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Obesity of politicians and corruption in post-Soviet countries

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Abstract

We collected 299 frontal face images of 2017 cabinet ministers from 15 post-Soviet states (Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan). For each image, the minister's body-mass index is estimated using a computer vision algorithm. The median estimated body-mass index of cabinet ministers is highly correlated with conventional measures of corruption (Transparency International Corruption Perceptions Index, World Bank worldwide governance indicator Control of Corruption, Index of Public Integrity). This result suggests that physical characteristics of politicians such as their body-mass index can be used as proxy variables for political corruption when the latter are not available, for instance at a very local level.

KEYWORDS

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

JEL CLASSIFICATION

D73

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1 | INTRODUCTION

Grand political corruption is a clandestine economic activity that is difficult (even life-threatening) to measure directly. Conventional indirect measures of corruption often rely on aggregated opinion surveys typically conducted among foreign experts (e.g. Transparency International Corruption Perceptions Index). Aggregation of subjective beliefs about corruption is problematic due to perception biases (cf. Donchev & Ujhelyi, 2014; Reinikka & Svensson, 2006) and heterogeneity of subjective notions, which constitutes corruption in different countries (cf. Bardhan, 2006).

Corruption boosts the income of corrupt public officials and it can be measured through the expenditures of those officials. Yet, actual expenditures of corrupt public officials are often unobservable, particularly in developing and transition countries. Thus, empirical research is again limited to survey data with self-reported income and expenditures. For example, Gorodnichenko and Peter (2007) found that public and private sector employees in Ukraine report a similar level of expenditures and asset holdings but the former claim to receive 24%–32% less wages than the latter. This sectoral gap in reported earnings allows Gorodnichenko and Peter (2007) to estimate the extent of bribery in Ukraine at the level of 0.9%–1.2% of national gross domestic product. Micro-level data on self-reported earnings and expenditures are valuable in measuring petty corruption but not grand political corruption. Self-reported expenditures of corrupt top governmental officials are incomplete at best.

Lan and Li (2018) recently measured grand political corruption in China through the gross import value of luxury Swiss wristwatches that are a popular medium for corrupt transactions. Lan and Li (2018) found that this measure of political corruption (but not the imports of non-luxury watches) was correlated with leadership transitions in China (but not in Hong Kong) till 2011–2012. Lan and Li (2018) argue that the rise of social media and Internet anti-corruption platforms in 2011–2012 made it no longer possible to measure grand political corruption through visible luxury Swiss watches. Luxury Swiss watches could still be a popular expenditure of corrupt governmental officials, but these officials are now more careful not to reveal their Swiss watches to the general public.

When actual expenditures in the upper echelons of the government are unobservable and/or under-reported, it is useful to find proxy variables that are highly correlated with conventional measures of grand political corruption. This paper focuses on physical characteristics of public officials, in particular, on their body-mass index.[1] Unfortunately, medical records of public officials are usually unobservable (records may not be kept at all) and direct calculation of their body-mass index is still not feasible. However, recent advances in machine learning (computer vision) produced algorithms for estimating a person's body-mass index from their frontal face image (cf. Kocabey et al., 2017; Wen & Guo, 2013). Top public officials such as cabinet ministers of the government are routinely in the spotlight of mass media and their facial photographs are widely available. A median body-mass index of cabinet ministers is a convenient proxy variable that can be calculated retrospectively across time (as long as photographic data are available) and can be meaningfully compared across countries and regions.

We use the sample of 15 post-Soviet states because corruption is perceived to be a significant problem in the region. For example, according to Transparency International Corruption Perceptions Index 2017, Uzbekistan, Tajikistan and Turkmenistan ranked 157th, 161st and 167th correspondingly among 180 countries, where the bottom of the scale indicates a greater level of corruption. Moreover,

[1]The body-mass index (BMI) is the body weight in kilograms divided by the square of the body height in metres. World Health Organization classifies a person with a body-mass index equal to or greater than 25 as overweight and equal to or greater than 30 as obese.

micro-level expenditure data are not available for several countries in the region, leaving opinion surveys as the only corruption measurement tool.

The remainder of the paper is organized as follows. Section 2 describes our collected dataset of frontal face images. Section 3 briefly outlines the algorithm that was used for estimating body-mass indexes from the collected dataset of photographical data. Section 4 presents our estimation results. Section 5 concludes.

2 | DATASET

We collected 299 frontal face images of cabinet ministers from 15 post-Soviet states who were in office in 2017.[2] In case of a cabinet reshuffle, when two (sometimes even three) individuals occupied the same ministerial position in 2017, we collected the image of the individual who occupied this position for the longest period in 2017.[3] Country-specific details are presented in the Appendix. For each minister, we conducted a Google image search in the form “Name Surname” + 2017. The minister's first name and surname were typed in the official language of his or her country (e.g. in Cyrillic script for Belarus, Kazakhstan, Kyrgyzstan, Russia, Tajikistan and Ukraine). Whenever possible, we selected a minister's image that resembled a passport photograph—unobscured frontal face image preferably taken during an event in 2017 (such as an official press conference, an official visit abroad or a meeting with a counterpart minister from another country).

3 | ESTIMATION

For each image in the dataset, the minister's body-mass index is estimated using the computer vision algorithm recently developed by Kocabey et al. (2017).[4] This algorithm is a two-stage procedure. The first stage is a deep convolutional neural network VGG-Face developed by Parkhi, Vedaldi, and Zisserman (2015). This neural network extracts the features from a deep fully connected neuron layer *fc6* for the input image. The second stage is an epsilon support vector regression (Smola & Vapnik, 1997) of the extracted features to predict body-mass indexes of 3,368 training images (with known body-mass index values) collected by Kocabey et al. (2017).

Intuitively, this estimation procedure builds an artificial neural network that is first trained to recognize human faces. This stage is analogous to human visual recognition. Subsequently, the obtained artificial neural network is trained to associate recognized faces with body-mass indexes. This step can

[2]The 15 post-Soviet states are Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine and Uzbekistan. We do not consider disputed states with a relatively small degree of international recognition (Transnistria, Abkhazia, South Ossetia, Nagorno-Karabakh, the Donetsk People's Republic and Luhansk People's Republic).

[3]Alternatively, one could also collect the images of all ministers to calculate two median body-mass indexes (before and after the cabinet reshuffle) and take the weighted average of these two indexes (with weighting being proportional to the cabinet's period in power in 2017).

[4]The open source code of Kocabey et al. (2017) and training images were downloaded from https://docs.google.com/uc?id=0B5nogN4WAa_dQTVKNkVJVHdWTnc&export=download. We made only trivial syntax changes to execute it in Python 3.5.0 (cf. online Appendix P).

be interpreted as a continuous generalization of the process by which humans learn to classify other individuals into discrete categories: underweight, normal, overweight or obese.

As a robustness check, we also estimated body-mass indexes from our dataset of 299 images using the algorithm of Wen and Guo (2013). When this algorithm converged, it produced similar results to Kocabey et al.'s (2017) algorithm. However, for 43 out of 299 images (14.4%), the algorithm of Wen and Guo (2013) did not converge.

4 | RESULTS

The second column of Table 1 shows our median estimated ministers' body-mass index for the corresponding country in the first column. Countries are listed in the increasing order of the estimated ministers' body-mass index. The third column of Table 1 also shows the image of a cabinet minister who has the median body-mass index for countries with an odd number of ministers and two cabinet ministers who have the closest body-mass index to the median for countries with an even number of ministers.

Estimated body-mass index for ministers in our dataset is generally quite high. According to the estimated body-mass index, 96 out of 299 ministers (32%) are severely obese (estimated body-mass index between 35 and 40). In particular, 13 out of 24 Uzbek ministers (54%), 8 out 18 Tajik ministers (44%) and 10 out of 24 Ukrainian ministers (42%) are estimated to be severely obese. Another 13 out of 299 ministers in our dataset (4%) are very severely obese (estimated body-mass index greater than 40). In particular, 3 out of 20 Kazakh ministers (15%) and 2 out of 24 Ukrainian ministers (8%) are estimated to be very severely obese. Only 10 out of 299 ministers in our dataset (3%) are estimated to have normal weight (body-mass index between 18.5 and 25). In particular, the governments of Azerbaijan, Estonia, Georgia, Kazakhstan, Latvia, Lithuania, Ukraine and Uzbekistan each have one minister with an estimated normal weight. None of the ministers in our dataset is estimated to be underweight (body-mass index below 18.5).

The remaining five columns of Table 1 report five conventional measures of perceived corruption based on the surveys of foreign experts. Transparency International Corruption Perceptions Index 2017 is presented in the fourth column of Table 1. World Bank worldwide governance indicator 'Control of Corruption' 2017 is presented in the fifth column of Table 1. The European Research Centre for Anti-Corruption and State-Building Index of Public Integrity 2017 index is presented in the sixth column of Table 1 (this index is not available for Belarus, Turkmenistan and Uzbekistan). The International Institute for Democracy and Electoral Assistance sub-attribute 'Absence of Corruption' of Global State of Democracy Index 2017 is presented in the seventh column of Table 1. Finally, the Basel Institute of Governance Basel Anti-Money Laundering Index 2017 is presented in the eighth column of Table 1.

A visual inspection of Table 1 confirms the intuition presented in Section 1—as ministers' images in the third column get progressively more overweight and obese, conventional corruption indicators in the last five columns get progressively worse. Our median estimated ministers' body-mass index is highly correlated with all five conventional measures of perceived corruption. The correlation coefficient with Transparency International Corruption Perceptions Index 2017, World Bank worldwide governance indicator 'Control of Corruption' 2017, European Research Centre for Anti-Corruption and State-Building Index of Public Integrity 2017, the sub-attribute 'Absence of Corruption' of Global State of Democracy Index 2017 and Basel Anti-Money Laundering Index 2017 is −0.92, −0.91, −0.93, −0.76 and 0.8, respectively.

TABLE 1 Median estimated ministers' body-mass index and five conventional measures of corruption for 15 post-Soviet states

Country	Median estimated ministers' BMI	Image of a minister with median BMI	Corruption Perceptions Index 2017	World Bank Control of Corruption 2017	Index of Public Integrity 2017	IDEA Absence of Corruption 2017	Basel AML Index 2017
Estonia	28.7		71	1.24	8.93	0.807	2.73
Lithuania	30.3		59	0.55	7.82	0.641	3.67
Latvia	30.7		58	0.54	7.93	0.631	3.64
Georgia	30.9		56	0.74	7.30	0.652	5.28
Armenia	32.1		35	−0.56		0.352	4.44
Russia	32.5		29	−0.89	5.90	0.249	5.7
Moldova	32.7		31	−0.80	6.44	0.370	5.23

(Continues)

TABLE 1 (Continued)

Country	Median estimated ministers' BMI	Image of a minister with median BMI	Corruption Perceptions Index 2017	World Bank Control of Corruption 2017	Index of Public Integrity 2017	IDEA Absence of Corruption 2017	Basel AML Index 2017
Belarus	32.9		44	−0.26		0.467	5.22
Kyrgyzstan	33.3		29	−1.05	5.73	0.295	6.25
Azerbaijan	33.3		31	−0.88	6.43	0.040	4.77
Tajikistan	33.6		21	−1.33	5.43	0.042	8.27
Kazakhstan	33.8		31	−0.82	5.88	0.350	6.36
Ukraine	34.4		30	−0.78	6.2	0.386	6.45
Turkmenistan	34.7		19	−1.48		0.213	6.84
Uzbekistan	35.5		22	−1.16		0.316	5.99

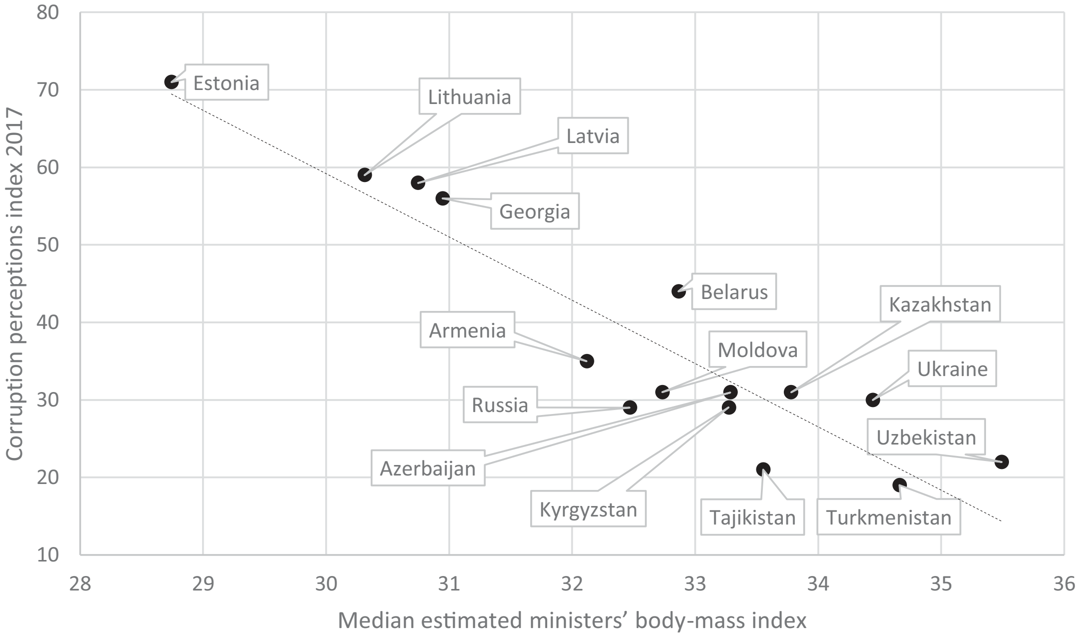

FIGURE 1 Scatterplot of median estimated ministers' body-mass index against Transparency International Corruption Perceptions Index 2017 (with a linear trend), where lower values of CPI indicate greater corruption

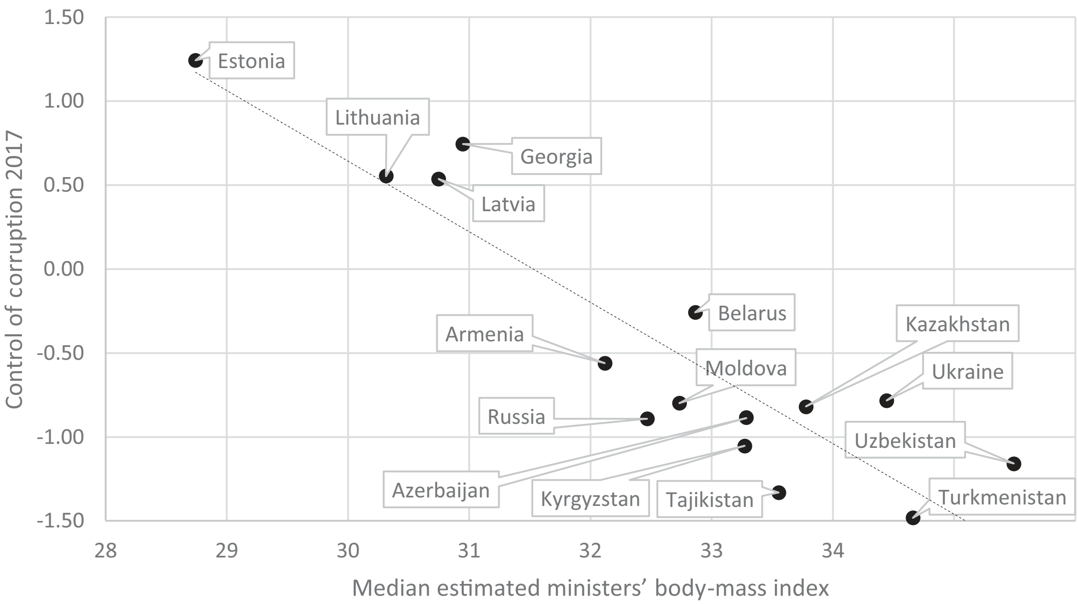

FIGURE 2 Scatterplot of median estimated ministers' body-mass index against World Bank worldwide governance indicator Control of Corruption 2017 (with a linear trend), where lower values of Control of corruption indicate greater corruption

Figure 1 plots our median estimated ministers' body-mass index against the Corruption Perceptions Index 2017. Figure 2 does the same for indicator 'Control of Corruption' 2017. According to all conventional measures of corruption, the least corrupt post-Soviet states are three Baltic countries

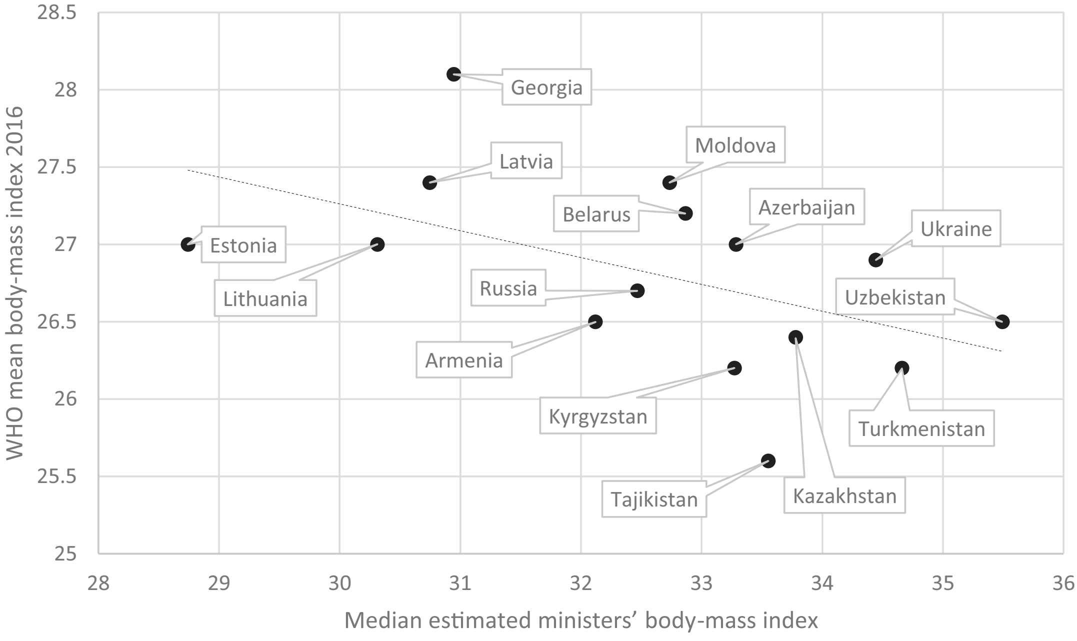

FIGURE 3 Scatterplot of median estimated ministers' body-mass index against World Health Organization mean body-mass index in population 2016 (with a linear trend)

(Estonia, Lithuania and Latvia) and Georgia. These are also the countries with the lowest median estimated ministers' body-mass index. According to the conventional measures of corruption, the most corrupt post-Soviet states are three Central Asian countries: Turkmenistan, Tajikistan and Uzbekistan. The three post-Soviet states with the highest median estimated ministers' body-mass index are Uzbekistan, Turkmenistan and Ukraine. Thus, foreign experts may underestimate the level of grand political corruption in Ukraine (a country with relatively less corrupt neighbours), and they may overestimate corruption in case of Tajikistan (a country with relatively more corrupt neighbours).

High correlation between our median estimated ministers' body-mass index (based on frontal face images) and conventional measures of corruption (based on perception surveys) is striking. Yet, one can plausibly argue that some countries have relatively overweight/obese politicians because the general population of voters is also relatively overweight/obese. Figure 3 plots our median estimated ministers' body-mass index against estimated mean body-mass index of the population of the corresponding country.[5] Figure 3 shows that there is a small negative relationship between the two (correlation coefficient −0.51). Countries with relatively more obese cabinet ministers tend to have a relatively less overweight population. Ironically, this suggests that there might be a health benefit to grand political corruption—it is correlated with higher obesity rates among top politicians (which is a very small fraction of the general population) but lower obesity rates in the general population. Relatively less corrupt countries have slimmer politicians but more overweight voters.

Does our median estimated ministers' body-mass index capture meaningful changes in grand political corruption? The Armenian velvet revolution (which is also known as #RejectSerzh movement) that occurred in spring 2018 offers a convenient natural experiment. The third president of Armenia, Serzh Sargsyan, at the end of his second (and last) term in office initiated a constitutional reform

[5]Data taken from the World Health Organization Global Health Observatory data repository 2016 http://apps.who.int/gho/data/view.main.BMIMEANADULTCv?lang=en (data for 2017 are not yet available at the time of writing).

transforming the country from a semi-presidential to parliamentary republic. Mass protests erupted when Serzh Sargsyan was elected as the new prime minister in spring 2018 setting him as a *de facto* head of government for the third term. The protests resulted in a minority coalition government formed on 12 May 2018 and headed by Nikol Pashinyan.

Our median estimated body-mass index of ministers in the Pashinyan government (cf. online Appendix Q) is 31.2, which is lower than Armenia's 2017 value of 32.1 (cf. Table 1). Thus, according to our measure, the Armenian velvet revolution lowered grand political corruption. Yet, the Transparency International Corruption Perceptions Index 2018 for Armenia is the same as it was in 2017, indicating no change in corruption before and after the Armenian velvet revolution. This is perhaps not surprising as the Transparency International Corruption Perceptions Index is based on subjective perceptions. Individual perceptions are known to be sticky and change relatively slowly over time. In contrast, our proposed measure of grand political corruption changes every time a median cabinet minister (on the body-mass index scale) is changed.

5 | CONCLUSION

Political corruption is often associated with many negative economic consequences. For example, it lowers economic growth due to additional uncertainty (ambiguity) created by unpredictable bribe extortion (Cieślik & Goczek, 2018). Political corruption also lowers development (Aidt, 2009; Glaeser & Saks, 2006). For example, Lehne, Shapiro, and Eynde (2018) recently found that political corruption increases the cost of road construction and decreases the length of constructed roads. At the same time, political corruption deters foreign direct investment in the country (Barassi & Zhou, 2012; Brada, Drabek, Mendez, & Fabricio Perez, 2019; Mathur & Singh, 2013). At the same time, political corruption increases public debt and the size of the shadow economy (Cooray, Dzhumashev, & Schneider, 2017). Political corruption also increases the cost of public borrowing (Depken & Lafountain, 2006); it leads to higher military spending (D'Agostino, Paul Dunne, & Pieroni, 2016) and bureaucratic delays (Ahlin & Bose, 2007). Political corruption can even lower the effectiveness of antiretroviral drugs in preventing AIDS deaths because disproportionately more clinics distribute imported antiretroviral drugs in areas that are predominantly represented by the government leader's ethnic group (Friedman, 2018).

Given its high cost for society, political corruption needs to be measured as accurately as possible. Rigorous empirical evaluation of anti-corruption policies also requires accurate corruption measurement (Gans-Morse et al., 2018). Existing methodology of corruption measurement is limited to perception surveys by foreign experts (such as the Transparency International Corruption Perceptions Index) and micro-level questionnaires such as public expenditure tracking surveys, service provider surveys and enterprise surveys (Reinikka & Svensson, 2006). This demands new objective measures of corruption similar to the indirect measurement of the shadow economy via electricity consumption (cf. Kaufmann & Kaliberda, 1996). Lan and Li (2018) recently proposed one objective measure of grand political corruption through the import value of luxury Swiss watches but the effectiveness of this measure faded away in recent years due to the rise of social media and Internet anti-corruption platforms.

This paper proposed another new proxy variable for grand political corruption—median estimated body-mass index of cabinet ministers. Using recently developed machine learning algorithms, we estimate body-mass indexes of 299 cabinet ministers who were governing 15 post-Soviet states in 2017 (or for the larger part of 2017 in case of a cabinet reshuffle). The estimation algorithm builds an artificial neural network that is first trained to recognize human faces (analogously to human vision) and then is trained to associate recognized faces with body-mass indexes. We find that the median ministers' body-mass index (estimated from frontal face images) is highly correlated with conventional measures of corruption (based on perception surveys among foreign experts). Moreover, when such conventional measures fail to capture changes in grand political corruption (as in the aftermath of the Armenian velvet revolution in spring 2018), our proposed measure of corruption changes in the expected direction. This suggests that latent grand political corruption is literally visible from the photographs of top public officials. Note, however, that our results do not necessarily imply that individual obese politicians are more corrupt than non-obese politicians.

Our proposed methodology is widely applicable across countries as photographic data of top public officials are relatively accessible in traditional mass media and social media. This creates the potential of measuring corruption in many regions where administering reliable micro-level surveys is problematic and foreign experts have limited direct access. Our proposed corruption measure can be also applied retrospectively in time. This introduces for the first time, the possibility of measuring corruption from a historical perspective (before the mid-1990s when the first indexes of perceived corruption were constructed).

By construction, our proposed corruption measure is affected by reshuffles and changes in the composition of the government. In democratic countries, significant changes in government are triggered by elections. This can rationalize positive correlation between the level of perceived corruption and electoral cycles recently discovered by Potrafke (2019). Lan and Li (2018) also found a positive correlation between the level of corruption objectively measured through the imports of Swiss watches and 5-year communist leadership transition cycles in China (till 2011–2012).

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section.

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APPENDIX

DETAILS OF COUNTRY-SPECIFIC IMAGES

For Armenia, our dataset includes 19 images of ministers of the Karapetyan government (cf. online Appendix A). There was only one change in this cabinet of ministers in 2017. Arpine Hovhannisyan served as a minister of justice in the Karapetyan government till April 2017. She was succeeded by Davit Harutyunyan who served as a Minister of Justice from May 2017. Consequently, we use the image of Davit Harutyunyan in our dataset.

For Azerbaijan, our dataset includes 26 images of ministers of the Rasizade government (cf. online Appendix B). There were two changes in this cabinet of ministers in 2017. The Minister of Industry Natig Aliyev died on 9 June 2017. He was succeeded by Parviz Shahbazov who served as the Minister of Energy from 12 October 2017. We use the image of Natig Aliyev in our dataset. Fazil Mammadov served as the Minister of Taxes in the Rasizade government till 5 December 2017 when he was replaced by Mikayil Jabbarov (on allegations of smuggling $1bn out of the country). We use the image of Fazil Mammadov in our dataset.

For Belarus, our dataset includes 30 images of ministers of the Kobyakov cabinet (cf. online Appendix C). There was a cabinet reshuffle in September 2017 when three ministers were replaced. Lilia Ananich served as the Minister of Information in the Kobyakov government till 28 September 2017 when she was replaced by Aleksandr Karlyukevich. We use the image of Lilia Ananich in our dataset. Boris Svetlov served as the Minister of Culture in the Kobyakov government till 28 September 2017 when he was replaced by Yury Bondar. We use the image of Boris Svetlov in our dataset. Andrei Kavkhuta served as the Minister of Natural Resources and Environmental Conservation in the Kobyakov government till 14 September 2017 when he was replaced by Andrei Khudyk. We use the image of Andrei Kavkhuta in our dataset.

For Estonia, our dataset includes 15 images of ministers of the first Ratas government (cf. online Appendix D). There was a cabinet reshuffle in June 2017 when one of the coalition parties replaced its ministers following a change in party leadership. Sven Sester was the Minister of Finance in the first Ratas government till 12 June 2017 when he was replaced by Toomas Tõniste. We use the image of Toomas Tõniste in our dataset. Mihhail Korb was the Minister of Public Administration in the first Ratas government till 12 June 2017 when he was replaced by Jaak Aab. We use the image of Jaak Aab in our dataset. Margus Tsahkna was the Minister of Defence in the first Ratas government till 12 June 2017 when he was replaced by Jüri Luik. We use the image of Jüri Luik in our dataset. Marko Pomerants was the Minister of the Environment in the Ratas government till 12 June 2017 when he was replaced by Siim Kiisler. We use the image of Siim Kiisler in our dataset.

For Georgia, our dataset includes 21 images of ministers of the second Kvirikashvili government (cf. online Appendix E). There was only one change in this cabinet of ministers in 2017. Aleksandre Jejelava served as the Minister of Education and Science in the second Kvirikashvili government till 13 November 2017 when he was succeeded by Mikheil Chkhenkeli. We use the image of Aleksandre Jejelava in our dataset.

For Kazakhstan, our dataset includes 20 images of ministers of the Sagintayev government (cf. online Appendix F). There was only one change in this cabinet of ministers in 2017. Askar Myrzakhmetov served as the Minister of Agriculture in the Sagintayev government till 15 December 2017 when he was succeeded by Umirzak Shukeyev. We use the image of Askar Myrzakhmetov in our dataset.

Kyrgyzstan saw a change of governments in 2017. The Jeenbekov government ruled Kyrgyzstan till 22 August 2017, succeeded by the Isakov government. We use 17 images of ministers of the Jeenbekov government in our dataset (cf. online Appendix G).

For Latvia, our dataset includes 14 images of ministers of the Kučinskis government (cf. online Appendix H). There were no changes in this cabinet of ministers in 2017.

For Lithuania, our dataset includes 15 images of ministers of the Skvernelis government (cf. online Appendix I). There was only one change in this cabinet of ministers in 2017. Mindaugas Sinkevičius resigned as the Minister of Economy on 13 October 2017. The ministry was subsequently reorganized and Virginijus Sinkevičius took over as the Minister of Economy and Innovations on 28 November 2017. We use the image of Mindaugas Sinkevičius.

For Moldova, our dataset includes 13 images of ministers of the Filip government (cf. online Appendix J). There were three changes in this cabinet of ministers in 2017. Eduard Grama was the Minister of Agriculture and Food Industry in the Filip government till 20 March 2017 when he was detained on alleged corruption charges. Vasile Bîtca took over as the Minister of Agriculture, Regional Development and Environment from 26 July 2017 to 21 December 2017. We use the image of Vasile Bîtca in our dataset. Corina Fusu resigned as the Minister of Education on 30 May 2017 after her party withdrew from the governing coalition. Monica Babuc took over as the Minister of Education, Culture and Research from 26 July 2017. We use the image of Monica Babuc in our dataset. Ruxanda Glavan was the Minister of Health in the Filip government till 25 July 2017 and Stela Grigoraș took over as the Minister of Health, Labour and Social Protection from 26 July 2017. We use the image of Ruxanda Glavan.

For Russia, our dataset includes 31 images of ministers of the first Medvedev government (cf. online Appendix K). This was a remarkably stable government that barely changed over 6 years in power and there were no changes in this cabinet of ministers in 2017.

For Tajikistan, our dataset includes 18 images of ministers of the Rasulzoda government (cf. online Appendix L). There were two changes in this cabinet of ministers in 2017. Sherali Ganchalzoda was the Minister of Transport in the Rasulzoda government till 23 January 2017 when Khudoyor Khudoyorzoda took over the post. We use the image of Khudoyor Khudoyorzoda in our dataset. Nusratullo Salimov was the Minister of Health and Social Protection of Population in the Rasulzoda government till 12 January 2017 when Nasim Olimzoda took over the post. We use the image of Nasim Olimzoda in our dataset.

For Turkmenistan, our dataset includes 12 images of the president and vice presidents of the Berdimuhamedow[6] government (cf. online Appendix M). Three vice presidents were replaced in 2017. Şamuhammet Durdylyýew was vice president responsible for Construction in the Berdimuhamedow government till 13 January 2017 when Dädebaý Amangeldiýew took over the post. We use the image of Dädebaý Amangeldiýew in our dataset. Satlyk Satlykov was vice president responsible for Transport and Communication in the Berdimuhamedow government till 13 January 2017 when Baýram Annameredow took over the post. We use the image of Baýram Annameredow in our dataset. Ýagşygeldi Kakaýew was vice president responsible for Oil and Gas in the Berdimuhamedow government till 5 April 2017 when Maksat Babaýew took over the post. We use the image of Maksat Babaýew in our dataset.

For Ukraine, our dataset includes 24 images of ministers of the Groysman government (cf. online Appendix N). There were no changes in this cabinet of ministers in 2017.

For Uzbekistan, our dataset includes 24 images of ministers of the Aripov government (cf. online Appendix O). This was a remarkably unstable government that was frequently reshuffled in 2017. Rustam Azimov was the Deputy Prime Minister till 6 June 2017 when he was replaced by Jamshid Kuchkarov. We use the image of Jamshid Kuchkarov in our dataset. Ulugbek Rozukulov was the Deputy Prime Minister till 6 June 2017 when he was replaced by Nodir Otazhonov. We use the image of Nodir Otazhonov in our dataset. Gulomjon Ibragimov was the Deputy Prime Minister till 30 October 2017 when he was replaced by Alisher Sultonov. We use the image of Gulomjon Ibragimov in our dataset. Aziz Abduhakimov was the Minister of Labour till 7 August 2017 when she was replaced by Aktam Haitov. We use the image of Aziz Abduhakimov in our dataset. Rustam Qosimov was the Minister of Higher and Secondary Special Education till 20 June 2017 when he was replaced by Inom Madzhidov. We use the image of Inom Madzhidov in our dataset. There were three ministers of internal affairs in 2017: Adham Ahmadboyev till 4 January 2017, Abdusalom Azizov till 4 September and Poʻlat Bobojonov afterwards. We use the image of Abdusalom Azizov in our dataset. Erkin Iskandarov was the minister of housing and communal services till 5 July 2017 when he was replaced by Muzaffar Saliev. We use the image of Erkin Iskandarov in our dataset. Adham Ikramov was the Minister of Public Health till 21 February 2017 when he was replaced by Alisher Shodmonov. We use the image of Alisher Shodmonov in our dataset. Mahmud Muratov was the Minister of Culture till 8 August 2017 when he was replaced by Bahtyer Sayfullaev. We use the image of Mahmud Muratov in our dataset. Tursinhan Xudayberganov was the Minister of Emergency Situations till 18 March

[6]Berdimuhamedow is both the chief of state and the head of government in Turkmenistan.

2017 when he was replaced by Rustam Jo'rayev. We use the image of Rustam Jo'rayev in our dataset. Muzraf Ikramov was the Minister of Justice till 14 August 2017 when he was replaced by Ruslanbek Davletov. We use the image of Muzraf Ikramov in our dataset.