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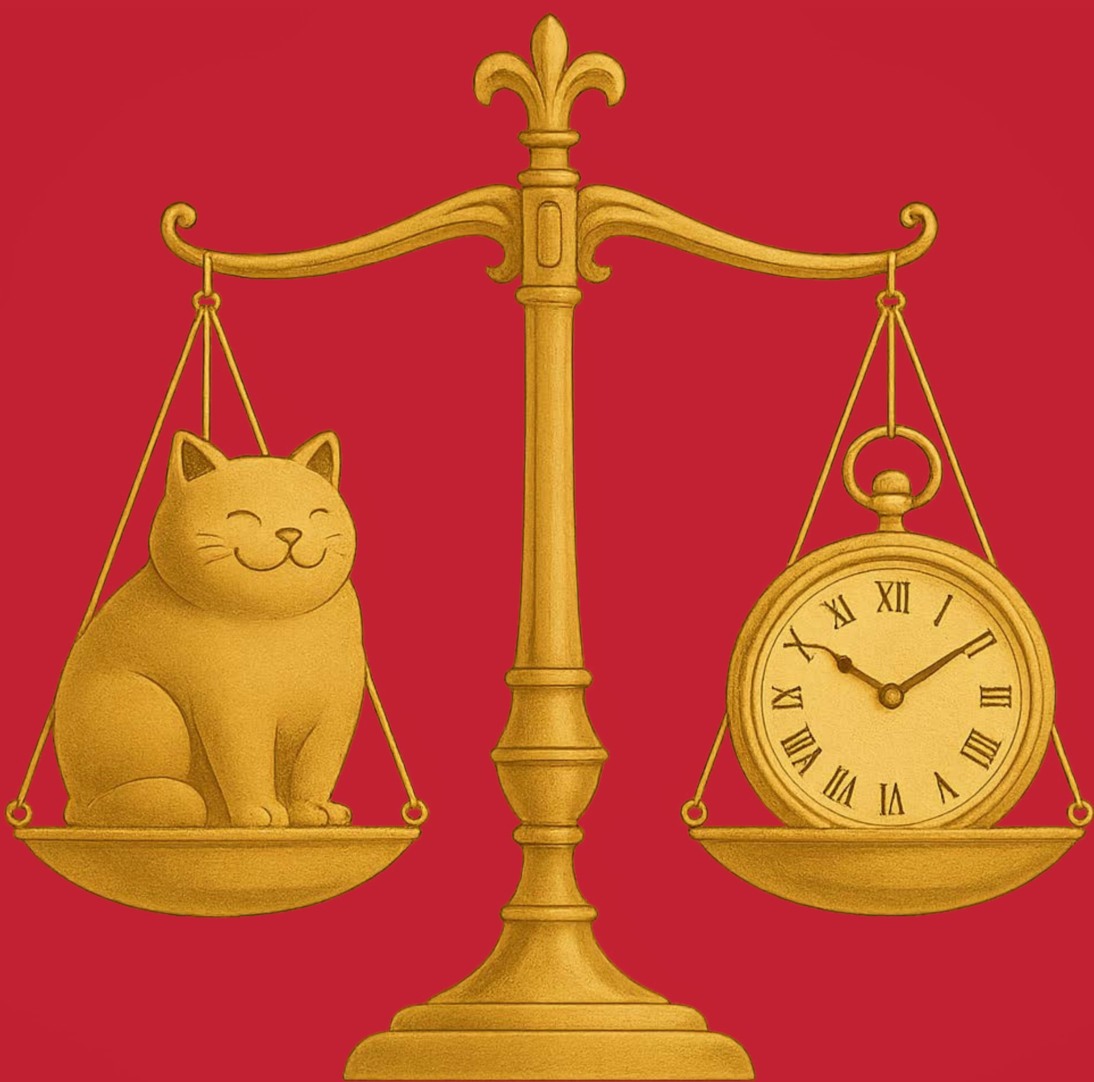
Reexamining the Blavatskyy Hypothesis: ARE THE FAT CATS FAT, OR JUST OLD?

Logan Cooper & Charles M. Becker

Working Paper #77



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WORKING PAPER #77, 2025

Reexamining the Blavatskyy Hypothesis: Are the Fat Cats Fat, or Just Old?[1]

Logan Cooper* & Charles M. Becker *

Abstract: Blavatskyy (2021) identifies a strong correlation between the estimated BMI of 299 transition economy politicians and perceived corruption. However, by not controlling for age or gender, it is possible that the patterns reflect demographic composition for which BMI is simply a marker. To address this, we obtain age and sex estimates for 249 of the politicians in the original sample, and also control for characteristics of the general population in each country. We then use data from the Health in Times of Transition survey to build a model to predict BMI from age and sex and use it to estimate how much of leaders' estimated BMI we can attribute to these factors. We find that a positive relationship between perceived corruption and estimated leader BMI still exists even after controlling for these factors.

Keywords: body-mass index, computer vision, corruption, government, post-Soviet states

JEL codes: D73

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Editor: Dr. Bakhytzhan Kurmanov, Senior Research Fellow, Institute of Public Policy and Administration, Graduate School of Development, University of Central Asia, bakhytzhan.kurmanov@ucentralasia.org

About the authors:

Logan Cooper is a data scientist and software developer with research interests in political economy, post-Soviet economics, and urban economics. He specializes in bringing modern techniques in data science, machine learning, and AI to questions in those fields. He holds a B.A. in Global Economics from U.C. Santa Cruz, and a M.S. in Economics and Computation from Duke University.

Dr. Charles Becker (BA, Grinnell; PhD Princeton) joined the Duke faculty in 2003, where he directed the American Economic Association's Summer Program and Minority Scholarship Program (2003-2007) and served as Associate Chair (2009-17). Becker previously taught at CU-Denver, Vanderbilt, and CU-Boulder. He served as Senior Advisor to the Ministry of Labor and Social Protection, and the National Bank of the Republic of Kazakhstan, 1999 – 2001; Senior Advisor to the Kazakhstan Actuarial Center, 2001 – 2006; and Team Leader, Pension Reform Technical Assistance (PRTA) program to the Government of the Kyrgyz Republic, for the Asian Development Bank, Bishkek, Kyrgyzstan, 1998 – 1999. In 2007, he was recognized as a lifetime member of the American Economic Association (AEA) for service to the profession; in 2019 he received the AEA's Committee on the Status of Minority Groups in the Economics Profession's mentorship award. He received Duke's equity, inclusion and diversity award in 2008 and graduate faculty mentoring award in 2014.

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125/1 Toktogul Street, Bishkek 720001, Kyrgyz Republic
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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; in other words, perceived corruption. These surveys are usually 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; for example, 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 generated 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 about 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 these papers comes from Blavatskyy (2021a). His approach has garnered attention for its unusual approach, having been featured in The Economist (2020) and receiving the 2021 Ig Nobel Prize in Economics. He hypothesized that the average Body Mass Index (BMI) of cabinet-level officials could reflect corruption in a country. The BMI of ministers is estimated from photographs with the help of a computer vision algorithm developed by Kocabey et al (2017) and the paper concludes that there is a positive correlation between perceived corruption indices and the median estimated BMI of cabinet ministers in countries of the former Soviet Union. The (implied) causal pathway is that ministers directly embezzling government money, or taking bribes to make make – or ignore – laws will have more money to spend on calorie-heavy things like banquets, high-class restaurants, and alcohol. [1]

This paper almost immediately attracted considerable criticism. Kis (2021) and Shopin (2020) both raise several issues with the BMI approach, among them the lack of obvious causality, the possibility of alternative specifications, and doubts about the BMI algorithm's validity[2]. However, the strongest critique is that the empirical exercise leads to "ableist conclusions." The study not only focuses on a group that is subject to "fat shaming"in some societies, but links them to corruption (adding further shame) in an empirical exercise. Indeed, Kis suggests controls for age distribution, income, and inequality, and we make an effort in that direction.

As we detail below, there is a strong correlation between senior politicians' body mass index (BMI) and estimates of corruption. The statistical problem with prior analysis is that BMI is not age-sex standardized, and corruption is likely to be correlated both with politicians' incumbency/tenure (and hence age) and sex. Furthermore, the causal link is likely to go both ways with incumbency/tenure via age: young politicians are relatively likely to present themselves as idealistic reformers, but will find irresistible opportunities as incumbency increases. Moreover, rewards from corruption also tempt (presumably older and heavier) incumbents to distort rules to ward off competitors.

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

2 From our perspective this last issue does not appear to be obviously problematic, especially given the substantial range of predicted BMIs in the sample.

Consequently, one might be tempted to dismiss a positive correlation between BMI and corruption as simply reflecting the age and sex structure of government ministers. This is analogous to the "shocking" finding that Japan has a higher crude death rate (CDR) than Somalia or the Central African Republic and, indeed, has one of the highest CDR's in the world. In reality, though, the high CDR reflects differing age structures: Japan actually has the highest life expectancy in the world (excluding small city states such as Hong Kong and Macao).

We therefore focus in the following pages on the relationship between standardized BMI and corruption measures. Rather to our surprise, standardization does not reduce the correlation, though it does eliminate reverse-causal mechanisms and more strongly suggests that BMI is a "marker" of public corruption. Of course, it is possible that some societies are tolerant of corruption at all levels (and hence have higher BMI on average). We explore this by controlling for estimates of national BMI. Once again, the results are clear: it is the BMI of politicians, and not the public, that is associated with a wide range of corruption measures.

This paper seeks to further examine the internal validity of "Obesity of Politicians and Corruption in Post-Soviet countries."Section 2 further discusses the context and literature in this area. Section 3 describes the data sets, both those used in the original paper and those we have gathered independently. Section 4 details the methodology we use to reproduce Blavatskyy's results as well as the econometric techniques we use to further test them. Section 5 examines the results of those tests and how they ultimately bolster the paper's conclusion. To summarize: we standardize the BMI of the political leaders for age and sex, then repeat the methodology of the original paper. Doing so, we find that while the relationship between minister BMI and the corruption measures weakens slightly, but remains strong and statistically significant. Additionally, the relationship between minister BMI and mean population BMI fails to switch direction, suggesting that this is not an artifact of heavier countries having heavier leaders.

2. Context and Background Research

In Western Europe and North America, Blavatskyy's work appears to have been met either as a work of entertainment with a finding that corroborates stereotypes, or as fat-shaming data-mining with little to no scientific merit. In contrast, the post-Soviet press took note: a Google search for Блаватский ожирение политиков ("Blavatskyy obesity of politicians") turns up over 2,600 hits. Top business journals such as Forbes Ukraine provided an interview with Blavatskyy as their lead article (Vladisla, 2020); another interview appears in Ogonyok and reprinted in the top Russian business paper, Kommersant (Filina, 2020). Other major Russian and Ukrainian papers and magazines also wrote stories. With a lag it appeared in Kazakhstan's Tengrinews (2020) which may have had the most outrageous photos, and Vremya (Time, 2021), among many others. While these reports dwelt in part on the entertaining and outrageous, the interviews and stories also took it seriously as yet another, visible indicator of the idea in the popular imagination of rapacious fat cats (толстые коты) and their particular prevalence in poorer countries and relative absence in the prospering Baltic states.

As noted, the original paper has several 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). Despite this apparent omitted variable bias, a follow-up study (Blavatskyy, 2021b) suggests that this model does have some external validity, as the median estimated BMI of Ukrainian leaders tracks the perceived corruption indices closely from 2000-2020. Still, without further 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. Most obviously, 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.

While our contribution to this literature focuses primarily on the variables of age and sex, there are many additional confounding variables which might impact these findings in one way or another. These range from cultural perceptions of weight and body size, to health and life expectancy, to diet, to the lingering effects of famine on different populations. Investigations into any of these could be papers in their own right. As such, we do not include them in our analysis. However, we would be remiss to not at least discuss them.

Before we continue, we would like to offer a disclaimer. This paper gives researchers of political corruption one more tool in their belt when discussing corruption on a larger scale, both between countries and over time. The aim of this paper is to further examine a novel way of measuring corruption in aggregate, and any policy prescriptions should follow from there. It may be a way to examine trends in corruption, corruption in individual regions for which disaggregated corruption data may not be available, or even individual parts of government (e.g. looking at BMI trends among a country's judiciary. The following conclusions should by no means be applied to individual politicians or taken as firm proof of causality.

2.1. Cultural Perceptions of Weight and Body Size

There appear to be limited studies of popular perceptions of obesity among former Soviet Union populations. Elran-Barak et al. (2016) offer an interesting cross-cultural study from Israel in which it turns out that overweight long-term immigrant women from the former USSR were more aware of being overweight than both long-term Jewish residents and Arab women.

However, this awareness – at least if it is correlated with concern – may be fairly recent (following a

decade of prosperity in the 2000s) and/or may vary widely among groups. Earlier work by Cockerham et al. (2002) find that those who yearned for the Soviet past were less concerned about living healthy lifestyles than those who did not look fondly on their socialist past. Furthermore, if health status (including BMI) provides verbal cues as to attitudes toward the Soviet past, then high BMI among politicians may evoke nostalgia along some (even if they may associate it with corruption) and hostility among others. For both groups, though, high BMI likely reflects nostalgia bout the Soviet past or its absence, rather than Western-style "fat shaming."

On a slightly different theme, Craig and Kapysheva (2018) interview focus groups in Kazakhstan, and find that unhealthy, BMI-related health conditions and practices were linked to ethnic identity. The resulting theme was hardly one of shaming and more that of inevitability given one's nationality and external conditions. However, a quick online search in Russian for "how to lose weight Kazakhstan" (как похудеть Казахстан) results in hundreds of hits from sports programs/facilities and health sites that appear to be aimed at urban professionals. The impression one gets is that BMI likely reveals background and engagement in the global economy, and voters are more likely to respond to that identification rather than perceived obesity. Indeed, many former Soviet citizens who look back with nostalgia to a pre-globalized Soviet past may recognize that the era was associated with corruption but regard it as an acceptable price.

Additionally, from personal experience we do not believe that "fat-shaming" is nearly as prevalent in the former Soviet Union as in Western Europe or North America. A quick Russian-language web search suggests that it exists, at least in wealthy urban centers. We therefore emphasize the limited explanatory power of the relationships: our regressions have R2 values of 0.16 to 0.55, for small samples and aggregated values, which implies very little information about individuals. Furthermore, it seems overwhelmingly likely that local familiarity with individual politicians will be vastly more important in assessments of their characters than simple judgment of photographs.

2.2. Health, BMI, and Life Expectancy

A series of papers by Huffman and Rizov (notably, 2010) use Russian Longitudinal Monitoring Survey (RLMS) data to explore determinants of individual BMI in a lifestyle equilibrium model, incorporating demand for food types, smoking, and leisure over the period 1995 and 2004. Noting a 33% rise in obesity over this period, they find that sharply rising incomes during this period contribute to obesity, and that there are heterogeneous effects: weight gains (and slipping into obesity) are particularly prevalent for those characterized as overweight (base BMI of 25-29). Overall, caloric intake and, independently, consumption of sugars, fats, and dairy products (and to a lesser extent meat and fish) are positively associated with BMI. Smoking status and, perhaps surprisingly, alcohol consumption are associated with lower BMI. Finally, and consistent with our findings but at a different level, controlling for income, managerial status is associated with higher BMI; blue collar and professional workers have lower BMIs. The bottom line from these findings is that abnormally heavy politicians are no surprise in the former USSR setting: the unanswered question is whether there is an extra boost from apparent corruption.

These patterns are explored over a more extended period by Martinchik et al. (2015), who note that weight gain is especially pronounced in the male population. Aistov et al. (2021) use RLMS data through 2018 and find that BMI peaks among men at about age 40, and among women at about 60. These distinct patters will be important to control when we standardize politician BMI. Ulumbekova (2015) notes the stunning structure of mortality in Russia: in 2013, some 53% of all deaths are due to illnesses of the circulatory system. While age-standardized circulatory system death rates – a cause that is positively correlated with obesity – finally began to decline sharply after 2003, it remained roughly 3.5 times as great as in the "older" EU members (and roughly 60% greater than in the "new" member states).

As is well known, life expectancy plummeted and adult mortality soared with the collapse of the Soviet Union, especially among males and Slavic populations (Becker and Bloom, 1998). After reaching a nadir around 1994-95, there was erratic and slow recovery for the following decade, and then rapid recovery thereafter. By 2010 most former Soviet nations had regained or passed (low) Soviet-era peaks, and then made further rapid gains in the ensuing decade (Brainerd, 2021). Reduced alcohol consumption and smoking have been important contributing factors.

Nonetheless, adult mortality rates in Russia and several other countries are shockingly high – around the median for "third world" countries, despite having very high levels of educational attainment (Eberstadt, Nicholas (Эберштадт, Николас), 2024). These high mortality rates are in turn linked to unhealthy lifestyles, many of which are also associated with elevated BMI. Moreover, these patterns persist throughout the former USSR – as, for example, (Gulis et al., 2021) document for Kazakhstan.

However, recovery has been uneven. As Shchur et al. (2021) and Skipin et al. (2022) document, variance in life expectancy, and health outcomes more generally, have remained constant or increased over the past three decades in Russia (and likely in other former Soviet republics). Thus, for 2015-17, life expectancy in Moscow (74.2 years for males and 81.0 years for females) was nearly a decade longer for men and more than five years greater for women compared with small cities wither fewer than 100,000 people.

These patterns matter because they suggest that BMI is a recognizable marker of social background. Those who live affluent lives in major cities have life expectancies, health trajectories, and likely BMIs that are similar to their peers in Turkey or Central Europe. Those who live in decaying industrial towns and small cities have worse health outcomes and, quite likely, higher BMIs (a pattern also found in the United States: see Hales et al. (2018)). It is also plausible that quality of governance is positively related to regional prosperity, and hence that the "Blavatskyy effect" is a marker of regional impoverishment.

2.3. Nutrition and Famine

It is also worth exploring this question through the lenses of famine and nutrition. For one way of tackling this: it is possible that a link exists between mean BMI, corruption, and wealth. In our sample, we see a strong inverse relationship between corruption and GDP per capita. Similarly, we see a weaker relationship between BMI and GDP per capita (see A.7). Starting with the hypothesis that corruption reduced economic growth – one for which there is good evidence (Campos et al., 2010; Aghion et al., 2016; Uberti, 2022) – one could make the argument that more corrupt countries end up poorer and that poorer countries end up with lower BMIs in aggregate – again an argument for which there is some evidence (Mary, 2018). However, this link appears to have weakened over time (Hakeem et al., 2023), at least in children. Interestingly, a recent meta-analysis by Alao et al. (2021) reveals that low household wealth is associated with malnutrition and its effects, overweight and obesity do not increase with household wealth in Europe or Central Asia.

Another way of examining this issue is through the effects of famine. In the Soviet Union, there was a wave of famine in Central Asia in the 1920s (Ustagaliyev and Aitmagambetov, 2023), and another wave in the 1930s which notably affected both Central Asia and Ukraine (Pianciola et al., 2021; Ellman, 2007). In recent years, research has come out from a number of famines, revealing that they leave a lasting epigenetic legacy on the people who live through them, as well as their children. This pattern has been noted in the Dutch Hongerwinter of 1944-1945 (De Rooij et al., 2022), the Biafra famine (Hult et al., 2010) in the late 1960s, and the Great Chinese Famine from 1959-1961 (Luo et al., 2010). In each of these cases, the children of people who lived through the famine show an increase in a number of negative health outcomes including the prevalence of type 2 diabetes and heart disease and most importantly for us, the incidence of overweight and obesity. While the literature is vague on the inter-generational link between weight and famine in the Soviet Union, increased incidence of type 2 diabetes has been noted in people who were exposed to the famine in Ukraine while in the womb (Lumey et al., 2024). Additionally, cardiovascular risk factors were found in both survivors of the siege of Leningrad as well as their children (Rotar et al., 2015). Adding further complexity, in an upcoming paper, Bazarkulova, Becker, and Sagyndykova survey contemporary Kazakhstani women whose mothers were born before, during, and after the Great Famine (and in different locations). They find that women who were born under famine conditions tend to be shorter, but that these effects do not extend to a third generation.

3. Data

As there are several steps to this process, several datasets are needed. First, we use the 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 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. Appendix A.2 provides summary statistics and additional information about the data.

We also incorporate the five perceived corruption indicators [3] used in the original paper:

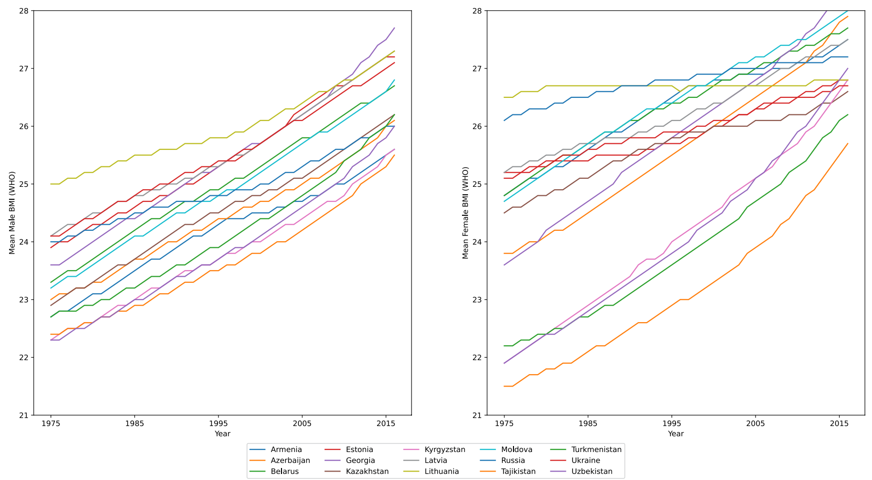
- Transparency International Corruption Perceptions Index
- World Bank worldwide governance indicator 'Control of Corruption'
- The sub-attribute 'Absence of Corruption' of Global State of Democracy Index
- European Research Centre for Anti-Corruption and State-Building Index of Public Integrity
- Basel Anti-Money Laundering Index

Most of our results will rely on the first three indicators, 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 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.

3 With the exception of the Basel Anti-Money Laundering Index, lower values on these measures mean more perceived corruption.

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), a product of the European Commision's Community Research and Development Information Service (CORDIS). While slightly older than the rest of our sample data[4], this dataset remains the most comprehensive large-scale demographic survey of multiple countries in the former USSR.

The survey provides data on a wide variety of health indicators from 18,000 individuals (16,943 of whom have data on age, sex, height, and weight) from a subset of the former Soviet Union: Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, and Ukraine (Wallace and Haerpfer, 2010). The data were gathered by field workers giving surveys to members of households in each of the above countries. The surveys were given in the local language of each country. The households and respondents therein were stratified and chosen according to the following methodology. Each country was stratified according to settlement size and type. Within each stratum, a random sampling point was chosen with an initial address and a random route generate from there. Households along that route were chosen randomly and capped at ten interviews, which were carried out outside of working hours. One adult per household was chosen at random based on their birthday and interviewed face to face. Houses were revisited twice before being dropped and resampled (CORDIS, 2013). Although the data is self-reported, it has been used in dozens of papers on public health in the former USSR even in recent years (Shkolnikov et al., 2020; Skrzynski and Creswell, 2021; Farrington et al., 2016). The omission of the Baltic States as well as Uzbekistan, Tajikistan, and Turkmenistan is unfortunate, but unlikely to bias our results strongly. The relationship between age, sex, and BMI is unlikely to vary much between countries, or over the seven years between the HITT data and the remainder of our data. Additionally, the aggregate BMI figures for the Baltic States are very similar to those of other European countries in the sample such as Moldova, Belarus, and Ukraine. Uzbekistan and Turkmenistan are also similar to Kazakhstan and Kyrgyztan. Tajikstan is an outlier in aggregate terms as well as in female BMI over time (see figure 1), but as we will see in section 5.3, Tajikstan is omitted from most of the remainder of this paper.

4 The HITT data consists of data gathered in 2001 and 2010. We use only the 2010 data.

4. Methodology

The methodology for replicating the paper's results can be summed up with this excerpt:

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). (Blavatskyy, 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 estimated for 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 based on WHO data. 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: [5]

$$(MaleRatio \times MaleBMI) + [(1 - MaleRatio) \times FemaleBMI] \tag{1}$$

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

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 (estimated) BMI and perceived 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 estimated leader BMI and with the perceived corruption measures.

On a more advanced level, we use the HITT data to 'correct' our photographic estimates of leader BMI. To do this, we construct a model for the effects of age and sex on BMI in the general population of the former USSR. After calculating the BMI of each person in the sample with available height and weight, 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 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 the leader BMI estimates for age and sex. The simpler of these models is a two-variable Ordinary Least Squares regression using age and sex: [6]

5 *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.

6 Sex is represented by the binary variable *Male,* which is 1 for males and 0 for females

$$BMIpredicted1 = \alpha + \beta0Age + \beta1Male + \epsilon \tag{2}$$

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:

$$BMIpredited2 = \alpha + \beta0Age + \beta1Male + \beta2(Male \times Age) + \epsilon \tag{3}$$

Once we have regression coefficients from the HITT data, we use them to estimate the BMIs of the leaders in the sample, and use these estimates to test the results with a series of regressions of the form: [7]

$$Measure = \alpha + \beta0BMIpredictedi + \epsilon \tag{4}$$

As noted in section 1, we assume that the causal pathway between obesity and corruption is that corruption enables certain lifestyle choices. If we were to build a more complete regression model to estimate 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 estimation will end up in the error terms of the above models. Therefore, to find an approximation of how much of the leaders' BMI estimates we can attribute to lifestyle, we subtract the regression BMI estimate from the photographic BMI estimate (equation 5) and test Blavatskyy's results against the resultant value (equation 6).

$$BMIdiff = BMIphoto - BMIpredicted \tag{5}$$

$$CorruptionMeasure = \alpha + \beta0BMIdiff + \epsilon \tag{6}$$

There is one other difference in between this paper and the one it builds upon: 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. However, as noted in the next section (specifically Table A1), 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; McKinney, 2010), Statsmodels (Seabold and Perktold, 2010), and matplotlib (Hunter, 2007).

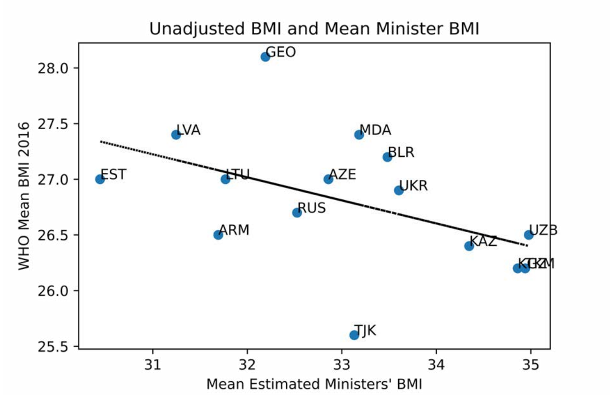
7 *Measure* is a stand-in for any of the three perceived corruption measures as well as mean BMI in each country. This also applies to equation 6.

5. Results

5.1. Reproducing Blavatskyy

In a nutshell, we can reliably reproduce Blavatskyy's results. [8] 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 A1). To reproduce the correlation between the original BMI estimates and the country-level data on perceived corruption, we use a standard OLS regression. While Blavatskyy does not report the exact coefficients for the correlations between estimated BMI and Figure 2. Unadjusted Country BMI and Mean Minister BMI the five perceived corruption indicators, our results in Table A2 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.

Figure 2. Unadjusted Country BMI and Mean Minister BMI.



5.2. Basic Controls for Sex

Our first control is for sex. As mentioned above (see equation 1), we construct a weighted BMI estimate (see section 4) and use linear regression to get a more rigorous measure of correlation. Redoing Blavatskyy's regressions 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 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 the claim that estimated 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 country 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 (Dollar et al., 2001; Goetz, 2007; Sundstro¨m and Wa¨ngnerud, 2016), though this is not without counterexamples (Afridi et al., 2017). 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. [9] 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.

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

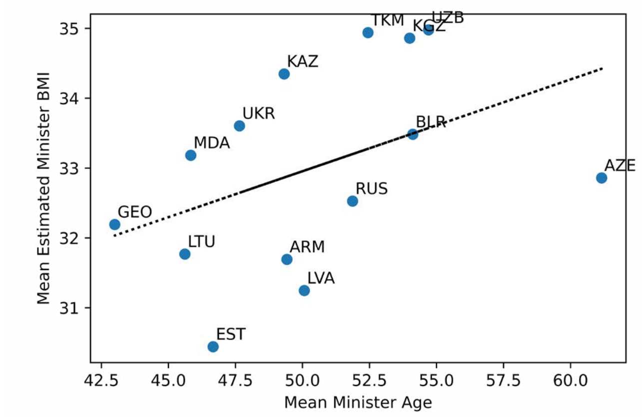
These bivariate regressions do not constitute a robust test, and there are possible confounding factors. Most notably, there may be a gender effect along with a sex effect [10] among the ministers. For example: thinner, more conventionally-attractive women may be more likely to succeed in politics, leading 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 estimates of the politicians in general, leading to a less negative relationship than we currently observe.

5.3. 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 estimates and their mean age. It turns out that there is. Regressing mean age on mean estimated 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).

Figure 3. Mean Minister BMI Estimates and Mean Minister Age Across Countries

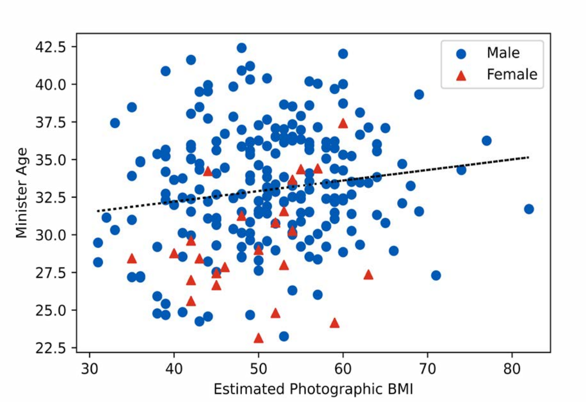


9 We speculate that this gap may be due in part to differences in smoking prevalence between males and females in these countries, but testing this is beyond the scope of our paper.

10 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.

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 an OLS regression on minister age and the photographic BMI estimates gives us a regression coefficient of 0.3277 which unlike the aggregated effect, is significant at the 2 percent level (p=0.018, see fig 4).

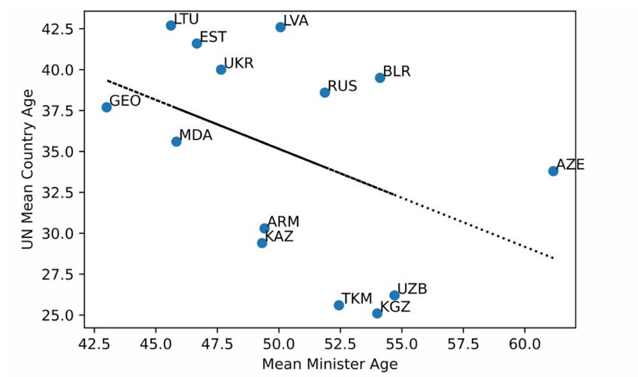
Figure 4. Minister Age and Estimated Minister BMI



Additionally, we find that the three measures of perceived 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. This would seem to cast major doubt on the BMI-Corruption 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 the original paper, 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.

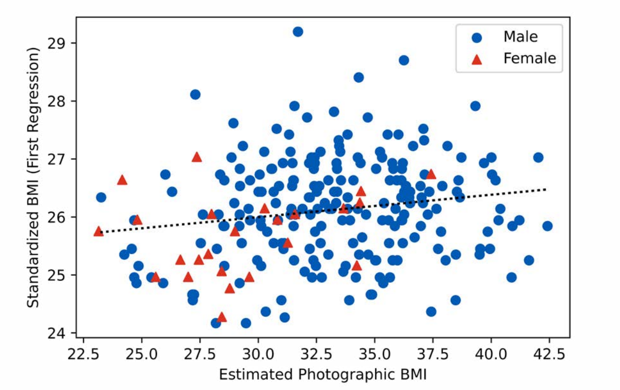
Figure 5. Mean Minister Age and Mean Country Age



5.4. Building a Normalized BMI

Running our first OLS linear regression (described in section 4) on the HITT data gives us a set of highly statistically significant coefficients summarized in table A3. We can use these results to estimate the BMI of the ministers. More specifically, this gives us an estimate of how much of a minster's photographic BMI estimate is attributable to their age and sex, which we can compare to the perceived corruption indices. Although the predicted BMI values are compressed into a smaller range of values when compared to the photographic BMI estimates (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 perceived corruption, we see that they maintain their negative correlations (see Table A4's rows labelled 'Age and Sex').

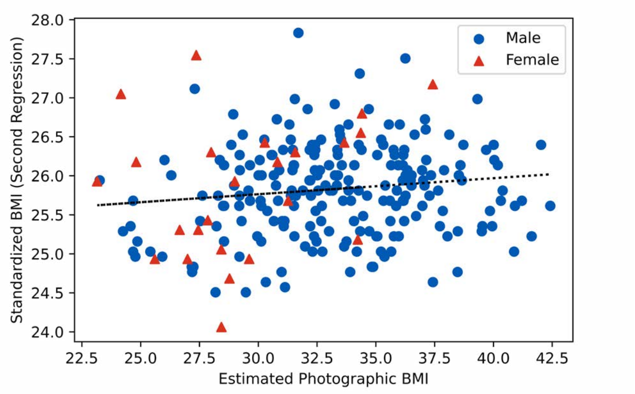
Figure 6. Estimated Minister BMI from Photographs and First Normalized BMI Estimates



The relationship between the mean BMI of a country ('country BMI') and the mean estimated BMI of its leaders ('estimated leader BMI') is a less clear picture. On the surface, they remain negatively correlated (-0.4943, see appendix A.3), although with a p-value of 0.1, this correlation is not strongly significant. However, the relationship between country BMI and estimated 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 percent level suggests that this is unlikely to be the case.

Our second regression (age-sex standardized with interaction term) yields results similar to the first. There is still a positive correlation between our normalized BMI estimates 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 A3.

Figure 7. Estimated Minister BMI from Photographs and Second Normalized BMI Estimates



Regressing this new normalized BMI estimates on the perceived 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 estimated 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 A4's rows labelled 'Age, Sex, and Interaction').

What this tells us is that some of the relationship between (perceived) corruption and (estimated) BMI is due to the age and sex differences between ministers and the general population of their respective countries. With that in mind, the next question is how much of the relationship is not due to those differences. As we discussed in section 4, we can get at this by subtracting the results of the regression predictions from the photographic predictions (see equation 5 in section 4). Doing so with the first regression's outputs (using only age and sex) and regressing the resultant subtracted BMI estimates gives us the results labelled 'Age and Sex Difference' and 'Age, Sex, and Interaction Difference' in table A4.

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 percent confidence interval. More notably, the relationship between country BMI and estimated 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 estimates, the results of which are recorded in table A4's 'Age, Sex, and Interaction 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 percent level, it does inch close to being significant at the 10 percent level. Between these two regressions, we have good evidence that there is a relationship between perceived corruption and estimated leader BMI that cannot be explained fully by the age and sex of leaders.

6. Conclusion

In sum, this paper refines and supports Blavatskyy's analysis of the relationship between the algorithmically-estimated BMI of a post-Soviet leaders and perceived corruption in those countries. We demonstrate that the relationship is not due to (aggregated) differences in age and sex between the leaders and their populations. Furthermore, our analysis suggests that estimated 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 perceived corruption indicators, or for country BMI. This suggests that there are lifestyle (or other unobserved) 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 5.2, 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. There may also be additional interactions between corruption, wealth, and nutrition, as we discuss in section 1. This may be a direction for future research.

Finally, as mentioned in section 3, 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.

While we caution against drawing any policy conclusions from this paper on the level of individual politicians, there may be more ways to incorporate a similar photographic BMI analysis in studies of corruption. Not only does it seem to be valid over time (Blavatskyy, 2021b), but it may be useful when examining sub-national corruption in cases where disaggregated data are not available. This could take the form of studying regional leaders, or leaders in different realms of politics (e.g. judges, legislators, bureaucrats, etc.)

In conclusion, these results reinforce Blavatskyy's initial hypothesis and empirics. However, they are only a refutation of one argument against them: namely that the relationship between estimated leader BMI and perceived corruption is due to age and sex differences. The precise causal mechanism remains unknown, and we can only say that unusually heavy heavy political leadership is a marker for greater corruption, at least in the formerly Soviet world.

7. References

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A Appendices

A.1 Tables

Appendix Table A1. Our BMI Estimates against Blavatskyy's

Country	Reproduced Median BMI	Reproduced Mean BMI	Blavatskyy's Median BMI Estimates
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

Appendix Table A2.

Regression coefficients of estimated minister BMI on five perceived corruption measures

Measure	Coefficient	P-Value	R2	n
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

Appendix Table A3. Regression Model Coefficients

Age-Sex Standardized 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
Age-Sex Standardized Regression with Interaction (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

Appendix Table A4. Country Metric Regression Results

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

A.2 Minister Data

The full data on ministers' ages and sexes can be found in our GitHub repository along with the code. This appendix contains several summary statistics about these new data.

Appendix Table A5. Counts of Male and Female Ministers in the Sample

Sex	Count
Male	268
Female	31

Appendix Table A6. Summary Statistics for Sexes of Ministers

Statistic	Value
Count	299.0
Mean	0.896
Std. Dev.	0.305
Min	0.000
25%	1.000
50%	1.000
75%	1.000
Max	1.000

Note: Male observations are denoted as 1.

Appendix Table A7. Summary Statistics for Ages of Ministers

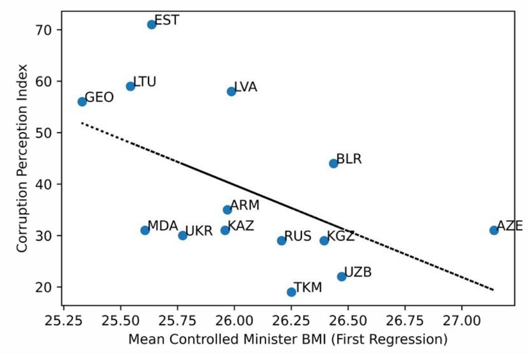
Statistic	Value
Count	249.000
Mean	51.042
Std. Dev.	8.679
Min	31.000
25%	45.000
50%	51.000
75%	57.000
Max	82.000

Appendix Table A8. White Lagrange Multiplier Test Results

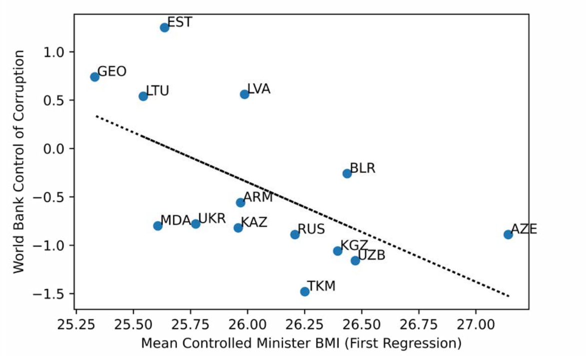
Regression	LM Statistic	p-value
One	438.064	<0.001
Two	491.271	<0.001

A.3 Age-Sex Standardized Regression Scatter Plots

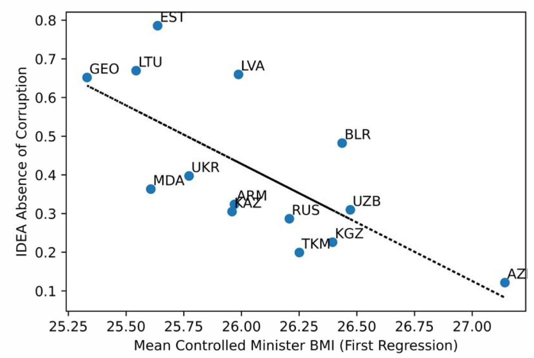
Figure C1. Mean Normalized Minister BMI plotted against...



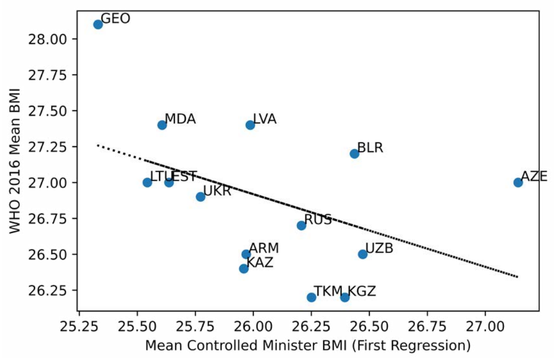
(a) Control of Corruption



(b) Corruption Perception Index



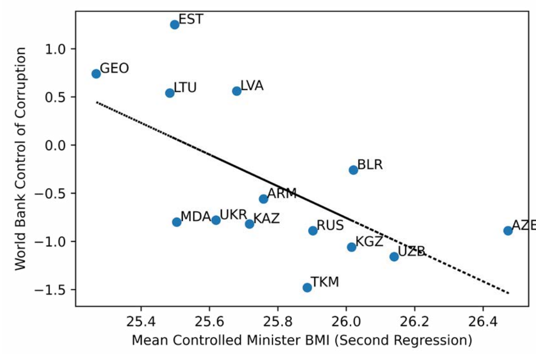
(c) Absence of Corruption



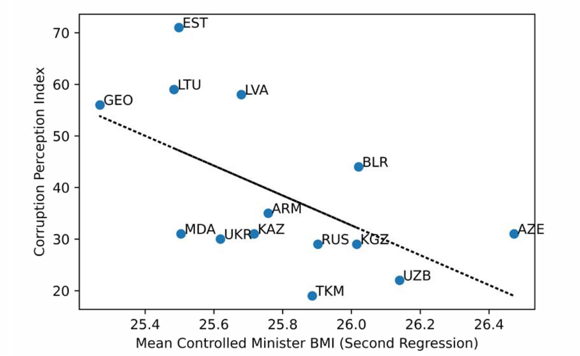
(d) Mean Country BMI

A.4 Age-Sex Standardized Regression with Interaction Scatter Plots

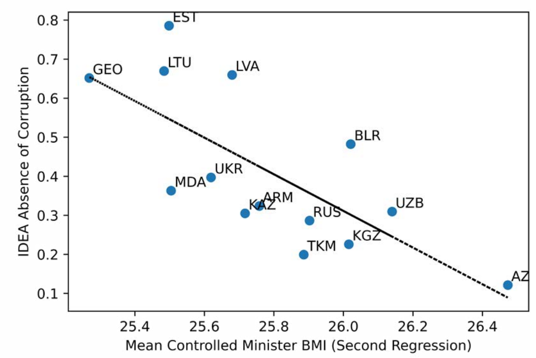
Figure C1. Mean Normalized Minister BMI plotted against...



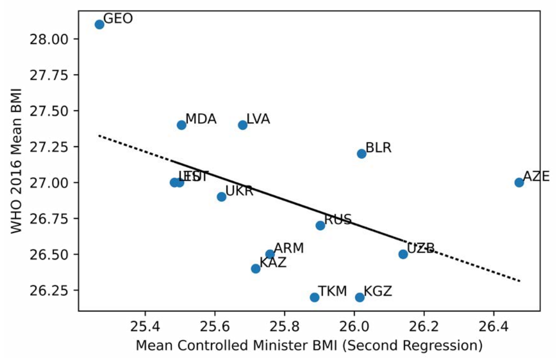
(a) Control of Corruption



(b) Corruption Perception Index



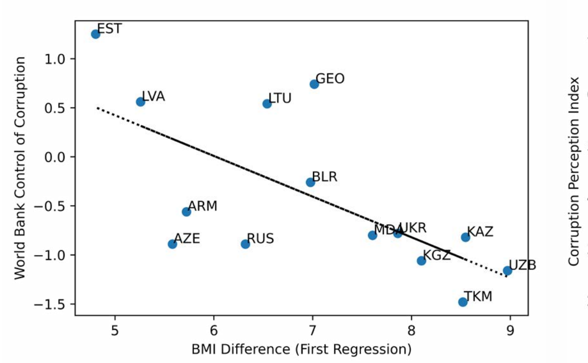
(c) Absence of Corruption



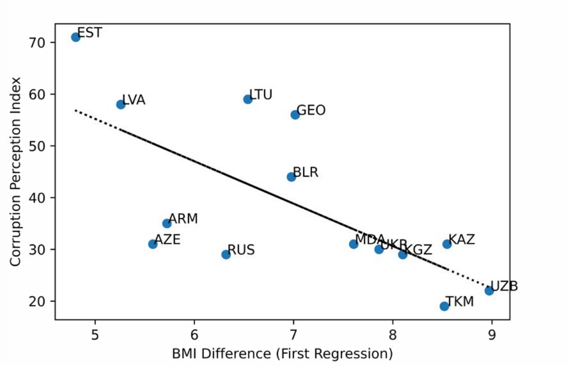
(d) Mean Country BMI

A.5 Age-Sex Standardized Difference Regression Scatter Plots

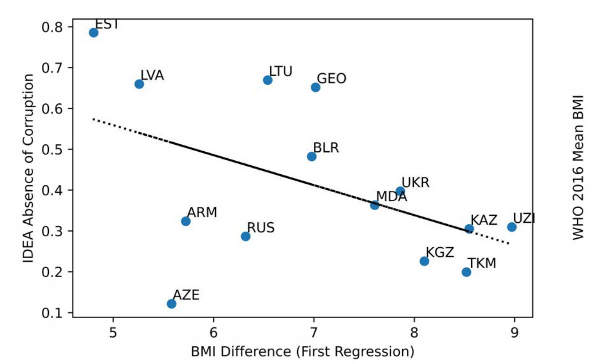
Figure C1. Mean Normalized Minister BMI plotted against...



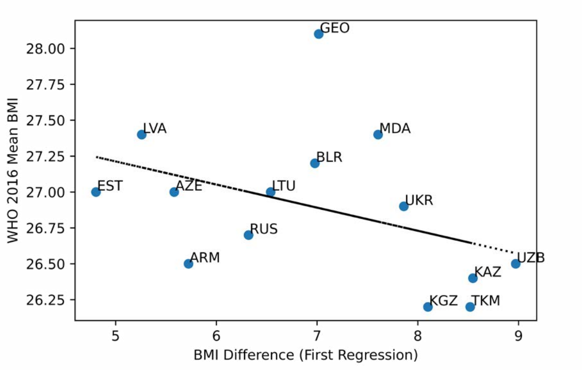
(a) Control of Corruption



(b) Corruption Perception Index



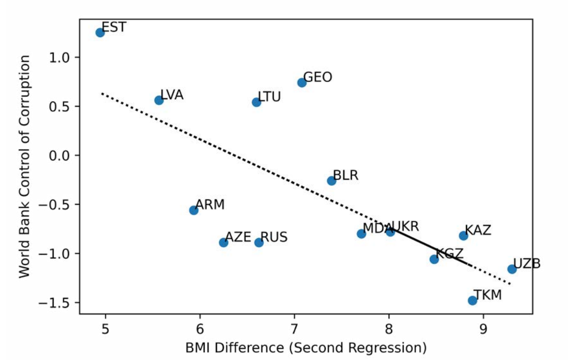
(c) Absence of Corruption



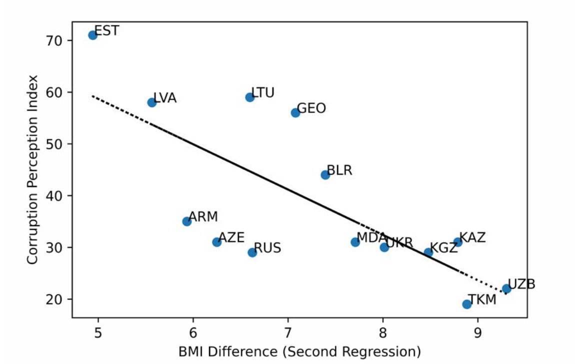
(d) Mean Country BMI

A.6 Age-Sex Standardized Difference Regression with Interaction Scatter Plots

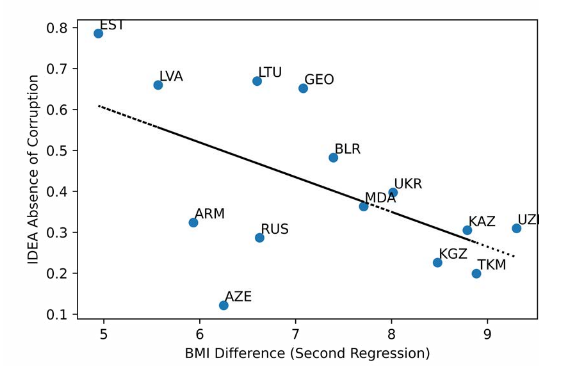
Figure C1. Mean Normalized Minister BMI plotted against...



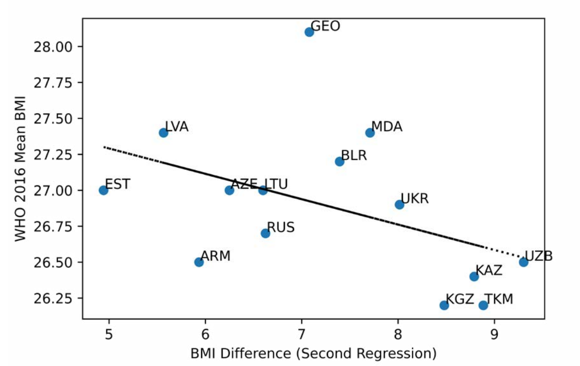
(a) Control of Corruption



(b) Corruption Perception Index



(c) Absence of Corruption

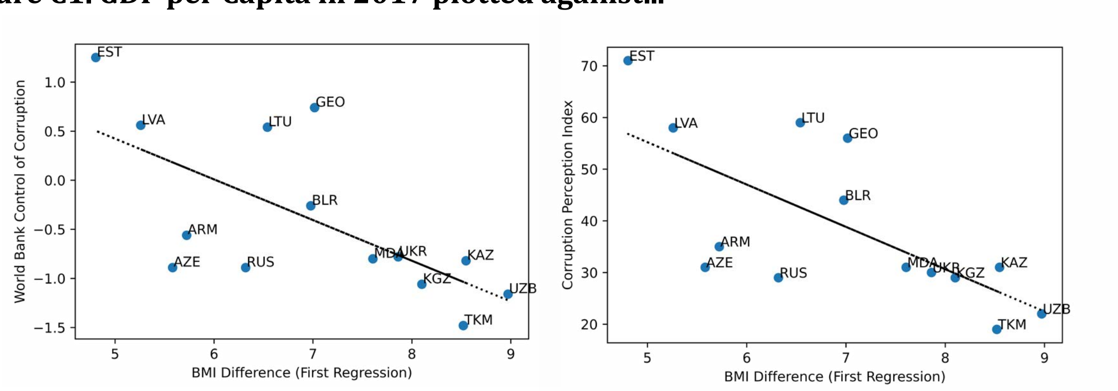


(d) Mean Country BMI

A.7 GDP per Capita, BMI, and CPI

The following figures use GDP per capita data from the World Bank. The data are from 2017 (the same year as the photographs are from) and are denominated in 2015 USD.

Figure C1. GDP per Capita in 2017 plotted against...



(a) Mean Body Mass Index (b) Corruption Perception Index

Sources: World Bank, WHO Global Health Observatory, Transparency International

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