference is that the coefficient for the Corruption Perception Index becomes statistically significant (see table below). Additionally, the relationship between leader BMI and country BMI becomes both much larger in magnitude – moving from -0.4943 to 0.8409 – while its p-value shrinks dramatically, from p=0.1 in the first regression to p=0.064 in this one. While this is still not a statistically significant relationship, it is much closer to one than we achieved with the initial regression.

Measure	Coefficient	P-Value	R-Squared	Observations
Control of Corruption	-1.5973	0.019	0.377	14
Corruption Perception Index	-27.9633	0.036	0.318	14
IDEA Absence of Corruption	-0.4546	0.004	0.508	14

5. Conclusion

On the surface, this result does not look especially good for Blavatskyy's hypothesis. While the correlations between minister BMI and corruption continue to hold up, the linchpin of his argument, that lighter countries have heavier leaders, does not seem to hold up to scrutiny. However, due to the dramatic decease in p-value we saw from introducing a single interaction effect into our model, further refinement of the model may vindicate the hypothesis.

First of all, there may be additional interaction effects which may be important to the regression model. This paper was initially intended to include both age-squared and age-squared multiplied by our IsFemale dummy variable, however that had to be abandoned for technical reasons. Once those can be resolved, our model may produce results which support Blavatskyy's hypothesis.

Additionally, there may be other variables which have been omitted. As was mentioned in section 4b, the negative effect of sex on BMI may be stronger for female politicians than for women in the general population. Other factors such as nutrition may also be worthy of consideration, as malnutrition and privation due to poverty could be a factor in pushing down the average BMI in the poorer countries in the sample, which are also the more corrupt ones.

Finally, as was mentioned in section 2, the HITT data were gathered in 2010, while the minister BMI estimates are from 2017. The HITT survey also leaves out several countries, most notably the Baltic states. A more complete, or more up to date dataset would be able to cast much more light on the relationship between age, sex, and BMI. The main candidate for a more complete dataset is the WHO World Health Survey, which would include data for more countries, as well as data up to 2014. However, these data are not easy to request, which is why they were not used here.

While this may be a less than clean-cut result, it is not one totally without merit. It casts some doubt on Blavatskyy's hypothesis to be sure, but because it is not an absolute refutation of his work, it also leaves avenues open for further research and refinement.

Acknowledgments

Special thanks to Otamurod Khamdamov for help identifying many of the Uzbek politicians in the dataset and to Jake Bobo for providing comments on an early draft.

Note

The code used to produce the above results can be found here on my GitHub.

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