Reexamining the Blavatskyy Hypothesis: Are the Fat Cats Fat, or Just Old?*

Logan Cooper & Charles M. Becker

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1 Introduction

Corruption is difficult to quantify. Most studies of corruption, including this one, rely to some extent on subjective surveys of how corrupt people think their country is. These surveys are usually – though not 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 its actual incidence (Donchev and Ujhelyi, 2014). Additionally, corruption is best thought of as a vector of many different factors, so aggregate measures may abstract away large differences in the corruption of individual institutions; e.g., corrupt police but strong courts (Reinikka and Svensson, 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 strategies such as comparing records of earnings to self-reported assets (Gorodnichenko and 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 and Li, 2018). Another alternative measure has emerged recently for individual politicians: facial features. Lin, Adolphs, and Alvarez (2018) find that study participants can determine (better than randomly guessing) whether or not a politician is corrupt from their facial features. More specifically, they find "that participants' judgments of how corruptible an official looked were causally influenced by the face width" (2018). Additionally, Konyakhin finds that corrupt politicians may be able to find collaborators by looking at their faces (2019).

One attempt in the same vein as Lin, Adolphs, and Alvarez comes from Blavatskyy (2021a). His paper has garnered online notoriety, and in fact was awarded the 2021 Ig Nobel Prize in Economics. 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 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[1]. 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 concludes

[1]Alternatively, the banquets, restaurants, and alcohol might be the direct form the corruption takes.

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 has some limitations. It lacks controls for several attributes of leaders that are known to correlate with BMI, such as age and sex (Masood and Reidpath, 2017; Reas et al., 2007). 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, 2021b) 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.

This paper seeks to further examine the internal validity of "Obesity of politicians and corruption in post-Soviet countries." We reproduce Blavatskyy's results, examine the correlation of several possible omitted variables, and finally construct a model to try and correct for those variables. Section 2 describes the data sets, both those used in the original paper and those we have gathered independently. Section 3 details the methodology used to test Blavatskyy's hypothesis. Section 4 examines the results of those tests, and section 5 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, we use Blavatskyy's original set of 299 images of cabinet ministers from the 15 former Soviet republics who were in power in 2017. We then run the images through his exact code — based on Kocabey et al. (2017) — to derive their BMI estimates.

To control for the omitted variables of age and sex, on both sets of images, we also gather additional information about the leaders pictured. 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 also incorporate the five corruption indicators [2] used in the original paper:

[2] With the exception of the Basel Anti-Money Laundering Index, lower values on these measures

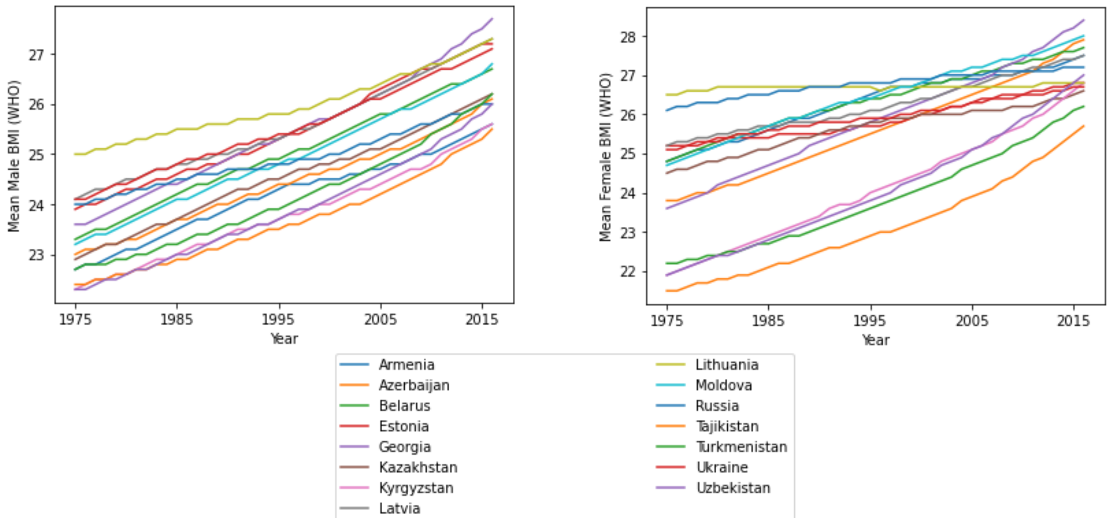
1. Transparency International Corruption Perceptions Index
2. World Bank worldwide governance indicator ‘Control of Corruption’
3. The sub-attribute ‘Absence of Corruption’ of Global State of Democracy Index
4. European Research Centre for Anti-Corruption and State-Building Index of Public Integrity
5. Basel Anti-Money Laundering Index

However, most of our results will only rely on the first three, as 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 direct our focus there as well.

For the first round of controls for sex, we use the World Health Organization’s Global Health Observatory’s data, which gives us the mean BMI of each country in the sample, as well as the means for men and women. As 2017 data are unavailable, we use 2016 data. For our first round of age controls, we use the mean age from the UN World Population Prospects. Once again, since 2017 data are not available, we use data from 2015. While these differences in year may introduce slight distortions, any errors are likely to be minor. As we can see in figure 1, 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.

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 1. BMI Trends in the Former Soviet Republics, 1975-2016



Source: WHO Global Health Observatory

For more advanced controls, we use data from "Health in Times of Transition: Trends in Population Health and Health Policies in CIS countries" (hereafter HITT). This survey provides 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 and 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 allows us to construct a good 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). 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 [(Drucker et al., 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). (2021a)

This paper differs primarily in having more extensive controls. Much of Blavatskyy's argument comes down to his observation that "[r]elatively less corrupt countries have slimmer politicians but more overweight voters." (2021a) 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 do not exist in a vacuum: they are affected by a variety of factors, notably their sex and age.

To initially control for sex differences, we determine the sex ratio of leaders in each country and use those ratios to create a weighted average BMI for each country. Simply put, this measure is what the mean BMI of a country would be if the population at large had the same sex ratio as the cabinet. We calculate this as follows [3]:

$$(MaleRatio \times MaleBMI) + [(1 - MaleRatio) \times FemaleBMI] \qquad (1)$$

We then use linear regression to test whether or not the negative correlation holds up when the mean BMI of a country's leaders is regressed on sex-adjusted BMI.

There is also evidence linking age and BMI (Masood and Reidpath, 2017; Reas et al., 2007), so controlling for age provides further 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 superficial level, we will be checking if leader age is correlated with leader BMI and with the subjective corruption measures.

On a more advanced level, we use the HITT data to 'correct' leader BMI. To do this, we will be constructing a model for the effects of age and sex on BMI. After calculating the BMI of each person in the sample, we remove outliers. Specifically, we remove 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 observations is that these people are far outside the typical BMI range, so including them will distort our estimates away from what is

[3] $MaleRatio$ is defined as the share of cabinet-level ministers who are male, and $MaleBMI$ and $FemaleBMI$ are the mean BMIs of males and females in the population at large respectively.

likely to be relevant for senior political figures. More specifically, the clustering of these people in younger ages will underestimate the effect of age on BMI.

After removing those outliers, we construct two models to attempt to correct leader BMI for age and sex. The simpler of these models is a two-variable Weighted Least Squares[4] regression using age and sex[5]:

$$BMI_{predicted_1} = \alpha + \beta_0 Age + \beta_1 Male + \epsilon \tag{2}$$

Our second model introduces an interaction effect: multiplying the dummy Male 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:

$$BMI_{predited_2} = \alpha + \beta_0 Age + \beta_1 Male + \beta_2 (Male \times Age) + \epsilon \tag{3}$$

Once we have regression coefficients from the HITT data, we use them to predict the BMIs of the leaders in the sample, and use these regression estimates as a form of 'corrected' BMI. We then use these results to test Blavatskyy's results with a series of regressions of the form [6]:

$$Measure = \alpha + \beta_0 BMI_{predicted_i} + \epsilon \tag{4}$$

Returning back to section 1, we assume that the causal pathway between obesity and corruption is that corruption enables certain lifestyle choices, e.g. eating lots of steak dinners paid for by favor-seeking oligarchs. If we were to build a more complete regression model for BMI, it might include a variable (or vector of variables) to represent lifestyle choices, such as diet, exercise, smoking, and drinking (among others). While some of these variables are present in the HITT data, they are not observable for the political leaders, and therefore are omitted. Since these are omitted variables, any effects they have on BMI will end up in the error terms of the above models. Therefore, to find an approximation of how much of the leaders' BMI we can attribute to lifestyle, we subtract the regression BMI estimate from the photographic BMI estimate (equation 5) and test Blavatskyy's results against that (equation 6).

[4] We use weighted least squares to correct for heteroskedasticity in the HITT data with respect to age, see appendix A.1.

[5] Sex is represented by the binary variable $Male$, which is 1 for males and 0 for females

[6] $Measure$ is a stand-in for any of the three corruption measures as well as mean BMI in each country. This also applies to equation 6.

$$BMI_{diff} = BMI_{photo} - BMI_{predicted} \tag{5}$$

$$Measure = \alpha + \beta_0 BMI_{diff} + \epsilon \tag{6}$$

There is one other difference in between this approach and that of Blavatskyy, and that is our choice of summary statistic. Blavatskyy's paper uses 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 (specifically Table 1), these values are generally very close.

In the process of carrying out this methodology, we make use of the Python programming language (version 3.5), as well as the libraries NumPy (Harris et al., 2020), pandas (pandas development team, 2020; Wes McKinney, 2010), Statsmodels (Seabold and Perktold, 2010), and matplotlib (Hunter, 2007).

4 Results

4.1 Reproduting Blavatskyy

In a nutshell, we can reliably reproduce Blavatskyy's results [7]. While there are minor discrepancies between the results we obtained from the BMI estimation process, those appear to be either the result of differences between the running environments, or rounding errors. In either case, they do not change the results (see Table 1). To reproduce the correlation between Blavatskyy's BMI data and the country-level corruption data, we use a standard OLS regression. While Blavatskyy does not report the exact coefficients for the correlations between BMI and the five corruption indicators, our results in Table 2 match his graphs in both sign and (upon visual inspection) 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.

[7] The code used to produce the following results can be found on GitHub at https://github.com/ldtcooper/ussr-obesity-corruption

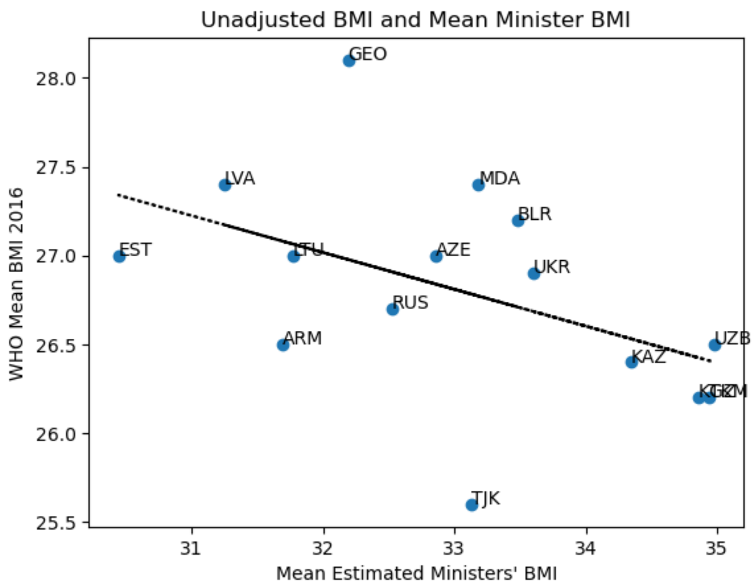
Table 1. Our BMI results against Blavatskyy's

Country	**Reproduced (unadjusted) Median BMI**	**Reproduced (unadjusted) 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

Table 2.
Our regression coefficients of unadjusted minister BMI on five corruption measures

Measure	Coefficient	P-Value	R2	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

Figure 2. Unadjusted Country BMI and Mean Minister BMI



4.2 Basic Controls for Sex

Our first control is for sex. As mentioned above (see equation 1), 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 mean estimated minister BMI as an independent variable and mean country BMI as a dependent variable, we get a regression coefficient of -0.174. 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. 2).

When we control for sex in this way, the coefficient becomes more strongly negative, but also less significant: the regression coefficient of median estimated minister BMI on sex-adjusted BMI is -0.224 (p=0.083). Furthermore, it lends some credence to the claim that relatively less corrupt countries may have more women in government. This is especially interesting in light of some of the WHO data: despite women being shorter and lighter on average, many of the countries in our sample actually have higher BMIs for women then men [8]. In Armenia, to bring out the most extreme

[8]We speculate that this gap may be due in part to differences in smoking prevalence between

of the examples, the mean BMI for women is 1.8 points higher than it is for men.

These bivariate regressions do not constitute a robust test, and there are possible confounding factors. Most notably, there may be a gender effect along with a sex effect [9] among the ministers. For example: thinner, more conventionally-attractive women may be more likely to succeed in politics, leading to more pressure on female politicians to control their weight than their male counterparts face. The above analysis could even be read as support of that hypothesis. Although we were unable to identify any academic literature on this topic in Russian or related to the former Soviet republics, 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.

4.3 Basic Controls for Age

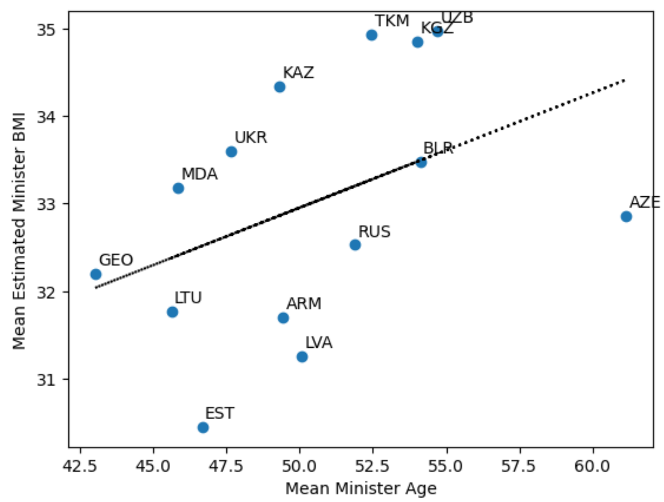
A second factor that could influence BMI is age. The leaders of all fifteen countries in the sample are notably older than the average citizen, and BMI tends to be positively correlated with age (Masood and Reidpath, 2017; Reas et al., 2007). In short: people tend to put on weight as they age, but don't grow taller after a certain point; in fact, they tend to shrink after around their mid-forties (Sorkin et al., 1999). We note that Tajikistan is omitted from this section (and future sections), as we were unable to find data for the ages of almost all Tajik politicians.

The first question that arises here is whether there is a correlation between the mean minister BMI and their mean age. It turns out that there is. Regressing mean age on mean minister BMI with OLS results in a coefficient of 1.3176, albeit with a p-value of 0.054. This tells us that the countries in the sample with older leaders are also those with heavier leaders (see fig. 3).

males and females in these countries, but testing this is beyond the scope of our paper.

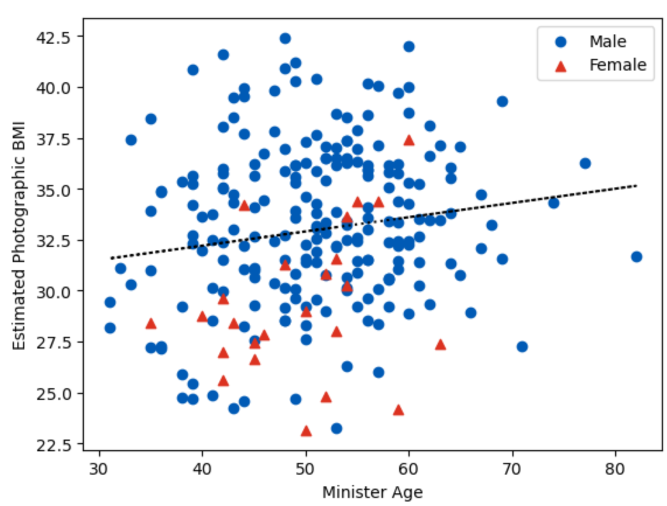
[9] Throughout this paper, we generally use "sex", as we are primarily interested in biological differences such as (aggregate) height and weight. "Gender" is used here to separate social effects from biological ones (Mazure, 2021). Some of the effects we find may be due to gender differences as opposed to sex differences, but this is beyond the scope of this paper.

Figure 3. Mean Minister BMI and Mean Minister Age



We also do this analysis on the level of individual politicians, and find that older leaders tend to be heavier on the individual as well as the country level. In fact, this relationship is much more robust than on the country level. Running a WLS regression on minister age and BMI gives us a regression coefficient of 0.3277 which unlike the aggregated effect, is significant at the 2% level (p=0.018, see fig 4).

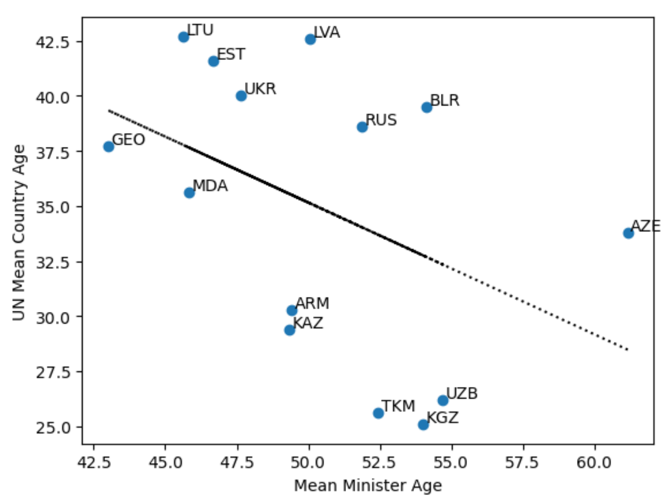
Figure 4. Minister Age and Estimated Minister BMI



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 distinguish countries with leaders who are heavy because they are old, from those who are heavy because they are corrupt.

To take another page from Blavatskyy, we 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 countries with older populations. This turns out not to be the case. Mean age within a country and mean age of its ministers are actually 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. 5), a possible avenue for further study.

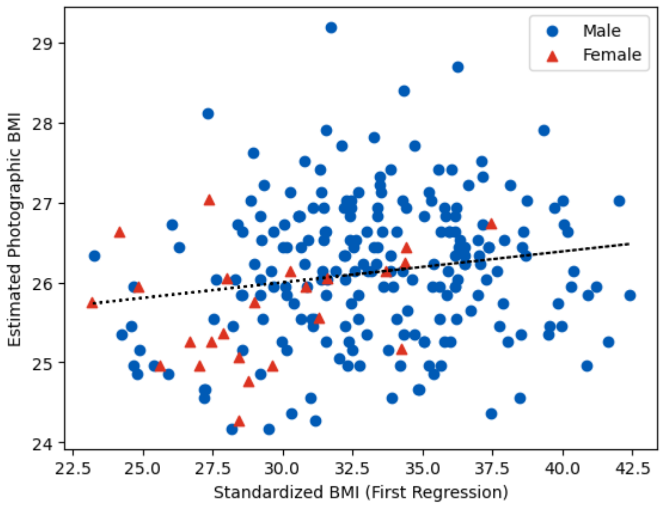
Figure 5. Mean Minister Age and Mean Country Age



4.4 Building a Normalized BMI

Running our first WLS linear regression (described in section 3) on the HITT data gives us a set of highly statistically significant coefficients summarized in table 3. We can use these results to predict the BMI of our ministers. More specifically, this gives us an estimate of how much of a minster's photographic BMI is attributable to their age and sex, which we can compare to the corruption indices. Although the predicted BMI values are compressed into a smaller range of values when compared to the photographic BMIs (see figure 6) this is reasonable as the predictions do not contain our unobservable lifestyle variables. When we compare these values to the measures of corruption, we see that they maintain their negative correlations (see Table 4's rows labelled "First").

Figure 6. Estimated Minister BMI from Photographs and First Standardized BMI



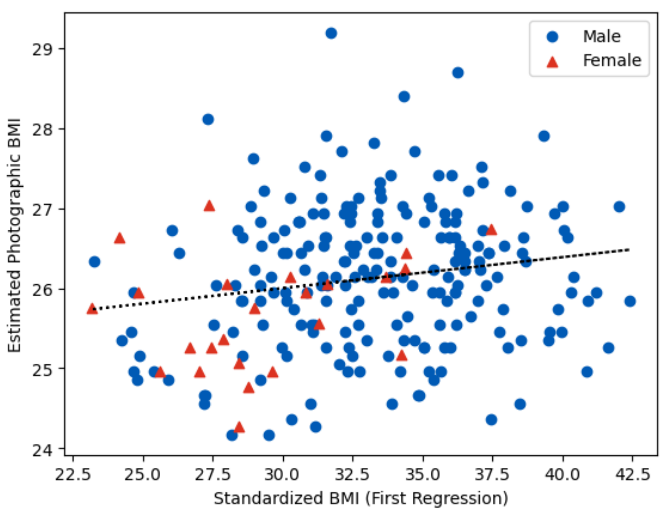
The relationship between the mean BMI of a country ("country BMI") and the mean BMI of its leaders ("leader BMI") is a less clear picture. On the surface, they remain negatively correlated (-0.4943, see appendix A.2), although with a p-value of 0.1, this correlation is not strong. However, the relationship between country BMI and leader BMI does not need to be negative in order for Blavatskyy's hypothesis to hold. This check is done to provide evidence against the hypothesis that countries with heavier people happen to be more corrupt, resulting in the leaders of those corrupt countries being heavier. A negative relation only significant at the 90% level suggests that this is unlikely to be the case.

Our second regression yields results similar to the first. There is still 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. 7). The coefficients of this regression are reported in table 3.

Table 3. Regression Model Coefficients

First Regression (equation 2)		
Variable	**Coefficient**	**P-Value**
Intercept	20.8271	<0.001
Age	0.0986	<0.01
Male	0.2860	<0.01
R2: 0.144		Observations: 16,932
Second Regression (equation 3)		
Variable	**Coefficient**	**P-Value**
Intercept	19.7083	<0.001
Age	0.1244	<0.001
Male	2.7787	<0.001
Age*Male	-0.0592	<0.001
R2: 0.157		Observations: 16,932

Figure 7. Estimated Minister BMI from Photographs and Second 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. Additionally, the relationship between leader BMI and country BMI becomes both much larger in magnitude – moving from -0.5156 to -0.8535 – while its p-value shrinks markedly, from p=0.1 in the first regression to p=0.064 in this one (see Table 4's rows labelled "Second").

What this tells us is that some of the relationship between corruption and BMI is due to the age and sex differences between ministers and the general population

Table 4. Country Metric Regression Results

Regression	Measure	Coefficient	P-Value	R2
First	Control of Corruption	-1.0398	0.025	0.352
	Corruption Perception Index	-18.1087	0.045	0.293
	IDEA Absence of Corruption	-0.3054	0.004	0.504
	Mean Country BMI	-0.5156	0.096	0.214
Second	Control of Corruption	-1.6614	0.016	0.395
	Corruption Perception Index	-29.2181	0.030	0.336
	IDEA Absence of Corruption	-0.4734	0.003	0.534
	Mean Country BMI	-0.8535	0.064	0.258
First Difference	Control of Corruption	-0.4145	0.010	0.440
	Corruption Perception Index	-8.1929	0.007	0.472
	IDEA Absence of Corruption	-0.0735	0.083	0.230
	Mean Country BMI	-0.1609	0.151	0.164
Second Difference	Control of Corruption	-0.4482	0.004	0.520
	Corruption Perception Index	-8.7509	0.003	0.546
	IDEA Absence of Corruption	-0.0848	0.039	0.309
	Mean Country BMI	-0.1765	0.110	0.199

of their respective countries. With that in mind, the next question is how much of this relationship remains. As we discussed in section 3, we can get at this by subtracting the results of the regression predictions from the photographic predictions (see equation 5 in section 3). Doing so with the first regression's predictions (using only age and sex) and regressing the resultant subtracted BMI gives us the results labelled "First Difference" and "Second Difference" in table 4.

By now, these results should look familiar: we see the Control of Corruption and CPI relationships hold up with the effects of age and sex removed. The Absence of Corruption relationship is negative but only significant at the 10% confidence interval. More notably, the relationship between country and leader BMI remains negative and becomes even less significant. We can do the same with the difference between the second regression's predictions and photographic BMI, the results of which are recorded in table 4's "Second Difference".

When using the second regression, all of our relationships get stronger. Most notably, the Absence of Corruption relationship becomes significant. While the Country BMI relationship still remains insignificant at the 5% level, it does inch close to being significant at the 10% level. Between these two regressions, we have good evidence that there is a relationship between corruption and leader BMI that cannot be explained fully by the age and sex of leaders.

5 Conclusion

In sum, this paper refines and supports Blavatskyy's analysis of the relationship between BMI and corruption. We demonstrate that the relationship is not due to (aggregated) differences in age and sex between the leaders of post-Soviet countries and their populations. Furthermore, our analysis suggests that leader BMI and country BMI are likely negatively correlated or possibly uncorrelated. Ultimately, age and sex standardization have virtually no impact on coefficient values for any of the corruption indicators or for country BMI. This suggests that there are lifestyle differences between leaders and citizens that vary with corruption.

However, there are multiple ways in which the analysis could be improved. First, there may be important additional interaction or non-linear effects. Additionally, there may be other variables which have been omitted. As mentioned in section 4.2, BMI differences 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 (also the more corrupt) countries in the sample, while not being relevant to the class of political leaders.

Finally, as mentioned in section 2, the HITT data were gathered in 2010, while the minister BMI estimates are from 2017. The HITT survey also omits several countries, most notably the Baltic states. A more complete, updated dataset would be able to cast much more light on the relationship between age, sex, and BMI in the former USSR. Beyond just expanding this analysis to the rest of the post-Soviet republics, it could also be applied to any set of countries and leaders at any time for which we have photographs.

In conclusion, these results reinforce Blavatskyy's. However, they are only a refutation of one argument against them: namely that the relationship between BMI and corruption is due to age and sex differences. There remains room for refinement of these results, as well as for further investigation into the relationship between BMI estimates and corruption measures.

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A Appendices

A.1 Appendix One: Heteroskedasticity Results

The White Lagrange Multiplier Test was used to determine that the HITT data were hetertoskedastic with respect to age for both regressions. The results of those tests (rounded to the thousandths place) are in the table below:

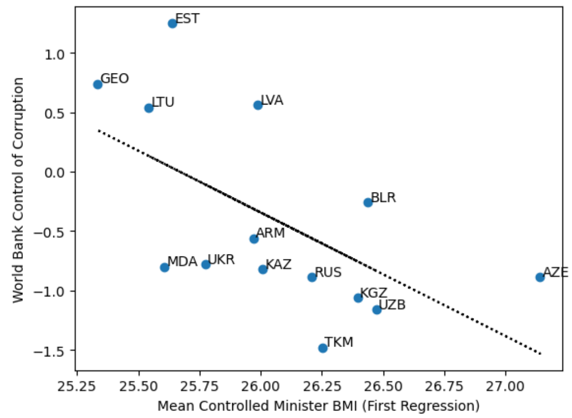
Appendix Table B1. White Lagrange Multiplier Test Results

Regression	**LM Statistic**	**p-value**
One	438.064	<0.001
Two	491.271	<0.001

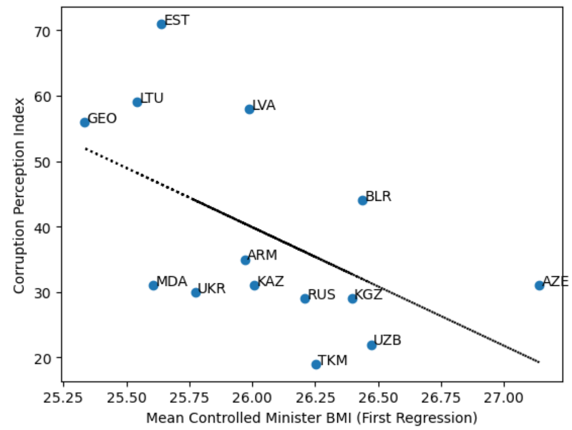
A.2 Appendix Two: First Regression Scatter Plots

Appendix Figure C1. Mean Normalized Minister BMI plotted against...

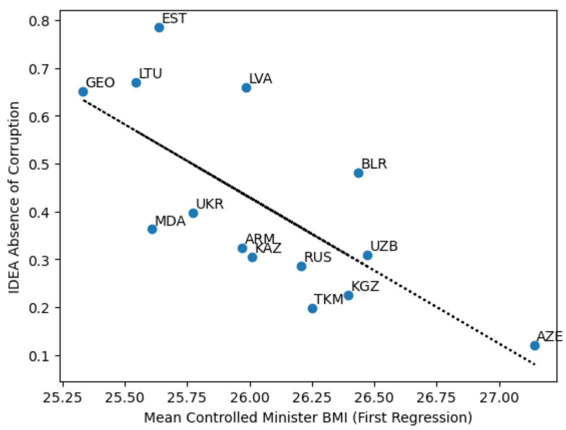
(a) Control of Corruption



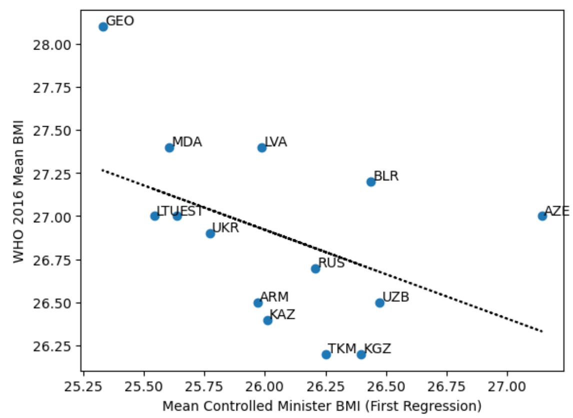
(b) Corruption Perception Index



(c) Absence of Corruption



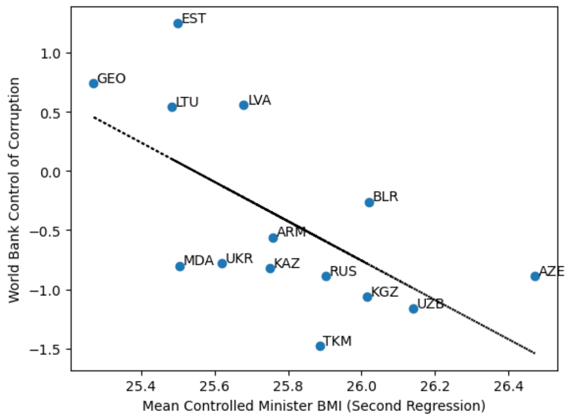
(d) Mean Country BMI



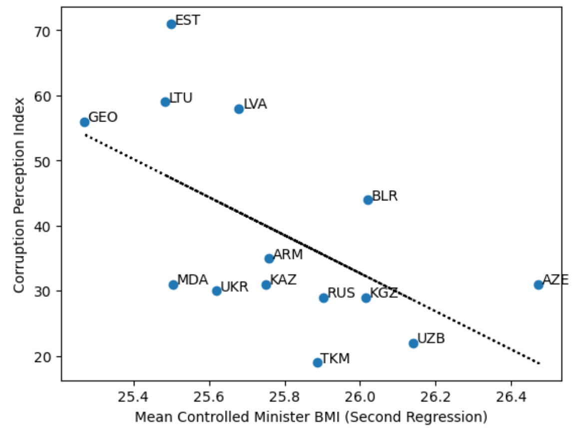
A.3 Appendix Three: Second Regression Scatter Plots

Appendix Figure C1. Mean Normalized Minister BMI plotted against...

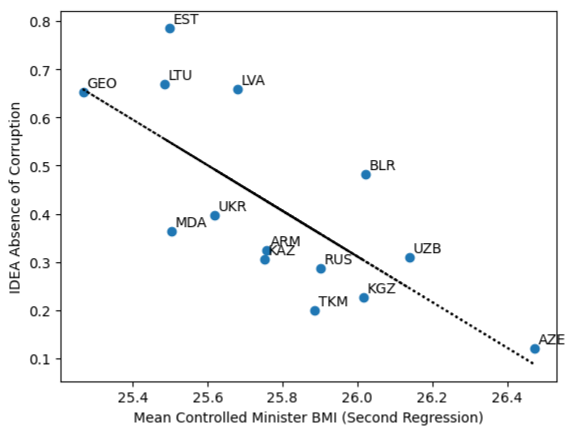
(a) Control of Corruption



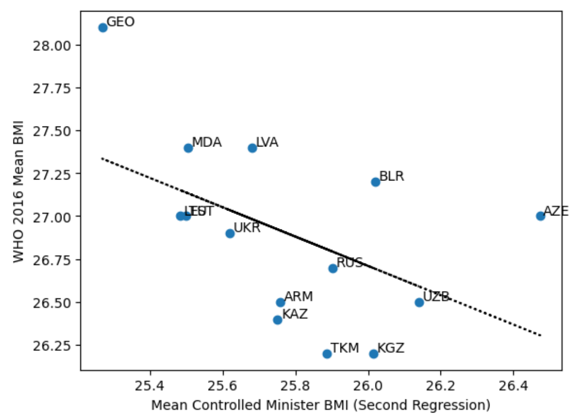
(b) Corruption Perception Index



(c) Absence of Corruption



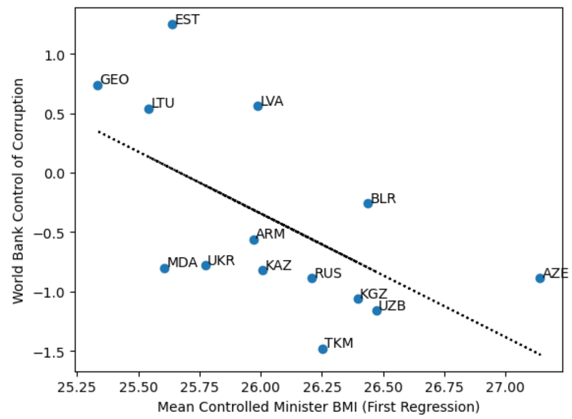
(d) Mean Country BMI



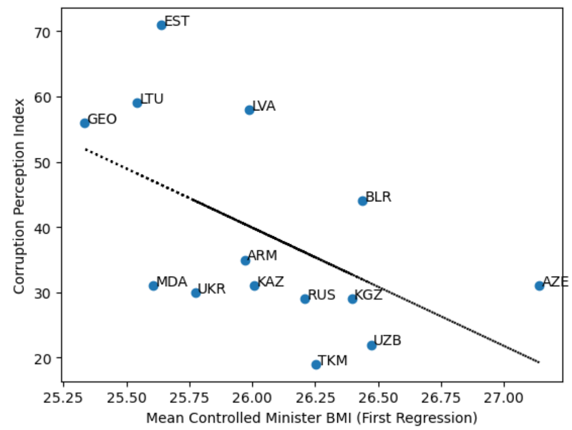
A.4 Appendix Four: First Difference Regression Scatter Plots

Appendix Figure C1. Mean Normalized Minister BMI plotted against...

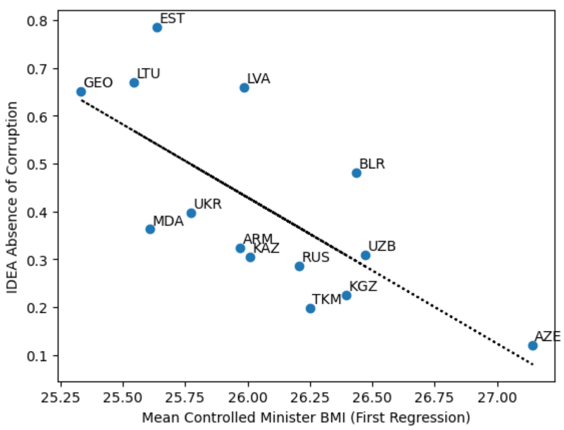
(a) Control of Corruption



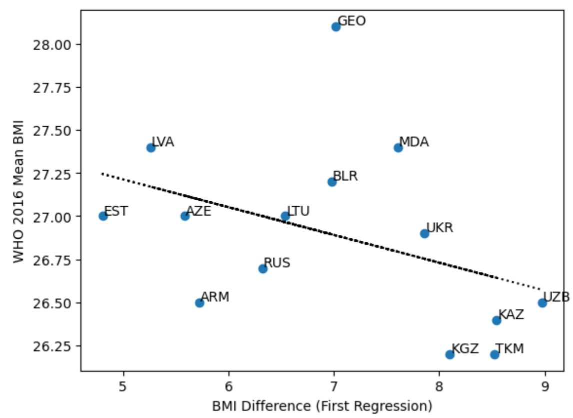
(b) Corruption Perception Index



(c) Absence of Corruption



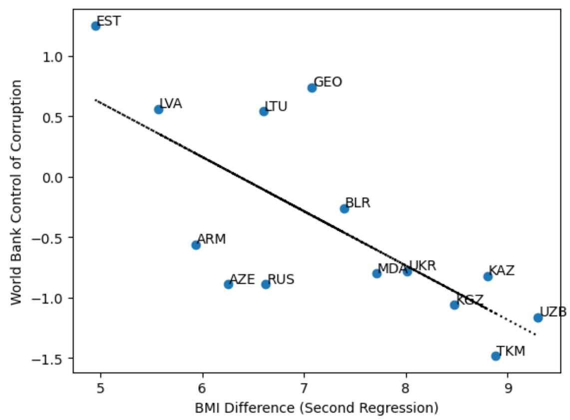
(d) Mean Country BMI



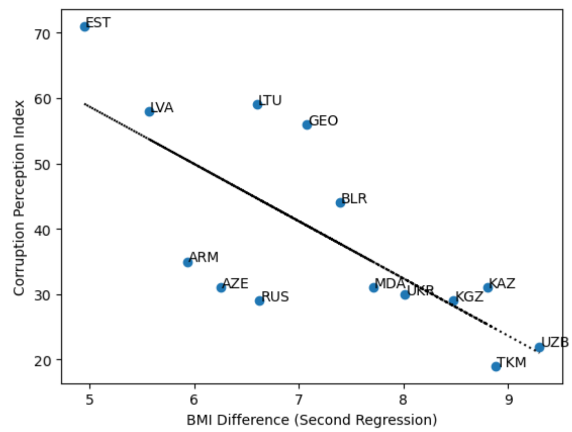
A.5 Appendix Five: Second Difference Regression Scatter Plots

Appendix Figure C1. Mean Normalized Minister BMI plotted against...

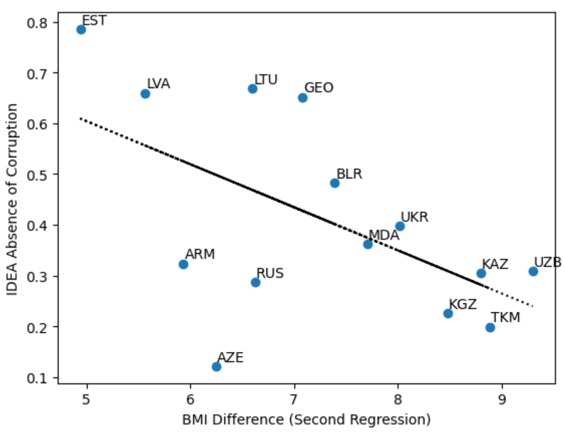
(a) Control of Corruption



(b) Corruption Perception Index



(c) Absence of Corruption



(d) Mean Country BMI