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Should one hire a corrupt CEO in a corrupt country? ☆

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ABSTRACT

This paper examines the interaction between the propensity to corrupt (PTC) and firm performance. Using a unique data set of Moscow traffic violations, I construct the PTC of every Muscovite with a driver's license. Next, I determine the PTC for the top management of 58,157 privately held firms. I find that a 1 standard deviation increase in management PTC corresponds to a 3.6% increase in income diversion and that firms with corrupt management significantly outperform their counterparts. This study contributes to the literature that characterizes corruption using objective (instead of perception-based) measures and provides evidence regarding the positive aspects of corruption at the firm level.

1. Introduction

Do corrupt managers deliver superior firm performance? The answer to this question is unclear from a theoretical perspective. Corrupt managers can advance shareholder interest in several respects. For instance, they can evade more taxes, generating de facto money transfers from the government to a firm. Corrupt managers can also obtain more government contracts and remove business impediments by paying bribes. Leff (1964) and Huntington (1968) suggest that corruption could help to maneuver around bad laws and institutions. In addition, Lui (1985) shows that bribery can be efficient in a queuing model if agents whose time has a higher value can use bribes to obtain a better place in line relative to other agents. However, corrupt managers could also use firm resources for their own private benefits and, therefore, destroy shareholder value. Desai, Dyck, and Zingales (2007) find that an increase in tax enforcement in Russia, which

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decreased the private benefits of control extracted by company insiders, was followed by a positive market reaction. Mironov (2013) shows that income diversion not only leads to the transfer of money from shareholders to management but also deteriorates firm performance.

In this paper, I analyze the relation between managerial corruption and firm performance using micro-level data from Moscow firms. The key idea of the paper is that individual propensity to corrupt (PTC) can be inferred from recorded traffic violation data. Drivers occasionally commit traffic violations. However, not all traffic violations are recorded in corrupt countries. A driver who is stopped by police can often avoid a formal penalty in exchange for a bribe. Therefore, observing a person's recorded traffic violations for a long period of time allows an inference of individual propensity for corruption. To better understand my approach to PTC measurement, consider the following example. Two persons, A and B, have identical demographic characteristics, the same income level, and a similar driving style. For some reason, however, driver A has a much higher number of recorded traffic violations than driver B. One possible explanation is that A is simply unlucky and that the police caught A every time that he or she was speeding. Another possible explanation is that A and B were stopped for approximately the same number of traffic violations but that B paid more police bribes than A and, therefore, has a lower number of recorded traffic violations.

Russia provides a unique environment in which to study corruption-related issues. Russia is the sixth largest economy in the world, with a per capita gross domestic product (GDP) of $23,549.[1] This figure is approximately equal to that of Eastern European countries, such as Estonia, Hungary, and Poland. However, the level of corruption in Russia is extremely high, similar to that of countries that are four to five times poorer. The 2012 Corruption Perceptions Index produced by Transparency International ranked Russia 133 out of 174 countries, slightly below Nicaragua, Uganda, Togo, and Honduras. In 2012, the World Bank Ease of Doing Business index ranked Russia 112 out of 185 nations, slightly above El Salvador and Guyana

Data availability is another important factor that makes Russia a unique case. Russia inherited a comprehensive system of government statistics from the Union of Soviet Socialist Republics. Different administrative agencies routinely collect large amounts of data at the individual and firm levels. The data used in this paper cover the entire population of Moscow and all its firms, which range from small firms to extremely large firms. Thus, a comprehensive analysis could be conducted of an economy with the size of a typical European country, such as Austria, Denmark, Greece, or Norway. It is difficult to imagine that such detailed data would become available for the US or any Western economy in the near future. Several recent studies have built on this comparative advantage of the Russian statistical system.[2]

This paper makes three contributions to the literature. First, I develop an individual measure of corruption propensity for 3.1 million Muscovites (PTC). Second, I show that the PTC for firm management is positively related to income diversion and undeclared wages paid to employees. Finally, I find evidence that a positive link exists between management PTC and firm performance measured as revenue growth, revenue per employee, and the ratio of revenue to assets. This paper is closely related to the rapidly growing body of literature on managerial malfeasance, including Desai, Dyck, and Zingales (2007), Johnson, La Porta, Lopez-de-Silanes, and Shleifer (2000), Bertrand, Mehta, and Mullainathan (2002), Mironov (2013), and Braguinsky and Mityakov (in press).

I build a measure of individual PTC based on the data on traffic violations, traffic accidents, and other personal characteristics, including gender, income, and distance to work. The data on traffic violations and traffic accidents cover the city of Moscow and the surrounding region for the period from 1997 to 2007. The data contain information on 6,784,971 traffic violations and 159,054 traffic accident participants. The important difference between these two data sets is that nearly all traffic accidents are recorded, whereas the decision to record a traffic violation is determined by individual police officers, who are frequently bribed (in which case, the violation goes unrecorded). I estimate the expected number of recorded traffic violations for each driver, using driver demographic characteristics, personal income, driving distance to work, the number of traffic accidents in which the driver was involved, and car characteristics as the explanatory variables. The individual PTC measure is constructed based on the difference between the predicted number of traffic violations and the actual number of traffic violations. The economic intuition that stems from the expectation that a lower number of recorded traffic violations, given observable driver characteristics, indicates a higher probability that some traffic violations were not recorded in exchange for bribes. Using this approach, I build the measure of PTC for 3,136,839 Muscovites. Next, I determine management PTC for a sample of 58,157 firms and 145,695 firm-years during the 1999–2004 period. The PTC for a given company is estimated as the average of the individual PTC figures of the company's five best-paid employees.

I also analyze the relation between PTC and existing metrics of managerial malfeasance, such as the income diversion measure developed by Mironov (2013) and the personal income transparency measure developed by Braguinsky and Mityakov (in press). The measure of income diversion is based on transfers to illegitimate fly-by-night firms. The money that is transferred to these firms represents a combination of tax evasion and managerial diversion. I find that PTC and illegitimate transfers are positively related. A 1 standard deviation increase in management PTC corresponds to a 0.3% firm revenue increase in income diversion (on average, each firm transfers 8.7% of its revenue to fly-by-night firms).

I also examine the relation between PTC and the measure of personal income transparency developed by Braguinsky and Mityakov (in press), based on the assumption that it is relatively easy to misreport earnings but costly to drive an unregistered vehicle. Thus, a person's unreported income can be inferred from the discrepancy

[1] Source: WorldBank 2012 data.

[2] See, for example, Braguinsky (2009), Braguinsky, Mityakov, and Liscovich (2010), Braguinsky and Mityakov (in press), Guriev and Rachinsky (2006), Mironov (2013), and Mironov and Zhuravskaya (2014).

between his or her reported income and value of the car he or she owns. I find that firm management PTC and income transparency are negatively related. A 1 standard deviation increase in PTC is associated with a 7% decrease in reported income, holding car value constant.

Finally, I analyze the relation between management PTC and firm performance. Measuring firm performance is challenging if firms are involved in income diversion activities. Traditional measures based on earnings, such as return on assets (ROA) or return on equity (ROE), cannot be applied. Thus, I employ revenue growth, revenue per employee, and the ratio of revenue to assets as measures of firm performance. I find that these measures and management PTC are positively related. A 1 standard deviation increase in management PTC corresponds to a 2.1% increase in the annual revenue growth rate, a 2.5% increase in revenue per employee, and a 0.5% increase in the ratio of revenue to assets. I provide several robustness tests of the last results. First, I use bank receipts instead of revenue as a performance measure. Corrupt management could underreport a firm's true revenue, and bank receipts could thus be a more accurate indicator of firm performance. The results are similar: increases in bank receipt figures, bank receipts per employee, and the ratio of bank receipts to assets are positively related to firm management PTC. Another robustness check pertains to companies that do not own cars. Chief executive officers (CEOs) commonly use chauffeurs provided by firms. These CEOs have a low number of traffic violations and, therefore, a spuriously high PTC. Eliminating CEOs with chauffeurs from the sample, the results are unchanged. As a final robustness check, I examine firm performance and alternative measures of corruption. Using income diversion measures developed by Mironov (2013) and the income transparency measure developed by Braguinsky and Mityakov (in press), I find a positive relation between all three measures of firm performance and the two alternative measures of corruption.[3]

Next, I analyze the firms that experience a change of CEO during the sample period. Similar to Bertrand and Schoar (2003), I require that each CEO serves for at least two years. This selection criterion yields a subsample of 1,027 firms and 5,188 firm-years. I estimate the relation between firm performance and CEO PTC by introducing firm fixed effects in the regressions. I find a positive and statistically significant relation for two of three firm performance measures: the log of revenue per employee and the log of the ratio of revenue to assets. It is important to note that managers are not randomly allocated to firms. Therefore, the results presented in this paper should not be interpreted as causal effects of managerial corruption on firm performance, even under the specifications that include firm fixed effects.

Finally, I study the relation between firm ownership and the observed positive link between PTC and firm performance. I find that firms in which the CEO is the sole owner exhibit better performance than firms in which the CEO is not the sole owner. However, the relation between PTC and firm performance does not differ between these groups of firms. Nevertheless, I find that the positive link between PTC and firm performance is not present in the sub-sample of foreign-owned firms. A possible explanation of this empirical finding could be that foreign owners restrict the corrupt behavior of their managers.

Several alternative explanations of the findings presented in this paper are possible. For instance, differences in PTC could be due to differences in driving style. In particular, drivers with high PTC could be notably conscientious, whereas conscientious people could tend to be both good drivers and good managers.[4] In view of the absence of statistical significance for the subsample of foreign-owned firms, foreign firms could impose stricter hiring criteria than domestic firms and, therefore, hire conscientious managers instead of corrupt ones. Unfortunately, the available data do not allow for discriminating between these alternative explanations.

This paper contributes to the rapidly growing literature that focuses on providing systematic evidence of corruption using objective (instead of perception-based) measures.[5] Reinikka and Svensson (2004) and Olken (2006) evaluate corruption by comparing the amount of federal grant transfer disbursements measured at the source with the amount that reaches the intended grant recipients. Caselli and Michaels (2009) estimate corruption by examining the effect of revenue windfalls across Brazilian municipalities. Bertrand, Djankov, Hanna, and Mullainathan (2007) and Olken (2007) measure corruption using randomized incentive schemes for corrupt behavior. Mironov and Zhuravskaya (2014) estimate corruption based on the linkage between shadow financing for election campaigns and the distribution of procurement contracts. Fisman and Miguel (2007) relate the number of unpaid parking tickets received by United Nations diplomats to country-level corruption norms.

By examining the relation between corruption and firm growth, this paper also contributes to the literature on the implications of corruption for economic development. Shleifer and Vishny (1993) present an analytical framework that could explain why "in some less developed countries, corruption is so high and so costly to development (p. 599)." Shleifer and Vishny (1994) analyze the economic effect of privatization and commercialization in the presence of corruption. Mauro (1995) provides evidence that corruption negatively affects growth based on a sample of 68 countries. Shleifer and Wei (2000) find a negative relation between corruption and foreign direct investment (FDI). Kaufmann and Wei (1999) show that "firms that pay more bribes are also likely to spend more, not less, management time with bureaucrats negotiating regulations, and face higher, not lower, cost of capital (p. 1)."

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 discusses the PTC

[3] Wage transparency is an inverse measure of corruption. Higher levels of wage transparency are associated with lower shares of "black" wages.

[4] I would like to thank Raymond Fisman for suggesting this interpretation.

[5] See, for example, Reinikka and Svensson (2006) for difficulties in the design of surveys to measure corruption.

measure. Section 4 presents the empirical results, and Section 5 concludes the paper.

2. Data and sample

This paper relies on several data sources (banking transaction data, personal income data, traffic violation data, and other data) leaked to the public domain from the Russian Central Bank and other government-affiliated entities. Appendix B discusses the legitimacy of these data.

2.1. *Traffic violations, traffic accidents, and personal income data*

The main data set that is used in this research is the list of traffic violations in the city of Moscow and the region of Moscow (Moscow oblast). This database contains 6,784,971 violations from the period 1997 to 2007. Each entry includes the violation date and the violator's identification data: his or her name, driver's license, and date of birth. Some records include a description of the violation. Unfortunately, the data quality does not allow classification by type of traffic violation. During the studied period, parking tickets were rarely enforced in Moscow. Thus, parking tickets represent only a tiny fraction of the total violations registered in the database.[6] The data for traffic accidents are available only for the city of Moscow. The data include information on 159,054 records. When multiple drivers were involved in an accident, the data include information for every driver. Each entry includes driver identification information (name, address, date of birth, and driver's license), the date, whether the driver was intoxicated, whether the driver fled the scene, driver culpability for the accident, and additional information.

I merge the data on traffic violations and traffic accidents with information from the database of issued driver's licenses. The data for the city of Moscow include information on 2,754,649 unique drivers. The data for the Moscow region include information regarding the driver's licenses of 2,154,104 individuals. Both data sets cover the time period through 2007.

These data are supplemented with the city of Moscow's auto registration database for 2005. Each entry contains information regarding the vehicle (make, model, and year) and its owner (person name or company name, address, and identification number) in addition to the record date. The database contains more than 11 million records. Multiple records per person (company) can exist if a person (company) owns, or has ever owned, more than one car.

I obtain employment information from the personal income data of Moscow residents. This data set contains 55 million records for the 1999–2004 period, approximately nine million records per year. Each entry contains unique identification data (name, address, and identification number) for both an employer and an employee. Multiple records per person can exist if a person receives income from several sources. Guriev and Rachinsky (2006) use these data to measure income inequality when the data set includes super-rich individuals. Braguinsky, Mityakov, and Liscovich (2010) and Braguinsky and Mityakov (in press) use these data combined with the auto registration database to estimate the hidden earnings of Muscovites.

Merging driver's license data with the data set of personal income yields a sample of 3,136,853 persons. Table A1 presents the summary statistics. All variables are winsorized at the top 99% percentile. An average driver commits 0.115 traffic violations per year and participates in 0.003 traffic accidents per year. A total of 54% of persons are from the city of Moscow, and 74.1% of drivers are men. The average driver is 38.9 years old and has 3.3 years of driving experience. Russian law states that a driver's license should be renewed every ten years. To estimate driving experience, I use the earliest driver's license present in the database. Missing previous driver's license data would lead to an underestimation of individual's driving experience. The average person earns $6,640 per year and travels 15.2 kilometers to work. Distance to work is calculated as a straight line between one's home zip code and his or her employer's zip code. I collect employer zip code–employee zip code pairs for 2,213,789 observations. Furthermore, 36% of drivers own a car. This percentage is low because the auto registry database is available only for the city of Moscow. Thus, 65% of residents in the city of Moscow own a car, and only 2% of residents in the Moscow region have a car. The average car is 6.77 years old, with a 98.2 horsepower engine.

2.2. *Sample of companies*

Company financial data are obtained from Rosstat, an official Russian statistical agency. This database contains information on company identification, names, addresses, dates of incorporation, industry, directors, owners, and basic accounting data, such as information on revenue, profits, net income, assets, and debt. According to Russian law, all firms (even small firms) must submit quarterly reports with balance sheets and income statements to Rosstat. Rosstat contains accounting data for approximately 2.5 million Russian firms.

I supplement company-reported financial data with the list of banking transaction for the six years between 1999 and 2004. This list was leaked to the public by the Russian Central Bank in 2005.[7] The data set contains 513,169,660 transactions involving 1,721,914 business and government entities with information on the date of each transaction and the payer, recipient, amount, and purpose.

Using the personal income data for Moscow residents, I select all firms that have at least ten employees. Next,

[6] There are two primary reasons for this situation. The first reason is a parking fine cost of approximately $3, which is much lower than fines for other violations. The second reason is that Russian law previously required that all tickets be given in person. A police officer must have been waiting for a violator to give him or her the ticket. The situation changed in 2012. The cost of a parking ticket in Moscow increased to $100, and police officers are no longer required to personally hand over parking tickets.

[7] See Mironov (2013) for a detailed description of these data and of numerous authenticity checks.

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I match this sample of firms to the Rosstat data and include companies that reported revenue greater than \$100,000. I impose these restrictions to avoid including tiny firms that might not accurately report their financial data, this method yields a sample of 60,402 companies and 156,373 company-years for 1999–2004. I calculate revenue growth as $\Delta Revenue_t = \log(Revenue_{t+1}) - \log(Revenue_t)$. All variables are taken as reported and are not adjusted for inflation.

Table A2 describes the summary statistics of a company sample. The average (median) company has assets of \$6,924,000 (\$180,000), revenue of \$6,217,000 (\$522,000), and pre-tax earnings of \$536,000 (\$9,000). The average (median) revenue growth is 11.8% (16.1%) per year. Employment data are obtained from the Moscow personal income database. The average (median) company has 122 (32) employees. Company bank receipts are obtained from the banking transaction data. The average (median) bank receipts are \$6,863,000 (\$390,000). I follow Mironov (2013) and estimate income diversion for every firm in the sample. The average (median) company transfers 8.7% (2.2%) of its revenue to fly-by-night firms. Appendix C describes the identification of fly-by-night firms in detail. To minimize the effects of outliers on the results, revenue growth, revenue per employee, the ratio of revenue to assets, and leverage are winsorized at the top and bottom 5% level. All variables are defined and explained in Appendix D.

3. Measuring propensity to corrupt

This section describes the empirical strategy to measure propensity to corrupt and presents summary statistics of this measure.

3.1. Empirical strategy

I construct a measure of PTC based on traffic violation, traffic accident, demographic and other personal data. The idea behind this measure derives from the observation that not all actual traffic violations are recorded. Previous survey results presented by Levin and Satarov (2000) show that the Russian police force is a highly corrupt entity. Avoiding formal punishment for a traffic violation is almost always possible with a bribe. Traffic accident reporting is handled differently. Russian law requires that all traffic accidents be reported to the police, which essentially means that the parties involved in a traffic accident cannot amicably resolve the issue without informing the police. If one party leaves the scene of an accident, then the other party can inform the police that the first party has done so. In this scenario, the first party automatically is considered culpable for the accident. Even if the parties reach an agreement about accident culpability, they should wait for police officers to record the terms of agreement. As a result, unlike traffic violations, nearly all traffic accidents are recorded in the police database. To build an individual corruption attitude measure, I estimate the following model:

$$Violations_d = f(\alpha + \beta Controls_d + \nu_d), \tag{1}$$

where d is the driver index, $Violations_d$ is the number of recorded traffic violations per year and $Controls_d$ is a set of driver-level controls, including traffic accidents, demographic characteristics, car characteristics and other variables. The number of traffic violations is a count non-negative variable. Thus, I use a Poisson regression to fit this model.

The difference between $Violations_d$ and $f(\alpha + \beta Controls_d)$ reflects the discrepancy between the expected number of recorded traffic violations and the actual number of recorded traffic violations.[8] I sort all drivers in descending order according to this difference and assign a continuous measure of PTC_d that varies from zero to ten, where zero represents the least corrupt driver in Moscow and ten represents the most corrupt driver in Moscow. If $PTC_i = 9$, then 90% of Moscow drivers have a residual ν_d that is greater than ν_i. Intuitively, a lower number of recorded traffic violations, for a given number of observed personal characteristics, indicates a greater probability that the traffic violations were not recorded in exchange for a bribe.

Next, I construct the PTC measure of firm management. Because the personal income data do not reveal job titles, I select the five best-paid employees in each firm. CEOs, deputy CEOs, chief financial officers, and chief accountants likely number among the best-paid employees in every company. Then, I calculate the average of the individual PTC measures for the best-paid employees who have a driver's license:

$$PTC^f = \frac{\sum_{i=1}^{5} PTC_i^f}{\sum_{i=1}^{5} I(d_i \in Drivers)}, \tag{2}$$

where f is the firm index, i is the employee index (employees are sorted based on their annual pay), PTC_i^f is the PTC for employee i who works at firm f, and $I(d_i \in Drivers)$ is an indicator function that equals one if employee i belongs to the set of drivers (i.e., has a driver's license). If an employee does not have a driver's license, then his or her PTC cannot be evaluated using the methodology described here. Therefore, I exclude those employees from my calculations of firm PTC. For robustness checks, I also estimate the PTC for the highest-paid employee.

I perform two robustness checks to validate the constructed measure. First, I analyze the relation between shadow transfers and firm PTC. To this end, I estimate the following regression:

$$ShadowR_t^f = \alpha + \beta PTC_t^f + \gamma Controls_t^f + \theta_t + \varepsilon_t^f, \tag{3}$$

where t is the time index and f is the firm index. $Controls_t^f$ is a set of firm-level controls, θ_t are year fixed effects, ε_t^f is the error term, and $ShadowR_t^f$ is the amount of firm transfers to fly-by-night firms divided by firm revenue. Mironov (2013) shows that *ShadowR* is a reliable measure of income diversion, which includes tax evasion and managerial diversion. If corrupt managers divert more income, then $\beta > 0$ should be expected.

Another robustness check relates PTC to the measure of wage transparency derived by Braguinsky and Mityakov (in press). The Braguinsky and Mityakov measure of wage

[8] The expected number of recorded traffic violations differs from the expected number of traffic violations. The available data do not allow for identifying a control group of people who never pay bribes. Thus, the expected number of traffic violations cannot be estimated without additional assumptions.

transparency is based on the difference between a person's reported income and the value of the car that he or she drives. This approach is founded on the observation that it is relatively easy to misreport earnings but costly to drive an unregistered vehicle. Thus, the discrepancy between reported income and car value reflects a person's unreported income. Braguinsky and Mityakov measure income transparency at a personal level:

$$Transparency_t^i = \log(Income_t^i) - \frac{1}{\lambda}\log(Car_t^i), \tag{4}$$

where t is the time index and i is the person index. $Income_t^i$ is a person's reported income, Car_t^i is the dollar value of the person's car, and λ is the demand elasticity for cars estimated at 0.35. I analyze the relation between wage transparency and PTC by estimating the following regression:

$$Transparency_t^f = \alpha + \beta PTC_t^f + \gamma Controls_t^f + \theta_t + \varepsilon_t^f, \tag{5}$$

where t, f, $Controls_t^f$, θ_t, and ε_t^f are the same as in Eq. (3) and where $Transparency_t^f$ is the wage transparency calculated as the average wage transparency of the employees of firm f. The validity of PTC implies that $\beta < 0$ because, ceteris paribus, more corrupt firm management is associated with higher unreported earnings of firm employees and higher levels of wage transparency.

3.2. Summary statistics of PTC measures

I estimate Eq. (1) to construct the individual PTC measures. Driver-level controls are traffic accidents, gender, age, driving experience, distance to work, the logarithm of income, a dummy for whether a driver is from the city of Moscow, a dummy for whether a driver owns a car, car horsepower, and car production year. Column 1 of Table 1 presents the estimation results for the entire sample (base specification). As the table data indicate, the number of traffic violations is negatively related to driver age, driving experience, and income. Men commit 0.089 more traffic violations than women. The number of traffic accidents and traffic violations are positively related,

Table 1

Traffic violations and traffic accidents.The table presents Poisson regressions of the number of traffic violations on traffic accidents and other driver-level controls. The sample period is from 1997 to 2007. Marginal effects are reported. *Traffic violations per year* is the average number of traffic violations per year committed by an individual in the city of Moscow and Moscow region. *Traffic accidents per year* is the average number of traffic accidents per year committed by an individual in the city of Moscow. *Driver is from Moscow* is a dummy variable equal to one if the person resides in the city of Moscow. *Male* is a dummy variable equal to one for men and zero for women. *Driver's age* is calculated as the average driver's age. *Driving experience* is the average driving experience. *Income* is the average person's income taken from the personal income data of Moscow residents. *Distance to work* is calculated as a straight line between person's home zip code and his or her employer zip code averaged over the sample period. *Distance to work* is obtained for 2,235,680 observations. *Driver owns a car* is a dummy variable equal to one if the person ever owned a car during the sample period (car registry data are available only for the city of Moscow). *Car age* and *Car power* are the average car age and car horsepower calculated over the period when the person owned a car or cars. Column 1 contains the entire sample. Column 2 covers only drivers from the city of Moscow. Column 3 presents the subsample of drivers for which distance to work is determined. Column 4 contains only drivers from Moscow who own a car. Column 5 has only drivers with a positive record of traffic accidents. The numbers in parentheses are standard errors. * and *** indicate statistical significance at the 10% and 1% level, respectively.

	Traffic violations per year				
	(1)	(2)	(3)	(4)	(5)
Traffic accidents per year	0.0936	0.0891	0.0914	0.0962	0.1208
	(0.0034)***	(0.0032)***	(0.0034)***	(0.0052)***	(0.0122)***
Driver is from Moscow	−0.0767		−0.0730		−0.1116
	(0.0005)***		(0.0006)***		(0.0055)***
Male	0.0894	0.0494	0.0747	0.0424	0.0873
	(0.0003)***	(0.0003)***	(0.0003)***	(0.0004)***	(0.0029)***
Driver's age (multiplied by 100)	−0.2666	−0.1517	−0.2241	−0.1688	−0.3395
	(0.0011)***	(0.0012)***	(0.0012)***	(0.0016)***	(0.0136)***
Driving experience (multiplied by 100)	−0.6090	−0.0299	−0.4103	−0.0295	0.0431
	(0.009)***	(0.0078)***	(0.0095)***	(0.0103)***	(0.091)
Dummy (*Income* > 0)	0.0335	0.0241	0.0303	0.0261	0.0651
	(0.0005)***	(0.0005)***	(0.0006)***	(0.0007)***	(0.0049)***
Log(*Income*)	−0.0061	−0.0052	−0.0061	−0.0059	−0.0146
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***	(0.0011)***
Dummy (*Distance to work* > 0)	−0.0230	−0.0115		−0.0040	−0.0261
	(0.0004)***	(0.0005)***		(0.0006)***	(0.0041)***
Distance to work (multiplied by 100)	0.0412	0.0609	0.0378	0.0260	0.0624
	(0.0006)***	(0.0012)***	(0.0006)***	(0.0023)***	(0.0081)***
Driver owns a car	0.0000	0.0020	0.0013		−0.0356
	(0.0012)	(0.0008)***	(0.0012)		(0.0105)***
Car age (multiplied by 100)	0.0385	0.0145	0.0313	0.0200	0.1872
	(0.0053)***	(0.0032)***	(0.0049)***	(0.0036)***	(0.0379)***
Dummy (*Car power* > 0)	0.0043	−0.0004	0.0042	−0.0019	0.0280
	(0.004)	(0.0023)	(0.0037)	(0.0027)	(0.0273)
Log(*Car power*)	0.0005	0.0010	0.0004	0.0014	−0.0051
	(0.0008)	(0.0005)*	(0.0008)	(0.0005)***	(0.0059)
Pseudo R-squared	0.140	0.078	0.136	0.058	0.083
Number of observations	3,136,839	1,692,300	2,235,680	1,097,089	60,128

with one traffic accident associated with 0.0936 more traffic violations per year. Residents of the city of Moscow commit 0.077 fewer traffic violations than residents of the region of Moscow. One possible explanation is that people from the city of Moscow use public transportation more frequently. Distance to work and the number of traffic violations are positively related. An additional kilometer of travel yields 0.0004 more traffic violations per year. The coefficient for the logarithm of income has a negative sign. A possible explanation is that richer people place a higher value on time. Formal punishment requires spending time in a bank to pay a fine and arriving at a local police office to retrieve one's driver's license after it has been retained by the police. Thus, people whose time has high value could prefer to resolve problems informally. Columns 2–5 contain estimations for Eq. (1) for different subsamples. Column 2 covers drivers from the city of Moscow. Column 3 presents the subsample of drivers for whom the distance to work was determined. Column 4 contains data only for Moscow car owners. Column 5 reports only drivers who have experienced traffic accidents.

Next, I use Eq. (2) to calculate PTC for firm management. Table 2 reports the summary statistics. *PTC* denotes the propensity to corrupt for the entire sample of drivers. *PTC*(*N*) for $N=\{2,\ldots,5\}$ denotes the propensity to corrupt for the corresponding subsample of drivers previously defined. As the table data indicate, the PTC for the top five highest-paid employees is 4.47, which is less than the average for the entire Moscow population (the average PTC for the Moscow population is 5, by design). The PTC top five for the other subsamples of drivers [PTC(2)–PTC(5)] varies from 4.64 to 4.82.

3.3. Verification of the measure

The underlying assumption of the PTC measure is that the difference between the expected number of traffic violations and the recorded number of traffic violations reflects the personal PTC. However, many alternative explanations could exist for the results. For example, this calculation could measure luck, reflecting that some drivers are caught more often than others. Another possible explanation is that drivers with low PTC drive more often. Thus, they have a higher number of recorded traffic violations. In this case, the PTC would reflect how often a person uses his or her car. Some other unobservable variable could explain why some drivers have a higher or lower number of recorded traffic violations, for example, drivers' caution or skill. Thus, it is important to analyze the relations among PTC and established measures of managerial malfeasance. I relate PTC to two different measures: shadow transfers to fly-by-night firms and wage transparency. I estimate Eqs. (3) and (5) using the *Debt/Assets*, *Industry*, *Tax district*, and *Assets* and *Revenue* decile dummies as control variables. Table 3 presents the results. As the data in Columns 1 and 2 indicate, a positive statistically significant relation exists between firm management PTC and income diversion. A 1 standard deviation increase in the PTC top five corresponds to a 3.6% increase (0.3% of firm revenue) in shadow transfers (an average firm transfers 8.7% of its revenue to fly-by-night firms). The presented evidence supports the hypotheses that firm management PTC and income diversion are positively related. The results reported in Columns 3 and 4 show that the PTC and wage transparency are negatively related (statically significant at the 1% level). A 1 standard deviation increase in PTC top five is associated with a 6.7% decrease in reported income when car value is held constant. This result indicates that managers with higher PTC pay a higher percentage of employee wages under the table.

Table 2
Summary statistics of propensity to corrupt (PTC) measures.The table presents summary statistics of propensity to corrupt measures defined in Section 2. The sample period is from 1999 to 2004. *PTC*(*N*) *top* 1 is the PTC for the companies' best-paid employee. *PTC*(*N*) *top 5* is the average PTC for the companies' five best-paid employees. Only employees with a driver's license are considered while calculating companies' PTCs. *PTC* is estimated for the entire sample of drivers. *PTC*(*2*) is calculated only for drivers from the city of Moscow. *PTC*(*3*) is estimated for the subsample of drivers for which distance to work is determined. *PTC*(*4*) is calculated only for drivers from Moscow who own a car. *PTC*(*5*) is estimated only for drivers with a positive record of traffic accidents.

	Mean (1)	Median (2)	Standard deviation (3)	Number of observations (4)	Number of firms (5)
PTC top 1	4.502	4.737	2.328	92,722	41,756
PTC top 5	4.477	4.419	1.654	145,695	58,157
PTC(*2*) *top 1*	4.853	5.425	2.675	77,318	35,395
PTC(*2*) *top 5*	4.758	4.739	2.049	136,051	55,182
PTC(*3*) *top 1*	4.669	5.021	2.478	88,896	40,387
PTC(*3*) *top 5*	4.635	4.599	1.784	143,485	57,635
PTC(*4*) *top 1*	4.816	5.073	2.663	69,765	32,303
PTC(*4*) *top 5*	4.815	4.771	2.177	127,067	52,159
PTC(*5*) *top 1*	4.532	4.697	2.267	2,479	1,421
PTC(*5*) *top 5*	4.721	4.782	2.326	8,693	5,064

4. PTC and firm performance

This section analyzes the relation between propensity to corrupt and different indicators of firm performance.

4.1. Empirical results

Measure firm performance is difficult in a context of tax evasion and income diversion. Popular measures of firm performance such as ROA and ROE cannot be used. As shown in Section 3, the misreporting of earnings and firm management PTC are positively correlated. I cannot rely on the market-to-book ratio because the sample companies are not publicly traded. Therefore, I use revenue growth, revenue per employee, and the ratio of revenue to assets as measures of firm performance. To analyze the relation between PTC and firm performance, I estimate the following regression:

$$Performance_t^f = \alpha + \beta PTC_t^f + \gamma Controls_t^f + \theta_t + \varepsilon_t^f, \tag{6}$$

where t is the time index and f is the firm index. $Performance_t^f$ refers to revenue growth, the log of revenue per employee, or the log of the ratio of revenue to assets. $Controls_t^f$ is a set of firm-level controls, θ_t are year fixed effects, and ε_t^f is the error term.

Table 3
Propensity to corrupt (PTC), shadow transfers, and wage transparency.The table presents the relation of PTC to income diversion and wage transparency. The sample period is from 1999 to 2004. *ShadowR* is the measure of income diversion developed by Mironov (2013). See Appendix C for details. *Wage transparency* is the measure of income transparency developed by Braguinsky and Mityakov (in press). *Revenue*, *Debt*, and *Assets* are taken from Rosstat. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. ** and *** indicate statistical significance at the 5% and 1% level, respectively.

	ShadowR		*Wage transparency*	
	(1)	(2)	(3)	(4)
PTC top 1	0.0013		−0.0242	
	(0.0002)***		(0.0043)***	
PTC top 5		0.0019		−0.0404
		(0.0003)***		(0.0051)***
Debt/Assets	−0.0059	−0.0043	−0.6396	−0.6362
	(0.0024)**	(0.0019)**	(0.0458)***	(0.0381)***
Assets decile dummy	Yes	Yes	Yes	Yes
Revenue decile dummy	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes
Tax district dummy	Yes	Yes	Yes	Yes
R-squared	0.063	0.063	0.068	0.064
Number of observations	92,722	145,695	43,970	66,501
Number of firms	41,756	58,157	23,914	33,066

Table 4 presents the estimation results for Eq. (6). The firm-level controls are *Debt/Assets*, *Industry*, *Assets* decile dummies, *Revenue* decile dummies, and *Tax district* dummies. According to the table data, PTC and firm performance are positively related. A 1 standard deviation increase in PTC top five corresponds to a 2.1% increase in annual revenue growth, a 2.5% increase in revenue per employee, and a 0.5% increase in the ratio of revenue to assets. All coefficients are statistically significant at the 1% level.

The presented empirical results could have at least three alternative explanations. The first is that corrupt managers misreport revenue and, thus, exhibit superior performance in the metrics based on revenue. Another explanation is that the suggested measures of corruption reflect other characteristics that are related to the quality of driving, not to PTC. For example, drivers with high PTC could be conscientious instead of corrupt, and one could expect that conscientious individuals are also good managers. Finally, many top managers commonly use personal chauffeurs, and these managers have a low number of traffic violations and high PTC. I perform several robustness checks to test some of these alternative explanations.

4.2. Robustness checks

The first robustness check analyzes bank receipts instead of revenue. Companies can underreport their true revenues. Thus, bank receipts could be a more accurate measure of performance than revenue is. I estimate Eq. (6) using bank receipt growth, bank receipts per employee, and the ratio of bank receipts to assets as dependent variables. The amount of bank receipts is an objective measure that is derived from banking transaction data. I report the results in Table 5. As the table data show, the results do not change. Firm management PTC is positively related to measures of firm performance. This relation is statistically significant at the 1% level. Notably, the magnitude of the coefficients in Columns 3–6 is significantly larger than the magnitude of the similar coefficients reported in Table 4. This result supports the hypothesis that corrupt managers underreport their true performance. Thus, the actual difference in performance measured as revenue per employee and the ratio of revenue to assets is even higher than the difference reported in Table 4.

The second robustness check examines whether the positive relation between PTC and firm performance results from the tendency of top managers to use chauffeurs instead of driving themselves. These managers have a low number of traffic violations and high PTC. This possible explanation could apply to the observed positive relation between PTC and firm performance: More successful managers, who tend to use chauffeurs, deliver superior firm performance. To test this hypothesis, I match the sample of companies with the city of Moscow auto registration database. I remove all companies that ever owned cars from the sample based on the assumption that a company that owns a car might give the CEO a car and a chauffeur, whereas if a company does not own a single car, then the CEO should not have a chauffeur. Granted, this exclusion does not ensure the elimination of all CEOs with chauffeurs from the sample. For instance, a company could lease a car for its CEO. However, according to the auto registration database, only 1,627 cars with engines greater than 100 horsepower belonged to leasing companies during the period under study. In total, the companies from my sample owned 16,918 cars. Thus, potential leasing represents only a small fraction of total car usage. Table A3 presents the summary statistics for the companies that do not own cars. The companies in this subsample are much smaller than the companies in the overall sample (see Table A2). An average (median) company has assets of \$3,058,000 (\$143,000), revenue of \$3,214,000 (\$460,000), and 92 (29) employees. Table A4 reports the estimation results for Eq. (6) for the subsample of firms without cars.

Table 4
Propensity to corrupt (PTC) and firm performance.The table presents the relation of PTC to different measures of firm performance. The sample period is from 1999 to 2004. *Revenue*, *Debt*, and *Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)–log($Revenue_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *** indicates statistical significance at the 1% level.

	Revenue growth		Log(*Revenue per employee*)		Log(*Revenue/Assets*)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	0.0077 (0.001)***		0.0113 (0.0015)***		0.0022 (0.0006)***	
PTC top 5		0.0124 (0.0011)***		0.0150 (0.0018)***		0.0032 (0.0007)***
Debt/Assets	−0.0504 (0.0118)***	−0.0448 (0.0094)***	0.1907 (0.0167)***	0.2016 (0.0141)***	−0.0474 (0.0084)***	−0.0581 (0.007)***
Assets decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Revenue decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tax district dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.033	0.031	0.579	0.577	0.895	0.894
Number of observations	78,039	122,434	92,722	145,695	92,722	145,695
Number of firms	35,100	48,948	41,756	58,157	41,756	58,157

Table 5
Propensity to corrupt (PTC) and firm performance (bank receipts).The table presents the relation of PTC to different measures of firm performance calculated based on the bank receipts. The sample period is from 1999 to 2004. *Revenue*, *Debt*, and *Assets* are taken from Rosstat. *Receipts growth* is defined as [log($Receipts_{t+1}$) − log($Receipts_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Receipts growth		Log(*Receipts per employee*)		Log(*Receipts/Assets*)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	0.0068 (0.0015)***		0.0302 (0.0031)***		0.0218 (0.0025)***	
PTC top 5		0.0088 (0.0017)***		0.0432 (0.0036)***		0.0331 (0.003)***
Debt/Assets	−0.0107 (0.0182)	0.0048 (0.0144)	−0.1862 (0.0358)***	−0.1555 (0.0299)***	−0.4000 (0.0298)***	−0.3751 (0.0248)***
Assets decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Revenue decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tax district dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.019	0.018	0.325	0.335	0.396	0.391
Number of observations	61,374	95,310	91,197	143,154	91,197	143,154
Number of firms	29,931	41,573	41,187	57,330	41,187	57,330

As the table data indicate, the results are similar to those reported in Table 4. Firm management PTC and firm performance are positively related.

The third robustness check uses PTC for different samples of drivers (see Tables 1 and 2I for reference). I estimate Eq. (3) using *PTC*(*2*)–*PTC*(*5*) as the dependent variables. Table A5 reports the estimation results.[9] The table data indicate that the results are similar to those reported in Table 4. Firm performance and firm management PTC are positively related.

The fourth robustness check employs a cardinal measure of PTC instead of the ordinal measure used in this paper. Specifically, I assign the residual from Eq. (1) as the cardinal PTC for every driver and then estimate Eq. (6) using this measure. The firm-level controls are leverage, *Industry*, decile dummies for *Assets* and *Revenues*, and *Tax district* dummies. Table A6 presents the results. The table data indicate that the coefficients for cardinal PTC are positive and are statistically significant with respect to most specifications.

The results obtained could be driven by some other unobserved variable that correlates with an individual's driving style. Thus, the final robustness test relates firm performance to alternative measures of corruption that are unrelated to an individual's driving records. As alternative measures of corruption, I employ the income diversion measure developed by Mironov (2013) and the wage transparency measure developed by Braguinsky and Mityakov (in press). Table 6 presents the estimation results. As the table data indicate, the firm performance

[9] To save space, I report the results for PTC top five only. The estimation results for PTC top one are similar.

Table 6
Firm performance, income diversion, and wage transparency.The table presents the relation of income diversion and wage transparency to different measures of firm performance. The sample period is from 1999 to 2004. *ShadowR* is the measure of income diversion developed by Mironov (2013). See Appendix C for details. *Wage transparency* is the measure of income transparency developed by Braguinsky and Mityakov (in press). *Revenue*, *Debt*, *Assets* are taken from Rosstat. *Revenue growth* is defined as $[\log(Revenue_{t+1}) - \log(Revenue_t)]$. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. * and *** indicate statistical significance at the 10%and 1% level, respectively.

	Revenue growth		Log(*Revenue per employee*)		Log(*Revenue/Assets*)	
	(1)	(2)	(3)	(4)	(5)	(6)
ShadowR	0.1797		0.5095		0.0693	
	(0.0145)***		(0.0196)***		(0.0088)***	
Wage transparency		−0.0004		−0.0432		−0.0066
		(0.0015)		(0.0023)***		(0.001)***
Debt/Assets	−0.0454	−0.0537	0.2084	0.2119	−0.0571	−0.0528
	(0.0091)***	(0.0132)***	(0.0138)***	(0.0203)***	(0.0068)***	(0.0101)***
Assets decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Revenue decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tax district dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.031	0.034	0.578	0.558	0.894	0.890
Number of observations	131,482	59,733	156,373	69,646	156,373	69,646
Number of firms	50,876	29,160	60,402	34,090	60,402	34,090

measures are positively related to income diversion and negatively related to wage transparency. The corresponding coefficients are statistically significant in five of six specifications.

One should interpret the ordinary least squares estimations presented in Table 6 with caution, as the relation between alternative measures of corruption and firm performance could be endogenous. Both measures of corruption—*ShadowR* and income transparency—reflect tax evasion. As Mironov (2013) observes, Russian entrepreneurs often prefer to register their businesses with tax agencies with which they have strong connections. Therefore, such firms could exhibit higher levels of tax evasion and stronger firm performance, owing to a more favorable business environment. The extreme case of such an endogenous relation is that of Yelena Baturina, the wife of the former mayor of Moscow, Yuri Luzhkov. According to *Forbes*, in 2010, she was the richest woman in Russia and the third-richest woman in the world, earning her fortune when her husband was mayor. Milov and Nemtsov (2010) describe Luzhkov as highly corrupt, noting that he allocated significant budget resources to Inteko, the company owned by his wife. After his dismissal, her fortune fell from $2.9 billion in 2010 to $1.2 billion in 2011. An endogeneity issue also acts in the opposite direction. The measure of income diversion, *ShadowR*, includes managerial diversion, concealment from firm owners and tax evasion, concealment from tax authorities. Desai, Dyck, and Zingales (2007) and Mironov (2013) argue that managerial diversion has a strong negative effect on firm performance.

These robustness checks cannot exclude all possible alternative explanations related to driving style. For example, safe drivers could exhibit a high PTC and also could be good managers. Unfortunately, as shown in Table 1, the variable *Accidents*, which is an objective measure of driving safety, explains only a small fraction of the variance of *Violations*. Hence, the available data do not allow distinguishing between safe and corrupt drivers.

4.3. *Are manager characteristics relevant?*

The results reported in Table 4 do not distinguish the effect of managers from the effect of the firms that they managed. In fact, some firms could have better growth prospects and attract more corrupt managers. Two important papers study the effect of managers on organization performance. First, Bertrand and Schoar (2003) show that manager effects are relevant for a wide range of corporate decisions, including investment, financial, and organizational practices. Second, the recent study of Lazear, Shaw, and Stanton (2012) provides a comprehensive analysis of various aspects of supervisor effects on worker productivity. The authors not only apply a basic fixed effects analysis but also employ mixed effects estimation, control for lagged boss effects, and test for nonrandom boss assignment.

My panel covers only six periods, with the average firm present in approximately 2.6 periods. Therefore, I follow the rationale behind the methods of Bertrand and Schoar (2003). Specifically, I study firms that experienced CEO turnover during the period of 1999–2004. Only CEOs with defined PTC are selected for this analysis. In addition, I require that each CEO manage a firm for at least two years.[10] These selection criteria yield a subsample of 1,027 firms and 5,188 firm-years. Then, I estimate Eq. (6) by including firm fixed effects. Panel A of Table 7 presents the estimation results. As the table data indicate, the coefficients for PTC are statistically insignificant for the revenue growth measure (Columns 1–3) and are positive and statistically significant for the log of revenue per employee and the log of the ratio of revenue to assets measures (Columns 4–6 and 8–9). Using ideas from the work of

[10] By analogy with Bertrand and Schoar (2003), this two-year requirement ensures that managers are given an opportunity to imprint their mark on a given company.

Table 7
Propensity to corrupt (PTC) and firm performance with firm fixed effects.The table presents the relation of PTC to different measures of firm performance controlling for firm fixed effects. Only firms that experienced a chief executive officer turnover are included. The sample period is from 1999 to 2004. *Revenue*, *Debt*, and *Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$) − log($Revenue_t$)]. *PTC top 1* is the PTC for the companies' best-paid employee. Panel A contains the basic specification. Panel B specification controls for lagged dependent variable. Panel C specification controls for lagged PTC. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Revenue growth			Log(*Revenue per employee*)			Log(*Revenue/Assets*)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: PTC and firm performance with firm fixed effects									
PTC top 1	0.0021	−0.0029	−0.0021	0.0099	0.0173	0.0162	−0.0008	0.0078	0.0122
	(0.0047)	(0.0053)	(0.0053)	(0.0035)***	(0.0048)***	(0.005)***	(0.0027)	(0.0046)*	(0.0054)**
Debt/Assets	0.0023	0.1521	0.1372	0.0601	−0.1696	−0.0875	−0.0784	−0.3329	−0.5290
	(0.0595)	(0.0662)**	(0.066)**	(0.0446)	(0.0615)***	(0.0633)	(0.0345)**	(0.0579)***	(0.068)***
Assets decile dummy	Yes	Yes		Yes	Yes		Yes	Yes	
Revenue decile dummy	Yes			Yes			Yes		
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.396	0.243	0.238	0.925	0.855	0.844	0.946	0.845	0.784
Number of observations	4,290	4,290	4,290	5,188	5,188	5,188	5,188	5,188	5,188
Number of firms	845	845	845	1,027	1,027	1,027	1,027	1,027	1,027
Panel B: PTC and firm performance with firm fixed effects and lagged dependent variable									
PTC top 1	0.0035	−0.0020	−0.0012	0.0088	0.0158	0.0133	−0.0002	0.0093	0.0149
	(0.0053)	(0.0058)	(0.0058)	(0.0039)**	(0.0052)***	(0.0053)**	(0.003)	(0.0049)*	(0.0057)***
Lagged dependent variable	0.0174	−0.1863	−0.1890	0.1010	0.1784	0.2087	0.0135	0.0338	0.0775
	(0.0188)	(0.0186)***	(0.0185)***	(0.0116)***	(0.0152)***	(0.0153)***	(0.0084)	(0.0136)**	(0.0159)***
Debt/Assets	0.0084	0.1585	0.1620	0.0927	−0.1294	−0.0718	−0.0822	−0.3415	−0.4943
	(0.0673)	(0.074)**	(0.0737)**	(0.051)*	(0.0675)*	(0.0688)	(0.0393)**	(0.063)***	(0.0739)***
Assets decile dummy	Yes	Yes		Yes	Yes		Yes	Yes	
Revenue decile dummy	Yes			Yes			Yes		
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.424	0.295	0.293	0.932	0.879	0.873	0.950	0.870	0.819
Number of observations	3,590	3,590	3,590	4,151	4,151	4,151	4,274	4,274	4,274
Number of firms	845	845	845	1,027	1,027	1,027	1,027	1,027	1,027
Panel C: PTC and firm performance with firm fixed effects and lagged PTC									
PTC top 1	0.0035	−0.0022	−0.0015	0.0075	0.0162	0.0135	0.0004	0.0103	0.0172
	(0.0058)	(0.0065)	(0.0065)	(0.0043)*	(0.0058)***	(0.006)**	(0.0034)	(0.0054)*	(0.0065)****
Lagged *PTC top 1*	−0.0003	0.0023	0.0029	0.0097	0.0075	0.0084	−0.0006	−0.0029	−0.0052
	(0.0057)	(0.0064)	(0.0064)	(0.0043)**	(0.0057)	(0.0059)	(0.0033)	(0.0053)	(0.0063)
Debt/Assets	0.0192	0.1706	0.1731	0.0981	−0.1365	−0.0731	−0.0621	−0.3214	−0.4948
	(0.0706)	(0.0792)**	(0.0789)**	(0.0533)*	(0.0711)*	(0.0728)	(0.0415)	(0.0665)***	(0.0788)***
Assets decile dummy	Yes	Yes		Yes	Yes		Yes	Yes	
Revenue decile dummy	Yes			Yes			Yes		
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.446	0.293	0.289	0.932	0.877	0.869	0.951	0.871	0.817
Number of observations	3,303	3,303	3,303	3,943	3,943	3,943	3,943	3,943	3,943
Number of firms	845	845	845	1,027	1,027	1,027	1,027	1,027	1,027

Lazear, Shaw, and Stanton (2012), I introduce a control for the influence of previous CEOs. Panel B of Table 7 includes a control for the lagged dependent variable, and Panel C of Table 7 includes a control for the lagged CEO's PTC. The results change very little. The coefficients for PTC in the revenue growth specification are statistically insignificant, and the coefficients for PTC in the specifications for the two remaining measures of firm performance are positive and statistically significant (with exception of the Column 7 specification, where assets and revenue decile dummies are included simultaneously and the log of the ratio of revenue to assets serves as a dependent variable).

In addition, I employ the alternative approach of Bertrand and Schoar (2003), namely, to estimate CEO fixed effects. Specifically, I select individuals who served as CEOs at multiple firms and worked at each of these firms for at least two years.[11] I also require that each firm managed by these CEOs be managed by at least one other CEO. If a firm were managed by only one CEO, then the CEO fixed effect would be indistinguishable from the firm fixed effect. This selection criterion yields a sample of 94 CEOs. For each firm in which these CEOs worked, I retain all observations. The resulting sample contains 184 firms and 789 firm-year

[11] Bertrand and Schoar (2003) require that every manager serves at each company for at least three years. However, their panel contains 31 years (from 1969 to 1999), whereas my sample period has only six years (from 1999 to 2004). Applying the three-year criterion of Bertrand and Schoar (2003) leads to a sample of only 16 CEOs.

Table 8
PTC, firm performance, and ownership.The table presents the relation of PTC to firm performance and ownership. The sample period is from 1999 to 2004. *CEO is the sole owner* is a dummy variable equal to one if the chief executive officer is also the sole firm owner. *Revenue*, *Debt*, and *Assets* are taken from Rosstat. *Revenue growth* is defined as $[\log(Revenue_{t+1})-\log(Revenue_t)]$. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. * and *** indicate statistical significance at the 10% and 1% level, respectively.

	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 5	0.0117	0.0115	0.0147	0.0160	0.0034	0.0037
	(0.0012)***	(0.0013)***	(0.002)***	(0.0022)***	(0.0008)***	(0.0009)***
CEO is the sole owner	0.0065	0.0015	0.2057	0.2491	0.0255	0.0356
	(0.0064)	(0.0177)	(0.0102)***	(0.0253)***	(0.0039)***	(0.0102)***
PTC top 5x		0.0011		−0.0095		−0.0022
x*CEO is the sole owner*		(0.0036)		(0.005)*		(0.0021)
Debt/Assets	−0.0401	−0.0401	0.1797	0.1795	−0.0612	−0.0612
	(0.0102)***	(0.0102)***	(0.0157)***	(0.0157)***	(0.0078)***	(0.0078)***
Assets decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Revenue decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tax district dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.031	0.031	0.588	0.588	0.893	0.893
Number of observations	99,475	99,475	116,334	116,334	116,334	116,334
Number of firms	37,441	37,441	43,004	43,004	43,004	43,004

observations. I then estimate the following regressions:

$$Performance_t^f=\alpha+\phi_f+\gamma Controls_t^f+\lambda_{CEO}+\theta_t+\varepsilon_t^f, \quad (7)$$

where t is the time index and f is the firm index. $Performance_t^f$ is revenue growth, the log of revenue per employee, or the log of the ratio of revenue to assets. $Controls_t^f$ is a set of firm-level controls that includes *Debt/Assets*, *Industry*, *Assets* decile dummies, *Revenue* decile dummies, and *Tax district* dummies; θ_t are year fixed effects; ϕ_f are firm fixed effects; λ_{CEO} are CEO fixed effects; and ε_t^f is the error term. After obtaining the CEO fixed effects for three measures of firm performance from Eq. (7), I estimate the following regression:

$$\text{FE\_Performance}_{CEO}=\alpha+\beta PTC_{CEO}+\varepsilon_{CEO}, \quad (8)$$

where $\text{FE\_Performance}_{CEO}$ are the CEO fixed effects (λ_{CEO}) for different measures of firm performance (revenue growth, the log of revenue per employee, and the log of the ratio of revenue to assets) obtained in Eq. (7), PTC_{CEO} is the PTC for *CEO*, and ε_{CEO} is the error term. I use a generalized least squares estimation technique to account for the measurement error in the left-hand side variable. All observations are weighed by inverse standard error on the CEO fixed effect variable, which I obtain in the first step regressions. The results are as follows. All β coefficients are statistically insignificant for all three measures of performance.[12] A possible explanation for the absence of significance could be the short panel with a small sample of CEOs who served in multiple firms.

To summarize the results of this subsection, I cannot reach an unambiguous conclusion as to whether corrupt CEOs can carry their abilities across firms. The results presented in Table 7 indicate that the coefficients on PTC are positive and statistically significant for two of three performance measures in the presence of firm fixed effects. However, the examination of the sample of CEOs who served on multiple firms does not provide any statistically significant result. Nevertheless, the positive relation between PTC and measures of firm performance in the presence of firm fixed effects does not imply the causality of this relation because CEOs are not assigned to firms randomly and because their movement across firms is not random.

4.4. Is ownership relevant?

The results reported in Tables 3 and 4 are not conclusive regarding the benefits to company owners of hiring a corrupt manager. Corrupt managers divert more income and have a lower level of transparency than non corrupt managers. However, managers with a high PTC are also associated with superior performance in terms of revenue growth and revenue per employee. Therefore, a question arises as to whether the latter effect depends on company ownership. The relationship between managers and shareholders is subject to agency costs [see Jensen and Meckling (1976) for a detailed discussion of the manager-shareholder conflict]. These costs could significantly deteriorate the possible benefits of managerial corruption for firm performance. To analyze the possible effect of manager-shareholder agency costs, I estimate the following regression:

$$Performance_t^f=\alpha+\beta PTC_t^f+\gamma Ceo\_owner_t^f$$
$$+\delta PTC_t^f Ceo\_owner_t^f+\phi Controls_t^f+\theta_t+\varepsilon_t^f, \quad (9)$$

where t is the time index and f is the firm index. $Performance_t^f$ refers to revenue growth, the log of revenue per employee, or the log of the ratio of revenue to assets. $Ceo\_owner_t^f$ is a dummy variable that is equal to one if the CEO is the sole owner of a company, $Controls_t^f$ is a set of firm-level controls, θ_t is year fixed effects, and ε_t^f is the error term.[13]

[12] The detailed results of this test are available upon request.

Table 9

Propensity to corrupt (PTC) and firm performance: foreign-owned firms.The table presents the relation of PTC to different measures of firm performance for a sample of foreign-owned firms. The sample period is from 1999 to 2004. *Revenue*, *Debt*, and *Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)–log($Revenue_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Revenue growth		Log(*Revenue per employee*)		Log(*Revenue/Assets*)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	−0.0024		−0.0016		0.0061	
	(0.006)		(0.0086)		(0.005)	
PTC top 5		0.0094		0.0001		0.0031
		(0.0057)*		(0.0097)		(0.0046)
Debt/Assets	−0.0717	−0.0305	0.0632	0.0575	−0.0717	−0.1359
	(0.0498)	(0.0371)	(0.0661)	(0.0567)	(0.0453)	(0.0356)***
Assets decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Revenue decile dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tax district dummy	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.078	0.053	0.652	0.640	0.810	0.803
Number of observations	2,814	4,885	3,317	5,757	3,317	5,757
Number of firms	1,294	1,880	1,538	2,237	1,538	2,237

Table 8 presents the estimation results for Eq. (9). As the table data indicate, firms whose CEOs are sole owners show superior performance (Columns 1, 3, and 5). However, the coefficients for the interaction of *PTC* and $Ceo\_owner_t^f$ are not significantly different from zero (Columns 2, 4, and 6). Based on this evidence, I cannot conclude that the effect of managerial corruption on firm performance differs between firms that are owned by CEOs and firms that are not owned by CEOs.

Another interesting question is whether foreign owners can restrict the corruption practices of their local managers. To study this question, I estimate Eq. (6) for the subsample of foreign-owned firms. Table 9 presents the results. As the table data indicate, the coefficients for PTC are statistically and economically insignificant in all specifications except Column 2, in which the corresponding coefficient is marginally significant. This finding is consistent with those of Braguinsky and Mityakov (in press), who report that income transparency (measured as reported earnings when car values are held constant) is four times higher in foreign-owned firms than in domestic firms. Alternatively, it is possible that foreign firms do not hire corrupt managers. Selection criteria in foreign firms are typically much stricter than in Russian firms. Therefore, managers of foreign firms could differ from managers of Russian firms.

5. Conclusion

This paper develops a novel method of measuring corruption at the individual level. I use a unique data set for Moscow traffic violations to infer the PTC for 3.1 million Muscovites.

Based on individual PTC, I build a measure of PTC for the management of 58,157 privately held firms. I show that firms with corrupt management significantly outperform those without corrupt management. A 1 standard deviation increase in company management PTC is associated with a 2.1% increase in the annual revenue growth rate, a 2.5% increase in revenue per employee, and a 0.5% increase in the ratio of revenue to assets. However, corrupt managers divert more income, and their firms exhibit lower income transparency. A 1 standard deviation increase in PTC corresponds to a 0.3% increase in firm revenue transfers to fly-by-night firms.

I suggest several areas for future research. First, it is important to analyze whether PTC is constant or variable over time. For example, does government agency employment increase individual PTC? Conversely, does employment with a foreign company with high corporate governance standards decrease PTC? Another interesting research question could involve the career movement of employees across firms and within the same firm. Who has better opportunities for promotion—a more corrupt employee or a less corrupt employee? Finally, it is important to estimate the effect of corruption on talent allocation across different economic sectors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jfineco.2014.03.002.

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[13] If a firm has multiple owners, then the firm is subject to a manager-shareholder conflict even if a CEO is one of the owners. The CEO can expropriate other owners of the firm, thus deteriorating firm performance.

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